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Three Essays on Economics

Li Yao
University of Colorado at Boulder, recordyao@gmail.com

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Three Essays on Economics

by

Li Yao

B.A., Qingdao Agricultural University, 2010
M.A., Murray State University, 2013
M.A., University of Colorado Boulder, 2015

A thesis submitted to the
Faculty of the Graduate School of the
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This thesis entitled:
Three Essays on Economics
written by Li Yao
has been approved for the Department of Economics

________________________________________
Professor Murat Iyigun, Chair

________________________________________
Professor Charles de Bartolomé

Date ____________

The final copy of this thesis has been examined by the signatories, and we find that both the content and the form meet acceptable presentation standards of scholarly work in the above mentioned discipline.
Yao, Li (Ph.D., Economics)

Three Essays on Economics

Thesis directed by Prof. Murat Iyigun, Chair

My first chapter proposes a general equilibrium of an urban model that generates an industry hierarchy within a city cluster, with primarily the service industries exhibiting a hierarchical pattern. The main mechanism is composed of monopolistic competition, heterogeneous economies of scale and love for variety in the service sector. The two-city model generates a unique and asymmetric equilibrium, where the larger city supplies a superset service variety over the smaller city. The simulations show that a decrease in trade costs always leads to urban convergence. The empirical section shows that there is a spatial dynamic interaction between service employment and the neighboring population. A one percent growth in the neighboring population increases the high-order service employment share by 0.116 percent in the city. This phenomenon holds significantly only for the largest city, but not for smaller ones within a city cluster.

In my second chapter, I try to answer the question whether consumers adjust tastes and participate in boycott in response to political disputes. Using an online review data set, this study shows that the political tension in China toward Korea, which was triggered by the installation of an American missile defense system in Korea, reduced by 29% the visits to Korean restaurants in China and reduced by 54% the entry of new Korean restaurants in China. In addition, the online rating of the Korean restaurants declines after the events of political tension, which suggests that the political tension affect not only people’s action but also their subjective quality judgment. I empirically find that the negative effects are more pronounced for lower priced, lower rated restaurants, and restaurants with more Korean-sounding names. Regions with higher economic openness tend to experience more consumption reduction. My conjecture for the cause, considering the fact that most of the Korean restaurants owned by Chinese, is that the worsening perception of a country reduces the taste for the foods of the associated country.
My third chapter builds an overlapping generations (OLG) model of endogenous growth, which is compatible with rapid urbanization in many emerging markets. A key assumption is that the rural-urban internal migration is motivated by maximizing lifetime earnings. When they arrive at the city, people with high talent receive education and expect to earn a higher income in the next period; people with low talent work in the informal sector for two periods. The formal and informal sectors coexist in the city. In the equilibrium, the expected incomes are equalized between the rural and the urban sector for migrants. Simulations of this model show that there’s a continuous urbanization process accompanied by continuous growth. The urbanization rate starts from 10% and ends up at 80%, and total educated population and average human capital persistently increase.
Dedication

To my parents who have loved me unconditionally.
Acknowledgment

I would like to thank my adviser Murat Iyigun for spending so much time reading my work and giving me helpful comments. I learned a great deal from him regarding economic intuitions, empirical techniques and an attitude of paying attention to details. I also like to thank Charles de Bartolomé for his efforts to check my work carefully. I enjoyed conversations with him, which encouraged me when I was in a state of stress and anxiety.
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Chapter 1

Urban Clusters and Location of Service Industries: Theory and Evidence

1.1 Introduction

The spatial concentration of economic activities varies significantly within a country or even within a region. Most of the cities are of small and medium sizes and only a couple of them are large cities. Many urban models either assume zero trade costs, ignoring inter-city interactions or assume costly trade in the manufacturing sector, ignoring the important role of the service industries as a channel of inter-city interaction and as a relevant determinant of urban size. However, service industries take up the lion’s share of the total employment in cities, and a larger city on average hosts a higher percentage of service employment.

This paper proposes a theory that focuses on the service sector as the determinant of urban size and as the channel of inter-city interactions due to the costly trade of service goods between cities. The model generates an equilibrium with a hierarchical pattern of service industries: the large city produces a superset of service varieties over the smaller cities (Davis and Dingel 2014).

