Airbnb's Role in Tourism Gentrification

Working Paper

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Abstract

Since its founding in 2008 Airbnb has spread to over 190 countries and has a total number of listings greater than the top five major hotel brands combined. In this study I document how the proliferation of Airbnb redistributes tourists within cities, and analyze how the redistribution affects the development of firms in the service and entertainment sectors. This is the first study to document the effects of Airbnb on firms outside of the hospitality and housing sectors. First a model of intra-city trade is developed from which two conjectures are drawn. These conjectures are then empirically tested using a novel dataset that combines data on Airbnb from Inside Airbnb with U.S. Census data. The results of the analysis show an increase in Airbnb usage leads to an increase in the number of entertainment sector firms within the area; however, no statistically significant effect is found for the number of firms in the service sector.

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1 Introduction

Airbnb has quickly risen to become the industry leader in peer-to-peer accommodations and is now operating in over 190 countries with over five million listings worldwide (Airbnb, 2018). The reason Airbnb has been able to grow at such a rapid pace is that it allows tourists to rent accommodations directly from local hosts. As a result tourists are redistributed from traditional tourists districts into residential areas. By increasing the presence of tourists within residential areas the local demand for businesses will change. In this paper, I show the presence of Airbnb redistributes tourists within cities and document how their redistribution affects the development of the service and entertainment sectors. This is the first study to analyze the effect of Airbnb outside of the hospitality and housing sectors by examining the role Airbnb plays in tourism gentrification. I develop a model of intra-city trade to examine firm location selection and empirically test two conjectures using a novel dataset. The analysis shows an increase in Airbnb usage within residential areas leads to an increase in the number of entertainment sector firms. In contrast, an increase in Airbnb usage is shown to have no statistically significant effect on service sector firms.

First introduced in 2007 as a solution to two problems, founders Joe Gebbia and Brian Chesky created Airbnb as a way to help pay their rent and resolve a shortage of accommodations for attendants of a San Francisco design conference.[1] Since then Airbnb has grown from a solution to a market shortage to a viable and sought out alternative to conventional tourist accommodations. As a result the hotel industry has experienced significant declines in revenues. Additionally by utilizing residential housing, the proliferation of Airbnb has led to increased rents and housing shortages. The effects have grown so large in some areas that cities, including San Francisco (Brousseau et al., 2015) and New York (NY State AG, 2014), have conducted their own studies documenting the effects Airbnb has had on rental availability and the cost of affordable housing. While it is important to understand the effects Airbnb has had on these industries the effects are not limited to the hospitality and housing sectors.

Airbnb has also impacted the flow of tourism, which is an important source of revenue for many cities. Data from the World Tourism Organization (UNWTO) shows tourist arrivals have shown virtually uninterrupted growth since 1980 (UNWTO, 2012). Furthermore, in their 2018 report the World Travel and Tourism Council (WTTC) states within the U.S. tourism directly accounts for 2.6% of total GDP, and is forecasted to rise by 3.4% in 2018 (WTTC, 2018). Consequently cities have invested substantial funds in new infrastructure, refurbishing, and developing new brand images (Judd, 1991). New infrastructure is typically centered around already established major tourist attractions (e.g. sports stadiums, convention centers, etc.), which has resulted in the creation of tourist districts.[2] Accordingly, most traditional tourist accommodations are located in or around these districts thus constricting tourists to locating in the tourist district as well. Because Airbnb allows tourists to rent directly from local hosts, individuals who are looking for an alternative to the traditional accommodation are able to stay in areas and city neighborhoods that were previous less accessible.

[1]See *The Airbnb Story: How Three Ordinary Guys Disrupted an Industry, Made Billions... and Created Plenty of Controversy* for more details about the founding and subsequent rise of Airbnb.

[2]Getz (1993) defines tourist districts as areas with high concentrations of entertainment businesses and visitor-oriented attractions and services located in conjunction with central business districts.

By redistributing tourists, Airbnb is changing the aggregate demand for goods and services within residential areas. Both tourists and residents patronize a variety of businesses, but tourists have a preference for entertainment like bars, restaurants, and clubs, while residents have a stronger preference for services like barbers, hardware stores, and grocers. The resulting change in the composition of demand stemming from the increased presence of tourists will alter the incentives for firms to enter the residential area. More tourists in the area increases the demand for entertainment, which can lead to an increase in the presence of entertainment firms. If left unchecked this process can lead to tourism gentrification. Gotham (2005) defines "tourism gentrification" as the "...transformation of a middle-class neighbourhood into a relatively affluent and exclusive enclave marked by a proliferation of corporate entertainment and tourism venues." He then goes on to discuss how the introduction of tourism into New Orleans' French Quarter resulted in tourism gentrification.[3] The purpose of this paper is to examine the role Airbnb plays in one part of tourism gentrification - the development of businesses within the entertainment sector.

To analyze the impact of Airbnb usage on firms in the entertainment and service sectors I adapt Krugman's (1980) model of international trade to address intra-city trade. The model shows an increased presence of tourists within an area leads to an increase in the number of entertainment sector firms and decreases the number of firms in the service sector. The incentive for entertainment sector firms to enter the area increases in response to a rise in tourism due to the increase in local demand. Conversely, the increased demand for retail space causes service sector firms to exit the market due to fixed costs, such as rents, rising faster than local demand. These two conjectures are empirically tested using a novel dataset that combines Airbnb data from Inside Airbnb with data from the U.S. Census. Results of the empirical analysis show that an increase in Airbnb usage leads to an increase in the number of entertainment sector firms within the area; however, no statistically significant effect is found for the number of firms in the service sector.

The remainder of the paper is structured as follows. Section 2 provides a brief overview of the relevant literature. Section 3 describes the theoretical model and conjectures. Section 4 details the estimation strategy and describes the data. Section 5 presents the empirical results. Finally, Section 6 concludes.

2 Literature Review

Airbnb's rapid rise in popularity combined with the lack of regulation has led researchers to consider it a disruptive innovation within both the hospitality and housing sector. Work by Guttentag and Smith (2017) and Zervas et al. (2017) have shown the negative effect Airbnb has had on hotel revenues. Additionally, Schäfer and Braun (2016) and Lee (2016) study the impact Airbnb has had on the availability of residential flats in the Berlin housing market and affordable housing in the Los Angeles area, respectively. While it is important to understand the impact Airbnb has had on these sectors, Airbnb has also been shown to have effects on industries outside the hospitality and housing sectors.

[3] See *Tourism and Gentrification in Contemporary Metropolises* for more case studies of tourism gentrification and a discussion of the literature.

Alyakoob and Rahman (2018) argue the introduction of Airbnb has spillover effects on complementary local industries. They focus specifically on the restaurant industry, and show an increase in the intensity of Airbnb activity has led to an increase in restaurant employment. Though Alyakoob and Rahman do not explicitly address it, their work also suggests the intensity of Airbnb activity effects the aggregate demand for goods and services within the area. For example, as more tourists utilize Airbnb the demand for restaurants will increase, which will lead to an increase in employment within the restaurant industry as documented by Alyakoob and Rahman. Ioannides et al. (2018) finds a similar result with respect to the Lombok neighborhood in the city of Utrecht.

Tourists, however, do not just have a demand for restaurants. Rather, an increase in tourism will raise the demand for a broader set of entertainment firms including restaurants, bars, clubs, and other tourist attractions. A more inclusive definition of the "entertainment" sector is used in this paper to allow for these other types of entertainment firms. Under this more general definition, the introduction of Airbnb into an area could lead to the growth of a thriving entertainment district, further increasing the area's appeal to tourists, and increase the incentive for firms in the entertainment sector to enter. Underlying this theory is the idea that a firm's entry decision responds to changes in local demand, which depends on the demographics of the area. This idea is closely related to the "home market" effect developed by Krugman (1980).[4] Therefore, this paper adapts Krugman's model of international trade in a novel way to model intra-city trade.[5]

Using this model a theoretical foundation for the connection between Airbnb and tourism gentrification is developed. The conjectures are then tested empirically using data from multiple cities within the U.S. Prior to this point the connection between Airbnb and tourism gentrification has been limited to case studies (Cócola-Grant, 2018; Sans and Domínguez, 2016). These studies provide detailed analyses of the impact Airbnb has had on the local community, but the implications of the results are limited to the particular case being studied. By analyzing data from multiple cities this paper is able to extend prior work by showing a systematic connection between Airbnb usage and the presence of entertainment and service sector firms.

3 Theoretical Model

A result of cities investing in the growth of their tourism industry has been the formation of tourist districts. In his research, Getz (1993) discusses planning strategies for the creation of tourist districts, mentioning zoning as a means to encourage the desired development within a controlled area. In order to promote its growth as a tourist destination the downtown area is zoned primarily for commercial use.[6] Conversely, areas outside the downtown area are zoned for residential and limited commercial use. As a result most tourist accommodations, and therefore tourists, are located downtown where as most residents are located outside the downtown area in residential districts or neighborhoods. Though residents and tourists reside in different districts within the city they are able to travel between districts to consume the products produced in the other district.

[4]The "home market" effect states that a country will be a net exporter in the industry for which it has the larger home market (local demand).

[5]The model developed in this paper is also closely aligned with the work of Fujita (1988).

[6]It should be noted more recent city zoning policies have adopted mixed use zoning; zoning allowing both commercial and residential use. This has mainly been in the downtown area and popular commercial districts.

The traveling between districts can be thought of as intra-city "trade."

In this section I develop a model of intra-city trade comprised of two geographic districts, two production sectors, and two types of consumers. The two districts are defined as district 1, the downtown district, and district 2, the residential district. The two sectors of production are an entertainment (E) sector and a service (S) sector. Both sectors are assumed to have a large variety of differentiated goods, so many that the production space for each sector can be represented as a continuum of products. Firms are able to occupy either district, and the distribution of firms across the two districts will be determined endogenously.

The two types of consumers in the model are defined as tourists (T) and non-tourists (N). Tourists are interpreted as consumers who do not reside in the city and are visiting for a short period of time. Since tourists are not spending extended time within the city they have little need for most of the products produced by the service sector and therefore predominantly consume goods from the entertainment sector. Conversely, non-tourists are consumers who are residents of the city or staying within the city for an extended period of time. As a result non-tourists have a stronger preference for service sector products, though they still consume some goods produced by the entertainment sector. The distribution of consumers across districts is determined exogenously.[7] Tourists and non-tourists in district j have Cobb-Douglas preferences over the two sectors given by the respective utility functions

$$U_j^T = C_{Ej}^{\mu} C_{Sj}^{1-\mu} \qquad U_j^N = C_{Ej}^{\lambda} C_{Sj}^{1-\lambda},$$

where μ (λ) represents the expenditure share on entertainment goods by tourists (non-tourists), $\mu > \lambda$, and C_{ij} represents a composite index of the consumption of sector $i \in \{E, S\}$ available to consumers in district j. The quantity index, C_{ij}, is a sub-utility function defined over the continuum of varieties available to consumers in district j. Let $c_{ijk}(\omega)$ denote the consumption of each available variety of sector i good in district j from district k, and n_{ik} denote the range or "number" of varieties available in sector i in district k. Assume C_{ij} is defined by a constant elasticity of substitution (CES) function

$$C_{ij} = \left[\sum_{k=1}^{2} \int_0^{n_{ik}} c_{ijk}(\omega)^{\rho} d\omega \right]^{\frac{1}{\rho}}, \quad 0 < \rho < 1,$$

where $k \in 1, 2$ represents the two districts in the economy: the downtown and the residential district.