Compared to many studies that study cities at a national level, this paper takes a less comprehensive but more focused approach and studies the urban hierarchy and industrial locations within a city cluster, a group of cities within traveling distance. The distance is approximately the maximum of resident’s willingness to travel for service consumption in another city. Such narrowing down of the focus emphasizes the interaction of nearby cities and gives account for some empirical facts that many urban studies ignore.

Figure 1.1 shows a US map where the dots indicate the sizes and locations of Core Based Statistical Areas (CBSAs) and the colors indicate the growth rate of population from 1990 to 2010: the darker the color, the faster the population growth. This map highlights a couple
of empirical regularities that current studies fail to fully explain.

First, the nearby cities tend to be of similar colors, which indicates that there is a positive spatial co-movement of city growth. This pattern of positive correlation implies that the inter-city spatial interaction is an important determinant of city growth. Many urban studies overlook this positive correlation because they ignore the inter-city interactions, especially for the cities within the same region.

Second, cities tend to cluster in certain regions. Hsu et al. (2014) show evidence that larger cities tend to be spaced apart with smaller cities organized around them. Drawing a 200 miles radius around some of the major cities in the US, I find the city size variation within 200 miles is extensive and the distribution resembles the Power Law distribution with a coefficient close to $-1$, which is known as the Zipf’s law. In Figure 1.2 and Figure D.1, I show that the Zipf’s law of city size distribution holds for most of the city clusters. This confirms Geisen’s (2010) finding that the Zipf’s law holds even at a regional level. Hsu et al. (2014) suggest that the city size distribution for nearby cities is more consistent than randomly grouped cities. These empirical regularities and studies suggest that a more regional perspective could help better understand the size distribution, formation and development
Many studies try to address the question of how city sizes are determined. One influential theory is that city growth follows a stochastic process. This random growth theory argues that city growth is random and orthogonal to its original size (Gabaix, 1999; Eeckhout, 2004). In the limit, the city size distribution is close to the log-normal or Pareto distribution, known as the Zipf law. The evidence for the random growth theory is the Gibrat’s law, an empirical observation that city growth is indeed orthogonal to city size. However, Davis and Weinstein (2002) use the Japanese city population data to show that there was a mean-reversion process after the Allies’ bombing during WWII, which contradicts the Gibrat’s law’s prediction of persistent effects from the negative shocks. Desmet and Rappaport (2015) use a 200-year span of US population census data to show that Gibrat’s law only holds in recent history. In the 1800s, the small cities tended to grow faster than the larger ones. Most of all, the caveat of the random growth theory is that it offers very weak policy implications and gives no insight into the question whether cities are optimal in size because no determinant economic factors are identified in this theory.

The deterministic theory focuses on city characteristics such as amenities, industrial spe-
cialization, human capital, firm productivity and market access, which potentially determine the size of cities, with randomness entering into this theory as residuals. Rossi-Hansburg (2007) focuses on industry specialization: a city that specializes in a more productive industry sustains higher congestion costs. Another line of such deterministic theories focuses on the sorting mechanism which generates ex-post difference from ex-ante identical locations (Behrens et al., 2014; Davis and Dingel, 2014; Gaubert, 2015). Behrens et al. (2014) construct a model that sorts the more talented workers into larger cities due to the complementarity between the talented and large cities. Gaubert (2015) assumes that more productive firms tend to locate in a larger city to exploit greater agglomeration benefits, hence, producing complementarity between productive firms and large cities. Those papers focusing on sorting depict cities as isolated entities that have no inter-city interaction by assuming either zero or infinite trade cost (Sasahara, 2014).

The New Economic Geography (NEG) literature focuses on market access and the inter-region interactions through costly trade of the manufactured goods (Krugman, 1991a; Tabuchi, 1998). However, the theory isn’t compatible with the modern economy with very low inter-regional trade costs, as Krugman (2010) admits that it “seem(s) more suited to the U.S. economy of 1900 than that of 2010.” More recent urban studies that focus on costly trade develop models in a system of cities with inter-city interaction from costly trade (Behrens et al., 2017; Allen and Arkolakis, 2014; Redding and Rossi-Hansberg, 2017). All those studies look at the inter-city trade of the non-service goods because the service goods are deemed as locally non-tradable. However, the service industry takes up the lion’s share of the total employment in the cities and plays a vital role in determining urban size. It is not an exaggeration to say that large cities are service hubs, rather than manufacturing hubs as proposed by the NEG theories.