Consumers are able to purchase products in either location; however, if a consumer from district j consumes a product from district k she will incur a transportation cost. The cost of transportation from district j to district k will be represented as a markup over the price of the good in district k. Therefore the price to a consumer in district j of consuming good i from district k will be the

[7] The exogeneity of the tourist distribution requires some additional assumptions. First, all tourists redistributed into the residential district are able to be accommodated. Second, non-tourists do not earn income from hosting a tourist. In reality, the movement of tourists is an endogenous process governed by the supply of and demand for Airbnb. However allowing the tourist distribution to be endogenous would necessitate the addition of a market for Airbnb, which would substantially complicate the model, and is left for future research.

price in district k times the transportation cost, $p_{ijk} = p_{ik}\tau_{jk}$ where $\tau_{jk} \geq 1$.[8] When $j = k$ $\tau_{jk} = 1$.

3.1 Consumer Problem

Consumers receive an exogenous income Y. Given Y, $p_{Ek}(\omega)$ for each entertainment firm, and $p_{Sk}(\omega)$ for each service firm the consumer's problem is to maximize utility subject to the budget constraint

$$Y = \sum_{k=1}^{2} \int_0^{n_{Ek}} p_{Ek}(\omega)\tau_{jk}c_{Ejk}(\omega)d\omega + \int_0^{n_{Sk}} p_{Sk}\tau_{jk}(\omega)c_{Sjk}(\omega)d\omega.$$

The consumer's problem can be solved in two steps. First, given the value of the composite for good i, C_{ij}, each $c_{ijk}(\omega)$ needs to be chosen so as to minimize the cost of attaining C_{ij}. Therefore, consumers will solve the following cost minimization problem

$$\min \sum_{k=1}^{2} \int_0^{n_{ik}} p_{ik}(\omega)\tau_{jk}c_{ijk}(\omega)d\omega \quad \text{s.t.} \quad C_{ij} = \left[\sum_{k=1}^{2} \int_0^{n_{ik}} c_{ijk}(\omega)^{\rho} d\omega\right]^{\frac{1}{\rho}}.$$

For simplicity assume all firms producing good i in district k sell their good for the same price, p_{ik}. Then the consumer's problem can be written as

$$\min \sum_{k=1}^{2} n_{ik}p_{ik}\tau_{jk}c_{ijk} \quad \text{s.t.} \quad C_{ij} = \left[\sum_{k=1}^{2} n_{ik}c_{ijk}^{\rho}\right]^{\frac{1}{\rho}}.$$

First-order conditions to the expenditure minimization problem gives

$$\frac{c_{ijk}^{\rho-1}}{c_{ijl}^{\rho-1}} = \frac{p_{ik}\tau_{jk}}{p_{il}\tau_{jl}}.$$

Plugging this condition into the budget constraint and solving for c_{ijl} yields the compensated demand function for a good in sector i produced in district l and consumed in district j,

$$c_{ijl} = \frac{(p_{il}\tau_{jl})^{\frac{1}{\rho-1}}}{\left[\sum_{k=1}^{2} n_{ik}\left(p_{ik}\tau_{jk}\right)^{\frac{\rho}{\rho-1}}\right]^{\frac{1}{\rho}}} C_{ij}.$$

We can also derive an expression for the minimum cost of attaining C_{ij}. Expenditure on a single variety of sector i is $p_{il}\tau_{jl}c_{ijl}$, so using the above equation, summing over all varieties and summing over districts l gives

$$\sum_{l=1}^{2} n_{il}p_{il}\tau_{jl}c_{ijl} = \left[\sum_{k=1}^{2} n_{ik}\left(p_{ik}\tau_{jk}\right)^{\frac{\rho}{\rho-1}}\right]^{\frac{\rho-1}{\rho}} C_{ij}.$$

[8]The transportation cost used in this model is similar to Samuelson's "iceberg" transportation costs. Consumers face higher prices as a result of having to travel to consume the product. However, unlike in the traditional application of iceberg costs, no physical product "melts away" or is lost in transport. Therefore, firms only have to produce what is actually demanded. The "transportation" cost is intended to capture the additional cost incurred by consumers for the inconvenience or time it take to travel to a different district.

The term multiplying C_{ij} on the right-hand side of the expression can be defined as the price index, so that the price index times the quantity composite is equal to expenditure. Denote the price index for sector i in district j as $\mathbb{P}_{ij}$ which gives

$$\mathbb{P}_{ij} = \left[\sum_{k=1}^{2} n_{ik} \left(p_{ik}\tau_{jk}\right)^{\frac{\rho}{\rho-1}}\right]^{\frac{\rho-1}{\rho}} = \left[\sum_{k=1}^{2} n_{ik} \left(p_{ik}\tau_{jk}\right)^{1-\sigma}\right]^{\frac{1}{1-\sigma}}$$

where $\rho \equiv \frac{\sigma-1}{\sigma}$. The price index, $\mathbb{P}_{ij}$, measures the minimum cost of purchasing a unit of the composite index C_{ij} of sector i. Demand for c_{ijk} can now be written more compactly as

$$c_{ijk} = \left(\frac{p_{ik}\tau_{jk}}{\mathbb{P}_{ij}}\right)^{\frac{1}{\rho-1}} C_{ij} = \left(\frac{p_{ik}\tau_{jk}}{\mathbb{P}_{ij}}\right)^{-\sigma} C_{ij}. \tag{1}$$

The upper-level step of the consumer's problem is to divide total income between entertainment and service sector goods in aggregate, that is, to choose C_{Ej} and C_{Sj} so as to

$$\max\ U = C_{Ej}^{\mu} C_{Sj}^{1-\mu} \quad \text{s.t.} \quad Y = \mathbb{P}_{Ej}C_{Ej} + \mathbb{P}_{Sj}C_{Sj}.$$

Since tourists and non-tourists have comparable problems the analysis conducted for the remainder of this subsection will focus on tourists, but a similar strategy can be applied to the non-tourist's problem. The results of the first-order conditions from the problem above are $C_{Ej} = \mu\frac{Y}{\mathbb{P}_{Ej}}$ and $C_{Sj} = (1-\mu)\frac{Y}{\mathbb{P}_{Sj}}$. Plugging these solutions into (1) gives the following uncompensated demand functions for products produced in district k and consumed in district j

$$c_{Ejk} = \mu Y \frac{(p_{Ek}\tau_{jk})^{-\sigma}}{\mathbb{P}_{Ej}^{-(\sigma-1)}} \qquad c_{Sjk} = (1-\mu) Y \frac{(p_{Sk}\tau_{jk})^{-\sigma}}{\mathbb{P}_{Sj}^{-(\sigma-1)}}.$$

Summing across all locations in which the product is sold, total sales to tourists for a single location variety k, denoted q_{ik}^{T}, is given by

$$q_{Ek}^{T} = \mu Y \sum_{j=1}^{2} s_j^T \frac{(p_{Ek}\tau_{jk})^{-\sigma}}{\mathbb{P}_{Ej}^{-(\sigma-1)}} \qquad q_{Sk}^{T} = (1-\mu) Y \sum_{j=1}^{2} s_j^T \frac{(p_{Sk}\tau_{jk})^{-\sigma}}{\mathbb{P}_{Sj}^{-(\sigma-1)}}, \tag{2}$$

where s_j^T represents the share of the total population that is tourists in district j. The indirect utility function is able to be obtained by plugging the solutions from (2) into the utility function,

$$U_j^T = \mu^{\mu}(1-\mu)^{1-\mu} Y \mathbb{P}_{Ej}^{-\mu} \mathbb{P}_{Sj}^{-(1-\mu)}.$$

The term $\mathbb{P}_{Ej}^{-\mu}\mathbb{P}_{Sj}^{-(1-\mu)}$ can be interpreted as the cost-of-living index for district j.

3.2 Firm Problem

Firms' profits from producing a specific variety of sector i good in district j is given by

$$\pi_{ij} = p_{ij}Q_{ij} - cQ_{ij} - F,$$

where Q_{ij} is the total demand by tourists and non-tourists, $Q_{ij} = q_{ij}^T + q_{ij}^N$, with q_{ij}^T and q_{ij}^N are defined by (2), p_{ij} is the price the firm charges in district j for the sector i good, c is the constant marginal cost of production, and F is the fixed cost of production. The fixed cost should be thought of as rent paid by the firm. For now fixed costs are assumed to be independent of the number of firms in the district, but this assumption will be relaxed in the next section. Each firm is assumed to choose its price taking the price index, $\mathbb{P}_{ij}$, as given. Entertainment and service firms have symmetric problems so this analysis will focus on entertainment firms for the remainder of this subsection. Profit maximization implies

$$p_{Ej}^{*} = \left(\frac{\sigma}{\sigma - 1}\right) c$$

for all varieties produced in location j.[9] Firms are allowed to freely enter and exit the market in response to profits or losses. Given the pricing rule derived above, the profits of a firm in district j are

$$\pi_{Ej} = \frac{cQ_{Ej}}{\sigma - 1} - F.$$

Imposing the zero-profit condition implies the equilibrium output of any active firm will be

$$Q_{Ej}^{*} = \frac{F(\sigma - 1)}{c}.$$

The equations for p_{Ej}^{*} and Q_{Ej}^{*} reveal the size of the market will not affect the markup of price over marginal cost nor the quantity at which individual goods are produced. Therefore, all market effects will work through changes in the number of varieties that are available. This result is an artifact of assuming demand has constant-elasticity of substitution along with assuming firms behave non-strategically, i.e. take the price index as given.[10]

To determine the optimal number of firms substitute the zero-profit quantity, Q_{Ej}^{*}, the optimal price, p_{Ej}^{*}, and the equation for the price index into the equation for Q_{Ej} to get

$$F\sigma = \frac{\mu Y s_1^T + \lambda Y s_1^N}{n_{E1} + n_{E2}\tau^{1-\sigma}} + \frac{\left(\mu Y s_2^T + \lambda Y s_2^N\right)\tau^{-\sigma}}{n_{E1}\tau^{1-\sigma} + n_{E2}}$$

for district 1 and

$$F\sigma = \frac{\left(\mu Y s_1^T + \lambda Y s_1^N\right)\tau^{-\sigma}}{n_{E1} + n_{E2}\tau^{1-\sigma}} + \frac{\mu Y s_2^T + \lambda Y s_2^N}{n_{E1}\tau^{1-\sigma} + n_{E2}}$$

for district 2. Setting these two equations equal to each other and solving yields

$$n_{E1}^{*} = \frac{\mu Y s_1^T + \lambda Y s_1^N}{F\sigma\left(1 + \frac{(\psi\tau^{1-\sigma}-1)}{(\tau^{1-\sigma}-\psi)}\tau^{1-\sigma}\right)} + \frac{\left(\mu Y s_2^T + \lambda Y s_2^N\right)\tau^{-\sigma}}{F\sigma\left(\tau^{1-\sigma} + \frac{(\psi\tau^{1-\sigma}-1)}{(\tau^{1-\sigma}-\psi)}\right)} \tag{3}$$

$$n_{E2}^{*} = \frac{\mu Y s_1^T + \lambda Y s_1^N}{F\sigma\left(\frac{(\tau^{1-\sigma}-\psi)}{(\psi\tau^{1-\sigma}-1)} + \tau^{1-\sigma}\right)} + \frac{\left(\mu Y s_2^T + \lambda Y s_2^N\right)\tau^{-\sigma}}{F\sigma\left(\frac{(\tau^{1-\sigma}-\psi)}{(\psi\tau^{1-\sigma}-1)}\tau^{1-\sigma} + 1\right)}, \tag{4}$$

[9] Derivation of the profit maximizing price can be found in the Appendix.