The Central Place Theory focuses on the hierarchy pattern of the consumption goods (Christaller, 1933). The essence of the theory is that the larger city produces a superset of variety over the smaller city. People in a large city consume everything locally, whereas
people in a small city consume the low-order consumption goods locally and the high-order in a large city. For example, in the US, every city produces service varieties such as retail stores and gas stations, but only a few big cities offer airport services or musical theaters. Christaller did not give an account of how this structure of city was formed from the decentralized actions of individuals. Hsu’s (2008) model uses partial equilibrium and generates a Central Place urban hierarchy. He assumes that industries vary in scale economies and that Hotelling competitive firms enter to maximize profits on a real line uniformly distributed with a immobile agricultural population. Tabuchi and Thisse (2011) build a new economic geography model that generates a central place city hierarchy. Within the hierarchy, the highly differentiated manufacturing industries are only located in large cities, and the less differentiated ones in small cities. Fujita et al. (1999) approach the hierarchy through urban evolution, but they only formulate the urban hierarchy without the hierarchical pattern of industries.

My paper differs from the existing related literature and makes following contributions. First, it provides a general equilibrium model that incorporates monocentric city structure, freely mobile population, hierarchical economies of scale, increasing returns to scale and monopolistic competition, and generates a unique and asymmetric equilibrium in a two-city model. It differs from Hsu (2008) in that it models people’s locations choices, where people face trade-offs between access to more service variety and high housing prices, within a general equilibrium. The advantage of the large city is that it offers more varieties of consumption goods, especially service goods (Couture 2016; Schiff 2012). Schiff (2012) uses online data of restaurants and finds that aggregate demand directly increases product variety and that the rare cuisines tend to locate in the largest and densest cities, a strong hierarchical pattern of restaurant locations. Lee (2010) shows that people with high skills tend to live in a larger city because the large city offers a greater variety of goods. This consumption-city literature shows that the consumption variety is an important reason for people’s choice of residence. My model also differs from Tabuchi and Thisse’s (2011)’s
work in that, first, the mechanism is through heterogeneity of scale economies rather than different elasticities of substitution between industries; second, the number of industries are endogenously determined, whereas, in their paper, the number of industries is fixed. Most of all, my paper offers a theory that matches empirical observation of the service sector, including the Number-and-Average size rule (NAS) rule and the dynamic correlation of service industries and population growth.

Second, the model generates a hierarchical pattern of service industries that is consistent with the NAS. The NAS rule proposed by Mori et al. (2008) states that there is a significant negative log-linear relationship between the number and average size of the cities in which a particular industry is located. For example, in 2010, the service “Language School” locates in 79 cities (MSAs) and the average population size of those cities is 1,986,013. When a service good is rarer, it tends to locate in larger cities. Mori et al. (2008) and Hsu (2008) both find the significance of the NAS rule using Japanese and US industry data. But in their studies, the NAS rule fails to hold at the finest level. Mori et al. (2008) show that the NAS rules hold well at the JSIC 3-digit level, but it fails at the 4-digit level. Using the US CBP data, Hsu (2008) shows that the NAS rule holds for the US economy at 3- and 4-digits, but it fails to hold at more refined 5- and 6-digits. In Figure 1.3, I show that the NAS rule holds for even at the most refined level for service industries but not for the manufacturing industries.\(^1\) This empirical fact is related to Behrens’ (2005) finding that the more differentiated service goods tend to exhibit strong home market effects.

My conjecture for this empirical fact is that the relatively low trade cost for the manufactured goods makes it possible for manufacturing firms to locate in relatively small cities even if the fixed costs are high. However, the trade cost of service goods is much higher due to the opportunity cost of inter-city traveling. Therefore the service industries that are of high scale economies tend to locate in large cities for greater market access.

Third, this paper uses numerical computation to solve the equilibrium for a two-city

\(^1\) I do the same at the urban cluster level in Figure D.2. At the regional level, the NAS rule still holds for the service industry but not for the manufacturing industry.
model. The numerical comparative statics show that a lower inter-city trade cost always leads to urban convergence. The model offers an alternative welfare analysis from Henderson’s celebrated inverted-U shape utility (Henderson, 1974). With population growth, it is always assumed that eventually the congestion cost dominates the agglomeration benefit; otherwise, everyone would choose to live in the largest city. Without inter-city interaction and immobile population, it seems this assumption is necessary. However, in my model, there are inter-city interactions in which the consumers in smaller cities consume high-order service varieties from the large city. The pecuniary externalities from the large city increases the real income in the smaller cities. With such a mechanism in the model, the agglomeration benefit can perpetually exceed the congestion cost and asymmetric equilibrium is still attainable.