[10] Relaxing either of these assumptions would allow the market size to have pro-competitive effects. As more firms enter the market the price-cost margin would decrease implying firms would need to operate at a higher quantity in order to break even (Fujita et al., 2001). This extension is left for future research.

where $\psi = \frac{\mu Y s_1^T + \lambda Y s_1^N}{\mu Y s_2^T + \lambda Y s_2^N}$. A similar solution method can be used to find the optimal number of service firms for district 1, n_{S1}^*, and district 2, n_{S2}^*. To ensure the number of firms in all locations is non-negative, $n_{i1}^* \geq 0$ and $n_{i2}^* \geq 0$,

$$\tau^{1-\sigma} < \psi < \tau^{\sigma-1}$$

and

$$\tau^{1-\sigma} < \phi < \tau^{\sigma-1}$$

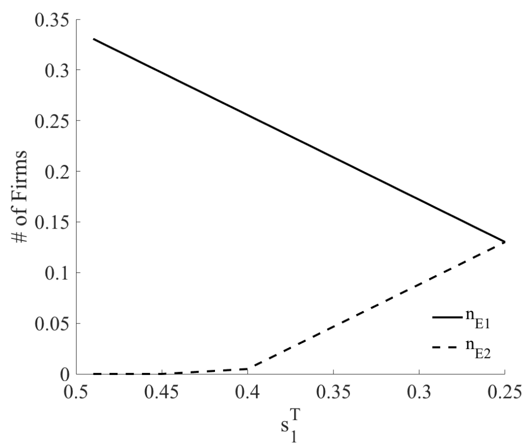
where $\phi = \frac{(1-\mu)Y s_1^T + (1-\lambda)Y s_1^N}{(1-\mu)Y s_2^T + (1-\lambda)Y s_2^N}$.

3.3 Numerical Analysis

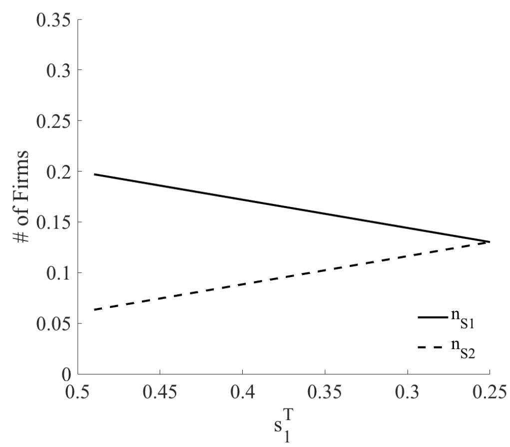
The purpose of this section is to better understand the relationship between the number of firms and the distribution of tourists by conducting a numerical analysis. Figure 1 plots equations (3) and (4) and the corresponding equations for the number of service firms as a function of the proportion of tourists in district one (downtown), s_1^T.[11] Assume there is a unit mass of consumers equally split between tourists and non-tourists, $s^T = 0.5$ and $s^N = 0.5$. Before Airbnb is introduced all the tourists reside downtown so $s_1^T = 0.5$ and $s_2^T = 0$. Figure 1a shows at this initial point all entertainment firms choose to locate downtown. As tourists start utilizing Airbnb s_1^T will decrease and s_2^T will increase. Consequently, the number of entertainment firms downtown will decrease while the number of entertainment firms in the residential district will increase. This result is consistent with the home market effect.

Conjecture 1. *Increasing the proportion of tourists within a district will lead to an increase in the number of entertainment sector firms.*

Figure 1



(a) Entertainment Sector



(b) Service Sector

[11]Other parameters are assumed to be $s_1^N = s_2^N = 0.25$, $\mu = 0.75$, $\lambda = 0.25$, $t = 1.5$, $\sigma = 3.5$, $F = 1$, and $Y = 2$.

Figure 1b shows the effect redistributing tourists has on the number of service firms. As the fraction of tourists downtown decreases the number of service firms downtown also decreases. Conversely, the number of service firms in the residential district increases in response to an increase in the fraction of tourists. Although tourists do not primarily consume service sector products, the model assumes tourists consume some service sector products. When combining the additional demand from redistributed tourists with the existing demand from non-tourists in the district the aggregate local demand for service sector firms increases. The subsequent increase in the number of service sector firms is consistent with the home market effect. However, this result does not agree with the observations about tourism gentrification made by Gotham (2005) and Cócola-Grant (2018). For the model to exhibit tourism gentrification the number of service firms in the residential district would need to decline as the presence of tourists and, thus, entertainment firms increased.

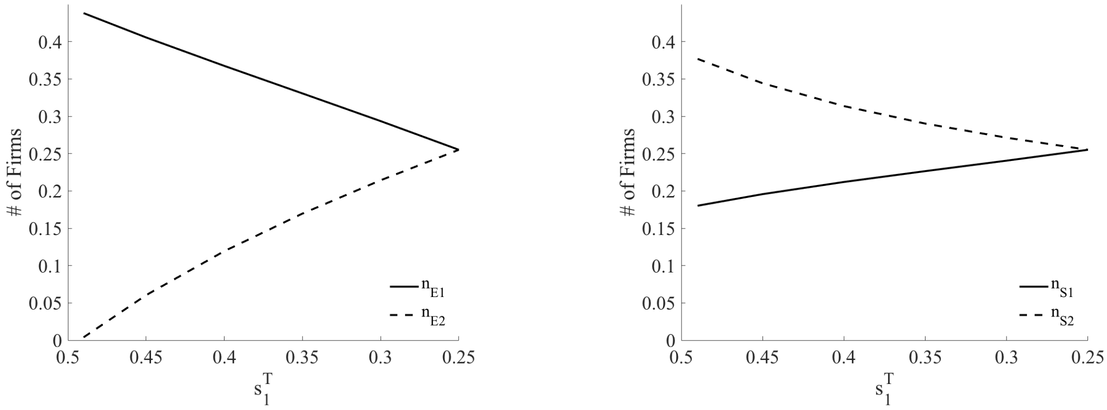
The reason the model does not exhibit tourism gentrification is because it does not incorporate the effects of congestion, land scarcity, and rising rents. By holding fixed costs constant the model assumes a district is able to accommodate an infinite number of firms at no additional cost, which is not realistic. Land rents rise with demand (Fujita, 1988; Sivitanidou and Wheaton, 1992; Anas and Xu, 1999). Therefore, as the number of firms in a district increases, and with it demand for retail space, the fixed cost of locating in the region will also increase. The next section extends the model to allow fixed costs to be a function of the number of firms and analyzes how the change impacts the results.

3.4 Endogenous Fixed Costs

Following the literature on urban economics, fixed costs for district j are assumed to be an increasing function of the number of firms within the district, $F_j(n_{Ej}, n_{Sj})$. For simplicity, the function for fixed costs is assumed to be linear, $F_j = n_{Ej} + n_{Sj}$. Figure 2 plots the number of firms for each district as a function of the number of tourists in district one (downtown), s_1^T. The mass of consumers is again assumed to be one and equally split between tourists and non-tourists.

The plot of entertainment firms in Figure 2a tells a similar story to what was seen in Figure 1a. When tourists reside in only the downtown district all entertainment firms choose to locate downtown. Then as tourists are redistributed to the residential district the number of entertainment firms in the residential district (n_{E2}) increases, while the number of entertainment firms downtown (n_{E1}) decreases. The results in Figure 2a are consistent with the home market effect. As the local demand for entertainment firms increases or decreases the number of entertainment firms increases or decreases, respectively.

Figure 2



(a) Entertainment Firms

(b) Service Firms

In contrast, the effect of redistributing tourists on the number of service firms within a district now runs counter to the home market effect. As tourists are redistributed into district two the number of service firms in the district declines even though local aggregate demand for service firms is increasing. This result occurs because fixed costs are increasing, due to an increase in the number of entertainment firms, at a faster pace than revenue. Therefore, profit maximizing service firms will choose to exit the more expensive district two and relocate to district one.[12] The result of Airbnb redistributing tourists into the residential district is an increase of firms in the entertainment sector crowding out firms in the service sector, also known as tourism gentrification.

Conjecture 2. *Increasing the proportion of tourists within a district will lead to a decrease in the number of service sector firms.*

4 Empirical model and estimation

The theoretical model presented in the previous section yields two main conjectures about how redistributing tourists affects firms within a local community. First, as more tourists enter the residential district the number of entertainment sector firms will increase due to an increase in local aggregate demand. Second, service sector firms in the residential area are crowded out as a result of fixed costs increasing faster than revenue. The empirical analysis presented in this section analyzes the validity of these conjectures for 248 Public Use Microdata Areas (PUMA) across the U.S. from 2005 to 2016.[13]

[12]The decision to relocate to district one should be interpreted more generally as a decision to relocate out of district two. Since the model only includes two districts service sector firms can only choose to locate in district one or district two. If the model was extended to allow more districts service sector firms may choose to relocate to a district other than district one.

[13]Data is aggregated at the PUMA level since this is the smallest geographic unit made publicly available by the U.S. Census. A PUMA is defined by the Census as statistical geographic area nested within states. It contains at least 100,000 people, is built on census tracts and counties, and is geographically contiguous (U.S. Census, 2015).

4.1 Empirical Model

To investigate the questions proposed by the theoretical model, the following reduced-form specification for the number of firms within a PUMA is developed:

$$n_{ijt} = \mu_{ij} + \beta_{1i}s_{jt-1} + \beta_{2i}X_{jt-1} + \epsilon_{ijt}, \tag{5}$$

where i denotes the business sector, $i \in \{E, S\}$, j denotes the PUMA, and t denotes time in years. The variable n_{ijt} denotes the number of businesses in sector i within PUMA j at time t, while s_{jt-1} denotes the measure of tourists within a PUMA from the previous year. Tourism data is routinely available at the city level; however, tourism data at a more disaggregated level is not as common. Therefore instead of using explicit measures of tourism at the PUMA level, data on Airbnb usage is employed as a proxy. Whenever an Airbnb listing is rented a tourist(s) is residing at the listing during the rental period. Therefore, by measuring the number of Airbnb listings rented within a PUMA during the year the model is able to approximate the number of tourists that were redistributed into the PUMA.

Of course, Airbnb is not the only way for tourists to reside outside of a city's downtown district; hotels can exist outside a city's central business district or downtown as well.[14] The empirical model attempts to separate the effects of tourists using Airbnb from those using hotels by including a count of the number of hotels.[15] This variable along with the total population and median income are included in X_{jt-1}, a vector of PUMA specific time-varying controls. Finally, μ_{ij} denotes PUMA fixed effects for sector i, the β's are the parameters to be estimated, and ϵ_{ijt} is the idiosyncratic error.