Fourth, to the best of my knowledge, this is the first paper to use a panel data to empirically test the dynamics of the hierarchical pattern of industries. The model predicts the dynamic effect of interaction between the local service employment and the growth of the neighboring population. People in smaller cities consume high-order service goods from nearby larger cities. This relation predicts that the neighboring population has a positive impact on the high-order service employments in the largest city, while the neighboring
population has a negligible effect on the low-order service employment. Using longitudinal data from the County Business Patterns and the Census Population data, the empirical results confirm the predictions of this model.

The remainder of the paper is organized as follows: Section 2 lays out the basic model and derives equilibria. Section 3 conducts numerical exercises to solve the equilibrium and carry out numerical comparative statics. Section 4 uses a panel data to evaluate the inter-city interactions. Section 5 concludes the paper.

1.2 Model

1.2.1 City Structure

The model features homogeneous agents, monocentric city structure, monopolistic competition and hierarchical economies of scale. The monocentric city model (Alonso 1964; Mills 1967; Muth 1969), assumes that all people work and consume at central business district (CBD) and people suffer disutility of commuting. The traditional monocentric models (Alonso 1964; Mills 1967; Muth 1969; Rossi-Hansberg and Wright 2007; Duranton and Puga 2013) assume people consume one fixed unit of housing good; in contrast, this paper assumes a Cobb-Douglas demand with a fixed share of expenditure on housing, which is commonly used in recent models (Tabuchi 1998; Li 2015; Gaubert 2015). Davis and Ortalo-Magné (2011) show evidence that the expenditure shares on housing are constant at around 24% over time, which justifies the Cobb-Douglas specification of housing demand. Another advantage of using the Cobb-Douglas function (as with all CES functions) is that the indirect utility function eventually can be simplified into a function of price indices. With equalized nominal income, people’s location choice decisions boil down to the price indices of consumption goods in each city.

The city is assumed to be a real line. The CBD locates at location 0. A worker who lives at \( r \), distance away from CBD, suffers disutility of commuting and her utility is a decreasing function of the distant \( r \):
Figure 1.4: Housing Price as Function of Distance to the CBD

Housing price is a decreasing function of the distance to CBD. The city ranges from 0 to R. At R the housing price equals to the marginal cost of land use $C$.

As population or income increases, the housing prices at all point increase, which expands the physical size of the city, from $R$ to $R'$.

\[ U = e^{-r} H^{\alpha_1} S^{\alpha_2} M^{\alpha_3} \]  

(1)

$e^{-r}$ is commuting disutility. $\alpha_1$, $\alpha_2$ and $\alpha_3$ are expenditure shares of housing, service and manufactured goods. To simply the mathematics, I assume equal expenditure shares $\alpha_1 = \alpha_2 = \alpha_3 = 1/3$. \(^2\)

The distaste for commuting drives up housing price at the CBD. As a result, the housing rent price is adjusted such that people’s utilities are equalized across the whole city. People face a tradeoff: if they want to live close to the CBD, they have to pay a higher housing price. Let $P_H(r)$ be the housing price at location $r$. $P_{CBD} = P_H(0)$ is the housing price at the CBD. This paper assumes the existence of competitive land developers who supply housing goods at a price of marginal cost, which is interpreted as land rent for agriculture. $C$ is the marginal cost and hence the lower bound of housing price.

\[ P_H(r) = P_{CBD} e^{-3r} \geq C, \quad C > 0 \]  

(2)

\(^2\)Numerical comparative analyses are conducted in Figure D.4 looking at the effects of changing parameters of $\alpha_1$. 

---

2 Numerical comparative analyses are conducted in Figure D.4 looking at the effects of changing parameters of $\alpha_1$. 

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9
At the rim of the city, the housing price equals to $C$ and the distance from the rim to the 
CBD is $R$. The rent price is a decreasing function of distance $r$, as illustrated in Figure [1.4](#).