Lagged measures of the independent variables are used because firm's entry decision is inherently a slow moving process. It takes time for a firm to find a location and acquire the necessary inputs. Consequently, a firm deciding that market conditions are right for entry at time $t-1$ will likely not be observed entering the market until time t. For this reason lag, rather than contemporaneous, measures of the independent variables are included in the reduced form model.

4.2 Estimation strategy

Standard fixed effects methodology can be implemented to estimate (5), which allows the model to control for unobserved heterogeneity across PUMAs. Additionally using fixed effects allows the unobserved heterogeneity to be correlated with the regressors. For example, median income and total population are likely correlated with unobserved attributes of the PUMA, such as the quality of the area. Not accounting for this relationship would bias the estimates.[16] By including fixed

[14] Tourists are not confined to the immediate area around their accommodation. They are able to travel throughout a city, which means the economic impact of a tourist may not be limited to the area immediately around their accommodation. Though without detailed data on tourist flows within a city it is not possible tract their economic impact. Additionally, research by Versichele et al. (2014) and Shoval et al. (2011) show tourists typically spend most of their time and money around the area of their accommodation, which suggests a majority of the economic impact of tourists will occur around where their accommodation is located.

[15] A count of hotel room rentals would be a more accurate measure of the number of tourists brought into the area by hotels, but the data on rental rates and room counts are not available at the PUMA level.

[16] Results of the Hausman test suggest a fixed effects specification is preferred to random effects, which supports the claim observed regressors are correlated with unobserved heterogeneity.

effects the model accounts for endogeneity caused by the unobserved heterogeneity; however it does not control for other sources of endogeneity.

The types of firms within an area depend on where tourists choose to locate. Additionally, it is likely where tourists choose to locate will be, at least partially, determined by the types of firms within the area. The cyclical nature of this problem leaves the model open to endogeneity bias that is not removed by the inclusion of fixed effects. Let Airbnb usage in district j at time t (s_{jt}) be represented by the following reduced form equation

$$s_{jt} = \nu_j + \beta_3 n_{Ejt} + \beta_4 n_{Sjt} + \beta_5 Z_{jt} + \gamma_{jt}, \tag{6}$$

where n_{Ejt} is the number of entertainment sector firms and n_{Sjt} is the number of service sector firms within PUMA j at time t, Z_{jt} is a vector of PUMA level observable characteristics, ν_j represents PUMA fixed effects, and γ_{jt} represents the error term. Unlike (5), the measure of Airbnb usage, s_{jt}, depends on contemporaneous regressors. A survey conducted by Gitelson and Crompton (1983) shows over 70% of individuals plan a vacation less than three months in advance, which suggests current, rather than lagged, characteristics of an area will influence their location decision. Therefore, the reduced form model states Airbnb usage at time t depends on PUMA level characteristics and sector firm counts at time t.

While estimating (6) is not the focus of this paper, the equation can be used to provide conditions for the exogeneity of s_{jt}, $\mathbb{E}[\epsilon_{ijt} s_{jt-1}] = 0$. Substituting (6) into the equation of strict exogeneity of s_{jt-1} yields

$$\mathbb{E}[\epsilon_{ijt}(\nu_j + \beta_3 n_{ijt-1} + \beta_4 Z_{jt-1} + \gamma_{jt-1})] = 0,$$

which will hold as long as (i) the errors in the two equations are independent, $\mathbb{E}[\epsilon_{ijt}\gamma_{jt-1})] = 0$, (ii) the error ϵ_{ijt} is independent of PUMA fixed effects, $\mathbb{E}[\epsilon_{ijt}\nu_j] = 0$, (iii) the error ϵ_{ijt} is independent of the explanatory variables in Z_{jt-1}, $\mathbb{E}[\epsilon_{ijt} Z_{jt-1}] = 0$, and (iv) the errors do not exhibit autocorrelation, $\mathbb{E}[\epsilon_{ijt}\epsilon_{ijt-1}] = 0$.[17] Results of both the Arellano and Bond (1991) and Wooldridge (2010) test for serial correlation reject the null hypothesis of no autocorrelation. The strict exogeneity assumption on s_{jt-1} fails.

A common method for addressing endogeneity is to estimate the model using an instrumental variable (IV) approach. The percentage of households with internet will be used as an instrument for Airbnb usage. To host an accommodation an individual needs to have access to Airbnb's website. If an individual has access to internet within the home it is more convenient for the individual to post a listing. As a result it is more likely the individual will choose to list their property. Furthermore, as the number of listings within an area increases so too will Airbnb usage.[18] Therefore, household internet penetration is positively correlated with Airbnb usage.

Conversely, a firm's entry decision does not depend on household internet penetration. The types of firms being studied in this paper are those that provide a good or service that must be consumed in person. An individual cannot go to a restaurant or bar online. Additionally,

[17] The final condition was obtained by substituting a lagged version of (5) into $\mathbb{E}[\epsilon_{ijt} n_{ijt-1}] = 0$.

[18] Though more listings within an area does not necessitate higher levels of Airbnb activity, based on the Airbnb data collected the correlation coefficient between the number of listings and number of reviews, a proxy for usage, within a PUMA is $R = 0.8710$.

traditional brick-and-mortar retailers as well as service providers like barbers and lawyers still require individuals to visit a physical location in order to consume their product. Thus, the entry decision for these firms will depend on the fixed cost and demographics of the PUMA, which are independent of internet accessibility.

There does exist a subset of firms whose entry decision is likely to be dependent on internet accessibility. Firms providing a good or service that can be consumed online, for example online retailers and service providers like Amazon and Google. Since their products can be consumed or purchased online, these firms do not need to be in the immediate vicinity of their consumers. Accordingly, any changes in local demand, such as from an increase in tourism, will have no effect on the location decision of online retailers. For this reason these firms are not included in either the entertainment or service sector count of firms.[19]

A potential criticism of using internet penetration as an instrument for Airbnb usage is that it is a weak instrument, and, therefore, any estimates will suffer from weak instrument bias. Though the Kleibergen-Paap Wald rk F statistic rejects the weak instrument hypothesis, the correlation between the Airbnb usage and internet penetration is low, $R = 0.15$. Moreover, data on internet penetration is only available from 2013 to 2016. Therefore estimates using this shortened time series will measure the effect for only the last four years. Ideally an alternative instrument would be used to check the robustness of the results, but a strong external instrument is difficult to find. A natural next step is to look within the dataset to generate instruments via lags of the endogenous regressors; however, by demeaning the data lagged values of Airbnb usage become embedded in the transformed error and, therefore, are invalid instruments.

Alternatively, first differences can be used to transform the data that will remove the fixed effects and avoid making lagged values of Airbnb usage endogenous.[20] Though, first differencing does result in the differenced error, $\Delta\epsilon_{ijt}$, no longer being i.i.d. Consequently, using 2SLS results in distorted estimates. Following the work of Arellano and Bond (1991) and Arellano and Bover (1995)/Blundell and Bond (1998), more efficient, better behaving estimates can be achieved using system Generalized Method of Moments (GMM).

System GMM utilizes moment conditions based on lagged levels, $E(s_{jt-L}\Delta\epsilon_{ijt}) = 0$ for $t \geq 3$ and $L \geq 2$, as well as lagged first differences, $E(\Delta s_{jt-1}\epsilon_{ijt}) = 0$ for $t \geq 3$. Including both sets of moment conditions improves the estimates by taking advantage of more information, but also opens up the model to possibly over fitting endogenous variables. The Hansen test can be employed to diagnose any over fitting. Following the work of Roodman (2009), if the Hansen test has a p-val of at least 0.25 then it can be concluded the endogenous variables are not being over fit.[21]

[19]Online retailers have a unique NAICS code, 454110, which allows them to be separately identified from brick-and-mortar retailers.

[20]The two most common transformations used when instrumenting with lags in the presence of fixed effects are first differencing and forward orthogonal projections (Arellano and Bover, 1995). Arellano and Bover show with balanced panels any two transformations of full row rank will yield numerically identical estimators, holding the instrument set fixed. The panel used in this paper is unbalanced, but only for one PUMA, PUMA 2400 in New Orleans that is missing two years of data. Results are robust to the use of the forward orthogonal transformation.

[21]If the model does suffer from over fitting, Hansen test p-val of less than 0.25, then the lag length will be restricted in order to reduce the number of moment conditions.

4.3 Variable construction and data

This section discusses the construction of the variables used to estimate the effects of Airbnb usage on the number of firms (5) as well as the data sources. A summary of the variable descriptions as well as summary statistics are provided in Table 1 at the end of this section.

4.3.1 Dependent variable

The annual counts and percentages of entertainment and service sector firms within a PUMA were constructed using data collected from the Census County Business Patterns (CPB) database. Data was collected from 2005 to 2016 for sixteen major U.S. cities.[22] The annual datasets pulled from the CPB report the number of businesses within a ZIP Code by six-digit NAICS code.

The data was converted from ZIP Code level to PUMA level using a crosswalk file obtained from the Missouri Census Data Center.[23] The crosswalk file reported the proportion of each ZIP Code that was contained within the relevant PUMAs. For example, 6% of ZIP Code 10003 (New York) falls within PUMA 3807, 24% falls within PUMA 3808, 44% falls within PUMA 3809, and 25% falls within PUMA 3810. These proportions are multiplied by the ZIP Code business counts and then totaled by PUMA.

This methodology implicitly assumes businesses within an NAICS are uniformly distributed across a ZIP Code, which is not the case. As this paper has already pointed out, businesses tend to cluster by sector as a result of zoning and agglomeration effects. Ideally, each business would be able to be assigned to a PUMA based on its geographic location, but this is not possible with publicly available data.[24]

After the data was converted to the PUMA level businesses were classified into the entertainment sector, service sector, or neither using their six-digit NAICS code. The general definition of an "entertainment sector" firm is a firm producing a good or service that is consumed by both tourists and residents. Examples of entertainment firms include bars, movie theaters, restaurants, and retail clothing stores. The general definition of a "service sector" firm is a firm producing a good or service consumed primarily by residents. Examples of service firms include auto mechanics, grocery stores, retail furniture stores, and tutoring services. Table 5 in the Appendix provides a detailed list of how every NAICS code was classified. After assigning each NAICS code to a sector the data was aggregated by year, PUMA, and sector to create an annual count of the number of firms in each sector by PUMA. Percentages were calculated by dividing the count for each sector by the total number of firms within the PUMA.

[22] The cities include in the dataset are: Asheville, NC; Austin, TX; Boston, MA; Chicago, IL; Denver, CO; Los Angeles, CA; Nashville, TN; New Orleans, LA; New York, NY; Oakland, CA; Portland, OR; San Diego, CA; San Francisco, CA; Santa Cruz, CA; Seattle, WA; and Washington, DC. These cities correspond to the cities available on Inside Airbnb, and were the only U.S. cities for which data was made available.

[23] See `http://mcdc.missouri.edu`.

[24] Alternatively, the Department of Housing and Urban Development has crosswalk files available for ZIP Codes to census tract, which can then be converted to PUMAs, that reports proportions based on business addresses. The proportion is the ratio of business addresses within the overlapping ZIP Code-tract part to the total number of businesses within the ZIP Code. Though the proportions are still assumed to be uniform across NAICS codes, weighting the proportions by business addresses more accurately represents how businesses are distributed. However, these crosswalk files are only made available starting in 2010. Therefore, for the entire dataset to be included in the analysis the Missouri Census Data Center crosswalk files must be used.

Every NAICS code was classified by manually going through the list of codes and classifying them based on the previously stated definitions. Although this procedure is somewhat ad hoc, the literature on tourism gentrification and urban economics provides no operational definitions for the "entertainment" or "service" sector on which to base the classification. Most of the literature on tourism gentrification discusses these sectors as abstract concepts, not seeking to quantify the effect of tourism gentrification, and thus have not had a reason to provide an operational definition. Therefore the classification system defined in Table 5 should be thought of as a first attempt at providing the literature with a operational definition of the entertainment and service sectors for the purpose of analyzing tourism gentrification.

4.3.2 Airbnb Usage

Data on Airbnb was collected from Inside Airbnb, an independent data collection project that compiles information about Airbnb listings for public use. The project scrapes Airbnb's website across various major U.S. and international cities for host level data.[25] The raw data files include information about when the host joined Airbnb, geographic coordinates for the listing, the listing availability over the next year, when the listing received reviews, as well detailed information about the listing's amenities.

Since Inside Airbnb collects data by scraping Airbnb's website the data includes only those hosts who are active at the time of the scrape. Additionally, Airbnb does not provide a record of hosts that have since removed their listing from the website. Therefore, hosts who have removed their listing before the time of the scrape will not be included in the dataset. Without access to a database of historical data, the snapshot provided by Inside Airbnb is the best available option for measuring the intensity of Airbnb usage.

With the data provided a count of all listings available in an area can be created, but would overstate Airbnb usage. Just because a property is listed does not mean that it is being rented. Furthermore, Airbnb listings in and of themselves do not cause tourism gentrification. Rather, tourism gentrification is a result of an increase in tourism, which occurs when more tourists are brought into the area. Therefore only those listings that are rented should be included in the measure. By exploiting data on listing reviews a more accurate measure of Airbnb usage can be generated.

Inside Airbnb provides a record of all reviews a listing receives as well as the date the review was posted.[26] Utilizing this record, an annual count of the number of reviews a listing receives is generated. It should be noted, guests are not required to submit a review after renting. As a result a listing maybe more active than what is reflected by the number of reviews. In addition, only an individual who has rented the listing is able to post a review. Therefore, the measure of Airbnb usage generated using review data should be thought of as a lower bound of Airbnb usage. It is

[25] Though tourism gentrification can effect any city this paper chooses to focus on U.S. cities for two reasons. First, demographic controls and business count data are easier to acquire for U.S. cities. Second, many cities outside the U.S. do not have as restrictive zoning laws. Rather than having separate zoning for residential and commerical areas, cities outside the U.S. more commonly implement mixed use zoning or allow for land-owners to apply to change the land use type. As a result it is more difficult to define distinct "residential" and "tourist" zones within a city.

[26] Guests have fourteen days to post a review after checking out. So even though the date does not correspond to the exact date of rental it is a close approximation.

also assumed the incentive to provide a review is consistent across time and PUMA since there is no explicit benefit to the renter for providing a review.

Using the geographic coordinates reported for each listing and boundary shape files obtained from the Census website each listing was assigned to a PUMA. The count of reviews was then aggregated by PUMA year. The resulting variable should be thought of as a lower bound estimate of the number of times Airbnb was rented within a PUMA during the year. More aptly this variable can be interpreted as the minimum number of tourists brought into the PUMA by Airbnb since at least one tourist will accompany every rental. Of course, it is possible for more than one tourist to stay in an Airbnb, and in fact many of the listings allow two or more people to stay. However, the review data does not identify how many individuals stayed during the rental period. Therefore, to be conservative, and not over estimate the effect, the minimum number of individuals that could have used Airbnb during the year is implemented as the measure of Airbnb usage.

4.3.3 Other controls

Controls for total population, median household income, and the number of hotels are also included in the model. Data on total population and median household income were collected from the American Community Survey (ACS) and were available at the PUMA level. Data on the number of hotels was collected from the CBP database. All businesses with the four-digit NAICS code 7211 (Traveler Accommodations) are included in the hotel count. The same methodology to convert business sector counts from ZIP Code level to PUMA level was applied to the ZIP Code level hotel counts.

The instrumental variable, percentage of households with internet, was also collected from the ACS. However, the ACS did not start collecting data on internet usage until 2013. Therefore, all IV estimates are calculated using only data from 2013 to 2016.[27]

[27] The Consumer Population Survey provides data on internet usage prior to 2013, but not at a level of disaggregation useful for this study.

Table 1

Variable	Description	Units	Mean	SD	Observations
Dependent variables					
n_{Ejt}	Number of entertainment firms	10s	70.52	52.80	2976
n_{Sjt}	Number of service firms	10s	146.58	90.82	2976
$\%n_{Ejt}$	Pct of entertainment firms	% point	19.81	3.84	2976
$\%n_{Sjt}$	Pct of service firms	% point	42.19	7.29	2976
Explanatory variables					
# of Reviews (s_{jt})	Number of Airbnb reviews	10s	70.31	261.62	2976
Pop_{total}	Total population	10,000s	14.04	3.30	2974
Y_{50}	Median income	\$1,000s	36.63	12.89	2974
# of Hotels	Number of hotels	10s	1.73	2.08	2976
Instruments					
% of HH with internet	Pct of households with internet	% point	78.20	10.15	992

Note: Census data is reported for PUMA 2400 in New Orleans was not available for 2006 and 2007. Regressions were run as unbalanced and balanced (without PUMA 2400) panels. There was no significant effect on the results. Additionally, the number of Airbnb reviews is used as a proxy for Airbnb usage.

5 Empirical Results

Table 2 presents the results of regressing the number of entertainment sector firms on Airbnb usage and the other independent variables (5). For completeness, the results of four specifications are presented to examine robustness. However, based on the issues discussed in the section on the estimation strategy, regard the fourth specification (GMM) as the appropriate model.

Specifications (1) and (2) present the OLS and FE estimates, respectively; however, both equations suffer from endogeneity bias. Specifically the number of reviews, which as noted earlier is a proxy for Airbnb usage, is likely to be correlated with any unobserved heterogeneity, represented by the PUMA fixed effects. For example, consider a PUMA experiences a negative idiosyncratic shock to the number of firms at $t-1$ for a reason not modeled, so that the shock appears in the error term. Note the shock is assumed to affect firms in both the entertainment and service sectors.[28] All else equal, the fixed effects for the PUMA - the deviation of its average unexplained number of firms from the sample average - will be lower.

Furthermore, Airbnb usage at $t-1$ should also be affected by a shock to the number of firms in accordance with equation (6). Results of regressing the number of reviews on the number of firms can be found in Table 6 in the Appendix. The estimates show the coefficient on the number of entertainment sector firms is positive, $\beta_2 > 0$, the coefficient on the number of service sector firms is negative, $\beta_3 < 0$, and the magnitude of the coefficient on entertainment sector firms is larger than the magnitude of the coefficient on service sector firms, $|\beta_2| > |\beta_3|$. Based on the results, a negative

[28]Shocks like a change in tax or regulation typically effect all businesses regardless of industry. Therefore the number of firms in both the entertainment and service sectors will be impacted.

shock to the number of firms should result in a decrease in the number of reviews. Therefore, both the number of reviews at $t-1$ and the fixed effects are lower as a result of the shock. The positive correlation between lagged number of reviews (s_{jt-1}) and the error (e_{ijt}) results in an inflated estimate of the OLS coefficient on the number of reviews.

Table 2

# of Entertainment Firms (n_{Ejt})	(1) OLS	(2) FE	(3) IV	(4) GMM
# of Reviews	0.0547***	0.0251***	0.0203***	0.0258*
(s_{jt-1})	(0.0056)	(0.0082)	(0.0046)	(0.0153)
Pop_{total}	2.5611***	0.4183	-0.3412	4.3003***
	(0.2081)	(0.5829)	(0.3636)	(1.2385)
Y_{50}	1.1723***	0.4519**	-0.2766*	-1.6373*
	(0.0568)	(0.2268)	(0.1513)	(0.9075)
# of Hotels	13.7920***	17.3385***	-0.7442	12.4061**
	(0.3582)	(1.9554)	(1.5270)	(4.9642)
PUMA FE	No	Yes	Yes	Yes
Year FE	Yes	Yes	No	Yes
F Stat	258.0035	21.7182	11.5635	
AR(2)				0.5622
Hansen Test p-val				0.5789
Instruments			1	33
Years	2005-2016	2005-2016	2014-2016	2005-2016
N Obs	2726	2726	744	2726

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Robust standard errors clustered at the PUMA level are reported in parentheses.

Including PUMA fixed effects in the estimation draws the unobserved heterogeneity out of the error term, and removes the endogeneity bias caused by the correlation between the number of reviews and the fixed effects. In spite of that, the number of reviews is still correlated with the error due to the presence of autocorrelation. Under the within group transformation the lag of the number of reviews becomes $s^*_{jt-1} = s_{jt-1} - \frac{1}{T-1}(s_{j2} + ... + s_{jT})$ while the error becomes $\epsilon^*_{ijt} = \epsilon_{ijt} - \frac{1}{T-1}(\epsilon_{ij2} + ... + \epsilon_{ijt})$. Assume again a negative shock to the number of firms at time $t-1$. The shock causes the transformed error at time t to increase, and s_{jt-1} will decline for the same arguments as before. The transformed error (ϵ^*_{ijt}) and the transformed number of reviews (s^*_{jt-1}) are negatively correlated. As a result estimation using FE is likely to underestimate the true effect of Airbnb usage.

Specification (3) attempts to correct for the endogeneity in the FE model by utilizing the percentage of households with internet as an instrument for Airbnb usage. The coefficient on the number of reviews is similar to the FE estimate, but given FE is predicted to underestimate the true effect the IV estimate is lower than expected. However, this outcome is not unexpected for a couple of reasons. First the percentage of households with internet is weakly correlated with the number of reviews, which can lead to weak instrument bias. Second, the estimation only utilizes data from 2013 to 2016; a period well after Airbnb was established and widely adopted. By not including the variation in the number of firms during the years prior to and shortly after the start of Airbnb the IV regression is estimating something slight different than if it were to utilize the full time series.

The final specification (4) is GMM with lags used as instruments for the endogenous regressors. The p-value for the Hansen test is above the threshold of 0.25, and thus cannot reject the null hypothesis of joint validity of the instruments. Furthermore, the coefficient on the number of reviews is significant at the 10% level. The results of the empirical analysis displayed in Table 2 suggest as Airbnb usage within a PUMA increases more entertainment firms will choose to enter the area, which supports the conjecture made by the theoretical model.

Result 1. *Increasing Airbnb usage within a PUMA leads to an increase in the number of firms in the entertainment sector.*

Now we turn to analyzing the effect Airbnb usage has on the number of firms in the service sector, n_{Sjt}. Table 3 presents the regression results. Again for completeness, the results of four specifications are presented to examine robustness; however, the fourth specification (GMM) should be regarded as the appropriate model.

The OLS estimate for the coefficient on the number of reviews, presented in the second column of the table, is an overestimate of the true effect due to the positive correlation between the error term and Airbnb usage.[29] Similarly, the FE estimate, presented in column three, underestimates the true effect due to the negative correlation between the transformed number of reviews (s^*_{jt-1}) and transformed error (e^*_{ijt}). Furthermore, the effect is insignificant at the 10% level. The IV estimate presented in the fourth column of the table is significant at the 1% level, but is larger than the OLS estimate, which is expected to overestimate the true effect. The inconsistency of the estimate is likely occurring because of weak instrument bias and constricted time series.

Specification (4) of the table presents the results of the GMM estimation. The Hansen test is found to be insignificant, so the instruments can be regarded as jointly valid. Furthermore, the estimate on Airbnb usage is similar to the OLS and FE estimates. While there is support for the validity of the estimation strategy the coefficient on the number of reviews is insignificant at the 10% level. Thus the empirical results are unable to conclude Airbnb usage has any effect on the number of service sector firms within a PUMA.

Result 2. *Airbnb usage does not have a statistically significant effect on the number of service sector firms within a PUMA.*

The absence of a statistically significant effect by Airbnb usage on the number of service firms does not support Conjecture 2 - increasing the proportion of tourists within a district will lead to a decrease in the number of service sector firms when the increase in fixed costs outweighs the increase in revenue. However a null effect could occur if the net effect of an increase in fixed costs and an

[29] Though the results of regressing the number of reviews on the number of firms shows the coefficient on the number of service sector firms is negative, it is smaller in magnitude than the coefficient on the number of entertainment sector firms. Therefore, the net effect of a positive shock to the number of firms will be an increase in number of reviews.

Table 3

# of Service Firms (n_{Sjt})	(1) OLS	(2) FE	(3) IV	(4) GMM
# of Reviews	0.0365***	0.0076	0.0383***	0.0142
(s_{jt-1})	(0.0099)	(0.0104)	(0.0101)	(0.0102)
Pop_{total}	5.7987***	1.6292	-0.2382	9.3962***
	(0.3658)	(1.0689)	(0.7505)	(2.9535)
Y_{50}	2.4193***	0.6874**	-0.5258	-3.2946
	(0.0999)	(0.3116)	(0.3313)	(2.6584)
# of Hotels	21.2947***	31.1340***	-1.7606	16.0910*
	(0.6297)	(7.3553)	(2.9777)	(9.1277)
PUMA FE	No	Yes	Yes	Yes
Year FE	Yes	Yes	No	Yes
F Stat	233.4746	31.2784	8.4620	
AR(2)				0.9902
Hansen Test				0.6407
Instruments			1	21
Years	2005-2016	2005-2016	2014-2016	2005-2016
N Obs	2726	2726	744	2726

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Robust standard errors clustered at the PUMA level are reported in parentheses.

increase in revenue was zero, which would happen with slight modifications to the assumptions of the theoretical model. The model assumes the utility of tourists depends on products produced in the service sector, which is not necessarily the case. Tourists typically visit a city or place for a short period of time, and as a result will primarily consume the products produced by the entertainment sector. Only those individuals staying within an area for an extended period of time typically consume the goods and services provided by the service sector. Therefore in an extreme case the utility of tourists can be assumed to put no weight on the consumption of service sector products.

In this extreme case tourists will not consume any products produced by the service sector. Therefore as Airbnb usage increases and tourists are redistributed into the residential area, the local aggregate demand for service sector firms will not change, and new service sector firms will have no incentive to enter the market. On the other hand, firms in the entertainment sector will still experience an increase in local aggregate demand, and thus have an incentive to enter the residential area. If the resulting increase in the number of entertainment sector firms does not affect the fixed cost of production then service sector firms will have no incentive to exit the market. The number of firms in the service sector will not change. However, if the increase entertainment sector firms does lead to an increase in fixed costs firms in the service sector will have an incentive to exit the market. When fixed costs increase without a sufficient increase in revenue an increase in Airbnb usage will lead to a decline in the number of service firms.

Therefore for the number of service sector firms to remain unchanged when fixed costs increase there must also be an increase in local aggregate demand, which will occur if the utility of tourists places a positive weight on products produced in the service sector. As more tourists enter the residential area aggregate demand for service sector firms increases resulting in an increase in revenue for the firms already in the market. At the same time fixed costs are also increasing as a result of higher demand for retail space. The net of these two forces will determine whether there is an increase, decrease, or no effect on the number of service firms.

In the numerical analysis conducted earlier the effect of rising fixed costs was assumed to dominate the increase in demand resulting in a net outflow of service sector firms as more tourists enter the residential area. If instead, the marginal effect firms have on fixed cost is reduced the resulting outflow of service firms will also diminish. Moreover, if the marginal effect is small enough such that the increase in fixed costs is exactly offset by an increase in revenue the outflow of service firms will cease. The result in this case is an increase in Airbnb usage leads to no observable change in the number of service sector firms.

An additional test of the empirical results can be conducted by estimating the effect of Airbnb usage on firms (5) using the percentage of entertainment/service sector firms as the dependent variable. Based on the results of Tables 2 and 3 the number of reviews is expected to have a positive effect on the percentage of entertainment sector firms and a negative effect on the percentage of service sector firms. Results 1 and 2 state the number of entertainment sector firms increases in response to an increase in Airbnb usage while the number of firms in the service sector remains unchanged. Therefore, the proportion of firms within a PUMA in the entertainment sector should increase as Airbnb usage increases. Conversely, the proportion of service sector firms in a PUMA should decrease. Table 4 presents the FE and GMM estimates using the percentage of firms as the dependent variable.[30]

[30] A linear probability model is assumed to be a good approximation since the dependent variables are not close to the bounds, $\%n_{Ejt}, \%n_{Sjt} \in [0, 1]$. The min and max of the percentage of entertainment sector firms , $\%n_{Ejt}$, are 8.61% and 33.19%, respectively, and the min and max of the percentage of service sector firms , $\%n_{Sjt}$, are 14.32% 64.39%, respectively.

Table 4

	% of Entertainment Firms ($\%n_{Ejt}$)		% of Service Firms ($\%n_{Sjt}$)	
	FE	GMM	FE	GMM
# of Reviews	0.0013***	0.0003**	-0.0019***	-0.0028**
(s_{jt-1})	(0.0004)	(0.0001)	(0.0005)	(0.0013)
Pop_{total}	0.0384	0.0129	0.0405	0.1430
	(0.0457)	(0.0533)	(0.0534)	(0.0911)
Y_{50}	0.0072	-0.0038	0.0017	0.0210
	(0.0193)	(0.0176)	(0.0192)	(0.0344)
# of Hotels	0.1211	-0.0224	-0.0967	-1.0197***
	(0.1740)	(0.1285)	(0.1998)	(0.1747)
PUMA FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
F Stat	17.5491		18.7799	
AR(2)		0.8059		0.8186
Hansen Test		0.5013		0.3206
Instruments		29		78
Years	2005-2016	2005-2016	2005-2016	2005-2016
N Obs	2726	2726	2726	2726

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Robust standard errors clustered at the PUMA level are reported in parentheses.

Columns two and three present the results for the entertainment sector, and columns four and five present the results for the service sector. The coefficient on the number of reviews is positive and statistically significant for both sets of regressions. The result suggests an increase in Airbnb usage leads to an increase in the concentration of firms in the entertainment sector. When the percentage of firms in the service sector is the dependent variable the coefficient on the number of reviews is negative, which suggests increasing Airbnb usage leads to a decline in the concentration of firms in the service sector.

The regression results presented in Table 4 provide support for Results 1 and 2. If the number of firms in the entertainment sector increased in response to an increase in Airbnb usage while the number of firms in the service sector remained unchanged then the percentage of firms in the entertainment sector should increase. The results in column two and three of Table 4 support this claim. Furthermore, if the number of firms in the service sector remains unchanged while the number of firms in the entertainment sector increase in response to an increase in Airbnb usage then the percentage of firms belonging to the service sector should decline. Column four and five of Table 4 support this claim.

6 Conclusion

An overlooked consequence of the introduction and proliferation of Airbnb has been the redistribution of tourists into parts of cities that previously have had little exposure to tourism. This paper examines, both theoretically and empirically, the effects redistributing tourists has had on the development of the entertainment and services sectors within city neighborhoods. To investigate this question theoretically a model of intra-city trade based on work by Krugman (1980) was developed. Two conjectures were drawn from the model. When tourists, entertainment centric consumers, are concentrated in the downtown area, as they have historically been, firms in the entertainment sector choose to agglomerate downtown. As tourists are redistributed into the residential district, as they are with Airbnb, the number of entertainment sector firms in the residential district increases. Furthermore, the number of service sector firms in the residential district will decrease if fixed costs (rents) increase, due to an increased demand for retail space, more than revenue increases.

An empirical analysis was then conducted to test the validity of the conjectures. A novel dataset was created by combining data from Inside Airbnb and a variety of U.S. Census Data sources. Data was collected from 2005-2016 at the PUMA level. The empirical results suggest Airbnb usage does have an effect on the development of businesses within a PUMA, which led to two primary results. First, an increase in Airbnb usage results in an increase in the number of entertainment sector firms. Second, the data does not provide sufficient evidence to suggest Airbnb usage has a statistically significant effect on number of service sector firms. A result that can be explained theoretically by the increase in local aggregate demand exactly offsetting the increase in fixed costs, which means there is no incentive for service sector firms to enter or exit the market. Thus there will be no observable effect on the number of firms in the service sector.

There are several ways in which the analysis of this paper can be extended. First, alternative definitions of the "entertainment" and "service" sectors could be tested. The definitions provided in this paper are a first pass, and more rigorous definitions should still be pursued. Second, the theoretical model could be modified to include a second residential district that does not have any tourists redistributed into it. By including this third district the model would be able to explore what effect, if any, Airbnb usage has on districts not directly affected by the redistribution of tourists. Additionally, the theoretical model could be extended to include a market for Airbnb. This extension would allow the distribution of tourists to be endogenous as well as allow the model to analyze how the additional income residents receive from hosting affects the location decision of firms.

Nevertheless, the results of this paper still have implications that bridge the empirical literature on Airbnb and tourism gentrification. Prior to this paper the research on Airbnb has been largely limited to analyzing the effects Airbnb has had on the hospitality and housing sectors, but this paper suggests Airbnb may also impact the development of a district's entertainment and service sectors. Specifically, an increase in Airbnb usage leads to an increase in the presence of entertainment sector firms. A characteristic the literature commonly associates with tourism gentrification. Cócola-Grant (2016; 2018) provides anecdotal evidence and motivation for the connection between the growth of Airbnb and tourism gentrification, but is limited to a case study of Barcelona. By focusing in on a singular aspect of tourism gentrification, the presence of entertainment sector firms, the results of this paper support and extend the work of Cócola-Grant by providing evidence of a systematic link between the increase in Airbnb usage and an increase in entertainment sector firms. However, this paper is not able to definitively conclude the use of Airbnb within an area will lead to tourism gentrification.

There are other aspects of tourism gentrification not explored within this paper that are needed to conclude a causal link exists. Similar to gentrification in general, tourism gentrification can lead to the displacement of residents as a result of higher rents as well as displacement resulting from long-term residential accommodations being converted to short-term tourist accommodations. Some states have begun addressing the latter issue by implementing policies restricting Airbnb hosts to listing only their primary residence or requiring hosts obtain a short-term rental license.[31] While these types of policies may help prevent the decline in availability of residential accommodations the potential issue of rising rents is still largely unaddressed. Additionally, congestion and the replacement of locally own firms with national chains are characteristics frequently associated with tourism gentrification that are not explored in this paper. Though no causal link between Airbnb usage and tourism gentrification is shown to exist, the results of this paper do show a connection between Airbnb usage and the presence of entertainment sector firms, which provides motivation for further research into the role Airbnb plays in tourism gentrification.

[31] Airbnb provides detailed information on its site about regulations in various cities. Additionally, Cohen (2018), Honan (2018), and Loudenback (2018) discuss various regulations being imposed by states.

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Appendix

Derive compensated demand

Using the FOC from the consumer's expenditure minimization problem the following equation for the marginal rate of substitution can be obtained

$$\frac{c_{ijk}^{\rho-1}}{c_{ijl}^{\rho-1}} = \frac{p_{ik}\tau_{jk}}{p_{il}\tau_{jl}}.$$

$$c_{ijk} = c_{ijl}\left(\frac{p_{il}\tau_{jl}}{p_{ik}\tau_{jk}}\right)^{\frac{1}{1-\rho}}$$

Plugging the above equation into the budget constraint yields

$$C_{ij} = \left[\sum_{k=1}^{2} n_{ik}\left(c_{ijl}\left(\frac{p_{il}\tau_{jl}}{p_{ik}\tau_{jk}}\right)^{\frac{1}{1-\rho}}\right)^{\rho}\right]^{\frac{1}{\rho}}$$

$$C_{ij} = c_{ijl}(p_{il}\tau_{jl})^{\frac{1}{1-\rho}}\left[\sum_{k=1}^{2} n_{ik}\left(\frac{1}{p_{ik}\tau_{jk}}\right)^{\frac{\rho}{1-\rho}} d\omega\right]^{\frac{1}{\rho}}$$

Solve for c_{ijl}

$$c_{ijl} = \frac{(p_{il}\tau_{jl})^{\frac{1}{\rho-1}}}{\left[\sum_{k=1}^{2} n_{ik}\,(p_{ik}\tau_{jk})^{\frac{\rho}{\rho-1}}\right]^{\frac{1}{\rho}}}C_{ij}$$

Solve for entertainment sector profit maximizing price

Taking the derivative of the profit function with respect to p_{Ej} yields

$$\frac{\partial \pi_{Ej}}{\partial p_{Ej}} = Q_{Ej} + (p_{Ej} - c)\frac{\partial Q_{Ej}}{\partial p_{Ej}} = 0.$$

Substitute in the definition of Q_{Ej}

$$q_{Ej}^{T} + q_{Ej}^{N} = (c - p_{Ej})\left(\frac{\partial q_{Ej}^{T}}{\partial p_{Ej}} + \frac{\partial q_{Ej}^{N}}{\partial p_{Ej}}\right).$$

Calculate the derivate of q_{Ej}^{T} and q_{Ej}^{N} with respect to p_{Ej}

$$\frac{\partial q_{Ej}^{T}}{\partial p_{Ej}} = \mu Y(-\sigma)p_{Ej}^{-1}\sum_{k=1}^{2} s_k^{T}\frac{(p_{Ej}\tau_{kj})^{-\sigma}}{\mathbb{P}_{Ej}^{-(\sigma-1)}}$$

$$\frac{\partial q_{Ej}^{N}}{\partial p_{Ej}} = \lambda Y(-\sigma)p_{Ej}^{-1}\sum_{k=1}^{2} s_k^{N}\frac{(p_{Ej}\tau_{kj})^{-\sigma}}{\mathbb{P}_{Ej}^{-(\sigma-1)}}$$

Plug the equations for q_{Ej}^{T} and q_{Ej}^{N} as well as the equations for $\frac{\partial q_{Ej}^{T}}{\partial p_{Ej}}$ and $\frac{\partial q_{Ej}^{N}}{\partial p_{Ej}}$ into the FOC of the firm's profit function.

$$\mu Y \sum_{k=1}^{2} s_k^T \frac{(p_{Ej}\tau_{kj})^{-\sigma}}{\mathbb{P}_{Ej}^{-(\sigma-1)}} + \lambda Y \sum_{k=1}^{2} s_k^N \frac{(p_{Ej}\tau_{kj})^{-\sigma}}{\mathbb{P}_{Ej}^{-(\sigma-1)}}$$
$$= (c - p_{Ej}) \left(\mu Y(-\sigma) p_{Ej}^{-1} \sum_{k=1}^{2} s_k^T \frac{(p_{Ej}\tau_{kj})^{-\sigma}}{\mathbb{P}_{Ej}^{-(\sigma-1)}} + \lambda Y(-\sigma) p_{Ej}^{-1} \sum_{k=1}^{2} s_k^N \frac{(p_{Ej}\tau_{kj})^{-\sigma}}{\mathbb{P}_{Ej}^{-(\sigma-1)}} \right)$$

Solve the above equation for p_{Ej}.

$$p_{Ej} = (p_{Ej}\sigma - c\sigma)$$
$$p_{Ej}(1-\sigma) = -c\sigma$$
$$p_{Ej}^* = \left(\frac{\sigma}{\sigma-1}\right) c$$

Solve for optimal number of entertainment sector firms

Plug the equations for Q_{Ej}, q_{Ej}^T, and q_{Ej}^N into the market clearing condition for the entertainment sector.

$$Q_{Ej} = q_{Ej}^T + q_{Ej}^N$$
$$\frac{F(\sigma-1)}{c} = \mu Y \sum_{k=1}^{2} s_k^T \frac{(p_{Ej}\tau_{kj})^{-\sigma}}{\mathbb{P}_{Ek}^{-(\sigma-1)}} + \lambda Y \sum_{k=1}^{2} s_k^N \frac{(p_{Ej}\tau_{kj})^{-\sigma}}{\mathbb{P}_{Ek}^{-(\sigma-1)}}$$

Expand the summations.

$$\frac{F(\sigma-1)}{c} = \mu Y \left(s_1^T \frac{(p_{Ej}\tau_{1j})^{-\sigma}}{\mathbb{P}_{E1}^{-(\sigma-1)}} + s_2^T \frac{(p_{Ej}\tau_{2j})^{-\sigma}}{\mathbb{P}_{E2}^{-(\sigma-1)}} \right) + \lambda Y \left(s_1^N \frac{(p_{Ej}\tau_{1j})^{-\sigma}}{\mathbb{P}_{E1}^{-(\sigma-1)}} + s_2^N \frac{(p_{Ej}\tau_{2j})^{-\sigma}}{\mathbb{P}_{E2}^{-(\sigma-1)}} \right)$$
$$\frac{F(\sigma-1)}{c} = (\mu Y s_1^T + \lambda Y s_1^N) \frac{(p_{Ej}\tau_{1j})^{-\sigma}}{\mathbb{P}_{E1}^{-(\sigma-1)}} + (\mu Y s_2^T + \lambda Y s_2^N) \frac{(p_{Ej}\tau_{2j})^{-\sigma}}{\mathbb{P}_{E2}^{-(\sigma-1)}}$$
$$\frac{F(\sigma-1)}{c} = (\mu Y s_1^T + \lambda Y s_1^N)(p_{Ej}\tau_{1j})^{-\sigma} \mathbb{P}_{E1}^{\sigma-1} + (\mu Y s_2^T + \lambda Y s_2^N)(p_{Ej}\tau_{2j})^{-\sigma} \mathbb{P}_{E2}^{\sigma-1}$$

Substitute in the equation for the optimal price, p_{Ej}^*.

$$\frac{F(\sigma-1)}{c} = \left(\frac{\sigma}{\sigma-1} c\right)^{-\sigma} (\mu Y s_1^T + \lambda Y s_1^N) \tau_{1j}^{-\sigma} \mathbb{P}_{E1}^{\sigma-1} + (\mu Y s_2^T + \lambda Y s_2^N) \tau_{2j}^{-\sigma} \mathbb{P}_{E2}^{\sigma-1}$$

Substitute in the definition of the price index, $\mathbb{P}_{Ej}$.

$$\frac{F(\sigma-1)}{c} = \left(\frac{\sigma}{\sigma-1} c\right)^{-\sigma} \Bigg[\left(\mu Y s_1^T + \lambda Y s_1^N\right) \tau_{1j}^{-\sigma} \left(\left[n_{E1}(p_{E1}\tau_{11})^{1-\sigma} + n_{E2}(p_{E2}\tau_{12})^{1-\sigma} \right]^{\frac{1}{1-\sigma}} \right)^{\sigma-1}$$
$$+ \left(\mu Y s_2^T + \lambda Y s_2^N\right) \tau_{2j}^{-\sigma} \left(\left[n_{E1}(p_{E1}\tau_{21})^{1-\sigma} + n_{E2}(p_{E2}\tau_{22})^{1-\sigma} \right]^{\frac{1}{1-\sigma}} \right)^{\sigma-1} \Bigg]$$

$$\frac{F(\sigma-1)}{c} = \left(\frac{\sigma}{\sigma-1}c\right)^{-\sigma} \Bigg[\left(\mu Y s_1^T + \lambda Y s_1^N\right) \tau_{1j}^{-\sigma} \left(n_{E1}(p_{E1})^{1-\sigma} + n_{E2}(p_{E2}\tau_{12})^{1-\sigma}\right)^{-1}$$
$$+ \left(\mu Y s_2^T + \lambda Y s_2^N\right) \tau_{2j}^{-\sigma} \left(n_{E1}(p_{E1}\tau_{21})^{1-\sigma} + n_{E2}(p_{E2})^{1-\sigma}\right)^{-1} \Bigg]$$

The profit maximizing price is independent of location, $p_{E1}^* = p_{E2}^* = p$.

$$\frac{F(\sigma-1)}{c} = \left(\frac{\sigma}{\sigma-1}c\right)^{-\sigma} p^{\sigma-1} \Bigg[\left(\mu Y s_1^T + \lambda Y s_1^N\right) \tau_{1j}^{-\sigma} \left(n_{E1} + n_{E2}\tau_{12}^{1-\sigma}\right)^{-1}$$
$$+ \left(\mu Y s_2^T + \lambda Y s_2^N\right) \tau_{2j}^{-\sigma} \left(n_{E1}\tau_{21}^{1-\sigma} + n_{E2}\right)^{-1} \Bigg]$$

$$\frac{F(\sigma-1)}{c} = \left(\frac{\sigma}{\sigma-1}c\right)^{-1} \left[\frac{\left(\mu Y s_1^T + \lambda Y s_1^N\right) \tau_{1j}^{-\sigma}}{n_{E1} + n_{E2}\tau_{12}^{1-\sigma}} + \frac{\left(\mu Y s_2^T + \lambda Y s_2^N\right) \tau_{2j}^{-\sigma}}{n_{E1}\tau_{21}^{1-\sigma} + n_{E2}} \right]$$
$$F\sigma = \frac{\left(\mu Y s_1^T + \lambda Y s_1^N\right) \tau_{1j}^{-\sigma}}{n_{E1} + n_{E2}\tau_{12}^{1-\sigma}} + \frac{\left(\mu Y s_2^T + \lambda Y s_2^N\right) \tau_{2j}^{-\sigma}}{n_{E1}\tau_{21}^{1-\sigma} + n_{E2}}$$

The equation for district 1 is

$$F\sigma = \frac{\mu Y s_1^T + \lambda Y s_1^N}{n_{E1} + n_{E2}\tau_{12}^{1-\sigma}} + \frac{\left(\mu Y s_2^T + \lambda Y s_2^N\right) \tau_{21}^{-\sigma}}{n_{E1}\tau_{21}^{1-\sigma} + n_{E2}},$$

and the equation for district 2 is

$$F\sigma = \frac{\left(\mu Y s_1^T + \lambda Y s_1^N\right) \tau_{12}^{-\sigma}}{n_{E1} + n_{E2}\tau_{12}^{1-\sigma}} + \frac{\mu Y s_2^T + \lambda Y s_2^N}{n_{E1}\tau_{21}^{1-\sigma} + n_{E2}}.$$

The transportation cost from district 1 to district 2 is equal to the transportation cost from district 2 to district 1, $\tau_{12} = \tau_{21} = \tau$.

$$F\sigma = \frac{\mu Y s_1^T + \lambda Y s_1^N}{n_{E1} + n_{E2}\tau^{1-\sigma}} + \frac{\left(\mu Y s_2^T + \lambda Y s_2^N\right) \tau^{-\sigma}}{n_{E1}\tau^{1-\sigma} + n_{E2}} \qquad F\sigma = \frac{\left(\mu Y s_1^T + \lambda Y s_1^N\right) \tau^{-\sigma}}{n_{E1} + n_{E2}\tau^{1-\sigma}} + \frac{\mu Y s_2^T + \lambda Y s_2^N}{n_{E1}\tau^{1-\sigma} + n_{E2}}$$

Set the two equations above equal to each other.

$$\frac{\mu Y s_1^T + \lambda Y s_1^N}{n_{E1} + n_{E2}\tau^{1-\sigma}} + \frac{\left(\mu Y s_2^T + \lambda Y s_2^N\right) \tau^{-\sigma}}{n_{E1}\tau^{1-\sigma} + n_{E2}} = \frac{\left(\mu Y s_1^T + \lambda Y s_1^N\right) \tau^{-\sigma}}{n_{E1} + n_{E2}\tau^{1-\sigma}} + \frac{\mu Y s_2^T + \lambda Y s_2^N}{n_{E1}\tau^{1-\sigma} + n_{E2}}$$

$$\mu Y s_1^T + \lambda Y s_1^N + \left(\mu Y s_2^T + \lambda Y s_2^N\right) \tau^{-\sigma} \frac{n_{E1} + n_{E2}\tau^{1-\sigma}}{n_{E1}\tau^{1-\sigma} + n_{E2}} = \left(\mu Y s_1^T + \lambda Y s_1^N\right) \tau^{-\sigma} + \mu Y s_2^T + \lambda Y s_2^N \frac{n_{E1} + n_{E2}\tau^{1-\sigma}}{n_{E1}\tau^{1-\sigma} + n_{E2}}$$

$$(\mu Y s_1^T + \lambda Y s_1^N)(1 - \tau^{-\sigma}) = (\mu Y s_2^T + \lambda Y s_2^N)(1 - \tau^{-\sigma}) \frac{n_{E1} + n_{E2}\tau^{1-\sigma}}{n_{E1}\tau^{1-\sigma} + n_{E2}}$$
$$\frac{\mu Y s_1^T + \lambda Y s_1^N}{\mu Y s_2^T + \lambda Y s_2^N} = \frac{n_{E1} + n_{E2}\tau^{1-\sigma}}{n_{E1}\tau^{1-\sigma} + n_{E2}}$$

$$\psi = \frac{n_{E1} + n_{E2}\tau^{1-\sigma}}{n_{E1}\tau^{1-\sigma} + n_{E2}}$$

$$\psi(n_{E1}\tau^{1-\sigma} + n_{E2}) = n_{E1} + n_{E2}\tau^{1-\sigma}$$

$$n_{E1}(\psi\tau^{1-\sigma} - 1) = n_{E2}(\tau^{1-\sigma} - \psi)$$

$$n_{E1} = n_{E2}\frac{(\tau^{1-\sigma} - \psi)}{(\psi\tau^{1-\sigma} - 1)}$$

$$F\sigma = \frac{\mu Y s_1^T + \lambda Y s_1^N}{n_{E2}\frac{(\tau^{1-\sigma}-\psi)}{(\psi\tau^{1-\sigma}-1)} + n_{E2}\tau^{1-\sigma}} + \frac{\left(\mu Y s_2^T + \lambda Y s_2^N\right)\tau^{-\sigma}}{n_{E2}\frac{(\tau^{1-\sigma}-\psi)}{(\psi\tau^{1-\sigma}-1)}\tau^{1-\sigma} + n_{E2}}$$

$$n_{E2}^* = \frac{\mu Y s_1^T + \lambda Y s_1^N}{F\sigma\left(\frac{(\tau^{1-\sigma}-\psi)}{(\psi\tau^{1-\sigma}-1)} + \tau^{1-\sigma}\right)} + \frac{\left(\mu Y s_2^T + \lambda Y s_2^N\right)\tau^{-\sigma}}{F\sigma\left(\frac{(\tau^{1-\sigma}-\psi)}{(\psi\tau^{1-\sigma}-1)}\tau^{1-\sigma} + 1\right)}$$

$$F\sigma = \frac{\mu Y s_1^T + \lambda Y s_1^N}{n_{E1} + n_{E1}\frac{(\psi\tau^{1-\sigma}-1)}{(\tau^{1-\sigma}-\psi)}\tau^{1-\sigma}} + \frac{\left(\mu Y s_2^T + \lambda Y s_2^N\right)\tau^{-\sigma}}{n_{E1}\tau^{1-\sigma} + n_{E1}\frac{(\psi\tau^{1-\sigma}-1)}{(\tau^{1-\sigma}-\psi)}}$$

$$n_{E1}^* = \frac{\mu Y s_1^T + \lambda Y s_1^N}{F\sigma\left(1 + \frac{(\psi\tau^{1-\sigma}-1)}{(\tau^{1-\sigma}-\psi)}\tau^{1-\sigma}\right)} + \frac{\left(\mu Y s_2^T + \lambda Y s_2^N\right)\tau^{-\sigma}}{F\sigma\left(\tau^{1-\sigma} + \frac{(\psi\tau^{1-\sigma}-1)}{(\tau^{1-\sigma}-\psi)}\right)}$$

An equivalent solution method can be used to solve for the optimal number of service sector firms, n_{S1}^* and n_{S2}^*.

Table 5

2-digit NAICS	Description	6-digit NAICS	Classification
11	Agriculture, Forestry, Fishing and Hunting		Neither
21	Mining		Neither
22	Utilities		Neither
23	Construction	236117, 236118, 237110, 237120, 238160, 238170, 238190, 238210, 238220, 238310, 238320, 238330, 238340, 238350, 238390, 238990	Service
31-33	Manufacturing	312120, 312130, 312140	Entertainment
42	Wholesale Trade		Neither
44-45	Retail Trade	445120, 445291, 445292, 445299, 445310, 446110, 446120, 446130, 446191, 446199, 447110, 447190, 448110, 448120, 448130, 448140, 448150, 448190, 448210, 448310, 448320, 451110, 451120, 451130, 451140, 451211, 451212, 451220, 452111, 452112, 452910, 452990, 453110, 453210, 453220, 453310, 453910, 453920, 453930, 453991, 453998, 454210, 454310, 454311, 454312, 454319, 454390	Entertainment
		441110, 441120, 441210, 441221, 441222, 441228, 441229, 441310, 441320, 442110, 442210, 442291, 442299, 443111, 443112, 443120, 443130, 443141, 443142, 444110, 444120, 444130, 444190, 444210, 444220, 445110, 445120, 445210, 445220, 445230, 454310, 454311, 454312, 454319	Service
48-49	Transportation and Warehousing	487110, 487210, 487990	Entertainment
51	Information	512120, 512131, 512132, 519120	Entertainment
52	Finance and Insurance	522120, 522130, 522190, 522210, 522220, 522291, 522292, 523910, 523930	Service
53	Real Estate Rental and Leasing	532292, 532299	Entertainment
		531110, 531130, 531190, 531210, 531311, 531312, 531320, 532111, 532120, 532210, 532220, 532230, 532291	Service

Note: Any codes not listed in the table are classified as “Neither.”

2-digit NAICS	Description	6-digit NAICS	Classification
54	Professional, Scientific, and Technical Services	541110, 541120, 541211, 541213, 541921, 541940	Service
55	Management of Companies and Enterprises		Neither
56	Administrative and Support and Waste Management and Remediation Services	561510, 561520	Entertainment
		561622, 561710, 561740, 561790	Service
61	Educational Services	611110, 611210, 611410, 611420, 611430, 611511, 611512, 611513, 611519, 611610, 611620, 611630, 611691, 611692, 611699	Service
62	Health Care and Social Assistance	621111, 621112, 621210, 621310, 621320, 621330, 621340, 621391, 621399, 621410, 621491, 621492, 621498, 621511, 621512, 621610, 621910, 621999, 622110, 622210, 622310, 623110, 623210, 623311, 623312 ,623990, 624110, 624120, 624190, 624210, 624221, 624229, 624310, 624410	Service
71	Arts, Entertainment, and Recreation	711110, 711120, 711130, 711190, 711211, 711212, 711219, 711510, 712110, 712120, 712130, 712190, 713110, 713120, 713210, 713290, 713910, 713920, 713930, 713950, 713990	Entertainment
		713940	Service
72	Accommodation and Food Services	721110, 721120, 721191, 721199, 721211, 721214, 721310, 722110, 722211, 722212, 722213, 722310, 722320, 722330, 722410, 722511, 722513, 722514, 722515	Entertainment
81	Other Services (except Public Administration)	812199, 812990	Entertainment
		811111, 811112, 811113, 811118, 811121, 811122, 811191, 811192, 811198, 811211, 811411, 811412, 811420, 811430, 811490, 812111, 812112, 812113, 812191, 812199, 812210, 812220, 812310, 812320, 812910, 812922, 812930, 812990, 813110, 813211, 813212, 813219, 813311, 813312, 813319, 813410	Service
92	Public Administration		Neither

Note: Any codes not listed in the table are classified as "Neither."

Table 6

# of Reviews (s_{jt})	(1) OLS	(2) FE
# of Service Firms (n_{Sjt})	-0.9620***	-2.3556***
	(0.2678)	(0.9008)
# of Entertainment Firms (n_{Ejt})	2.7863***	5.2002***
	(0.5164)	(1.4708)
Y_{50}	-0.2466	3.38856**
	(0.5924)	(1.5901)
# of Occupied Houses	0.8169*	2.5091
	(0.4904)	(2.0784)
PUMA FE	No	Yes
Year FE	Yes	Yes
Adjusted R^2	0.3420	0.3671
F	13.72	12.53
N Obs	2974	2974