People live within physical distance $R$, the maximum distance from the CBD, and $R$ is 
determined by $P_{CBD}$ and $C$ from following equation:

$$ R = \frac{1}{3} \ln \frac{P_{CBD}}{C} \quad (3) $$

As total population increases, the housing price at all locations increases simultaneously.

Figure [1.4](#) shows the physical size of the city expands outward as housing prices increases. 
At each location on the real line, there is one unit of land; each unit of land supplies one 
unit of housing good. A person at location $r$ has housing demand $H(r)$. Let $I$ denote the 
per capita income. Each person spends one-third of her income on housing:

$$ H(r) = \frac{I}{3P_H(r)} = \frac{I}{3P_{CBD}e^{-3r}} \quad (4) $$

The population density at distance $r$ is

$$ L(r) = \frac{1}{H(r)} = \frac{3P_{CBD}e^{-3r}}{I} \quad (5) $$

Taking the integral of the population density with respect to distance $r$ from the CBD 
to the maximum distance $R$ determines the whole population.

$$ \int_0^R L(r)dr = L \quad (6) $$

Given the total population, we can find the housing price at the city center $P_{CBD}$ as a 
function of $L$.

$$ P_{CBD} = C + IL \quad (7) $$

A more detailed derivation can be found in Appendix [A.1](#). A similar result is derived in
Duranton and Puga’s (2013) more general version of the monocentric urban model.

Many existing monocentric urban models assume that a certain fraction of labor is wasted on commuting. As the population expands, people have to live farther away, so the effective labor in use per person decreases. In my model, the effective labor per person in use holds constant at one unit. The congestion cost directly affects utility. In doing so, this model keeps the average nominal income constant and independent of the total population. This assumption is reasonable because people in a large city still have to work for the same hours, even though they do have to commute longer time on average. Puigarnau and Ommeren (2010) confirm that urban congestion and commuting do not affect labor supply.

The housing price at the city center can be interpreted as a congestion cost: more population causes higher housing price. Higher housing price is a disutility of living in large cities. The housing price at the center $P_{CBD}$ is useful because when comparing two cities, we only need to look at the person who lives at the center of the city, since people’s utilities are equalized across each city. The housing price $P_{CBD}$ at the CBD can be viewed as a bundle of housing rent and commuting disutility.

I further assume everyone equally owns the housing property, and thus, the rent equally distributes back to local citizens by a lump sum transfer $T$ per capita. Let $W$ be the wage rate. Each person owns and supplies one unit of labor. Each person pays an amount of housing rent that equals the lump sum transfer $T$. The equation is:

\[ \frac{1}{3}(T + W) = T \]  

(8)

where $I = T + W$ is the total income, including labor and rent income. The equation entails $T = W/2$. The total income of each person is

\[ I = \frac{3}{2}W, \quad T = \frac{1}{2}W \]  

(9)

Total income of a city is $\frac{3}{2}WL$. We get the housing price at the CBD:
\[ P_{CBD} = C + \frac{3}{2}WL \]  \hspace{1cm} (10)

Total land supply in the city is \( R \):

\[ R \equiv \frac{1}{3} \ln \frac{P_{CBD}}{C} \]  \hspace{1cm} (11)

This model generates a decreasing elasticity of land supply, unlike many studies assuming constant (Li, 2015) or zero elasticity of land supply (Sasahara, 2014; Rossi-Hansberg and Wright, 2007). Saiz (2010) finds that conditioning on urban policy and land terrain restriction, as population grows, the elasticity of land supply is decreasing, which coincides with my result.

### 1.2.2 Service and Manufacturing Industries

There is a homogeneous population and the representative’s utility is a Cobb-Douglas function of three consumption goods: housing, service and manufacturing goods. The ratios of expenditure on the three are all at 1/3. Each citizen is endowed with one unit of labor.

The consumer’s problem:

\[ \text{maximize} \quad U = e^{-r(H \times S \times M)^{\frac{1}{3}}} \]

subject to \[ P_H H + P_S S + P_M M = I \]

\( I \) stands for the income of each person. \( H, S \) and \( M \) stand for the consumption of housing, service, and manufactured goods. \( P_H, P_S, \) and \( P_M \) are price indices for respective goods.

The manufactured goods \( M \) are homogeneous and are traded tween cities without cost. A typical Core-Periphery model assumes that manufactured goods are costly tradable and agricultural goods are freely tradable (Krugman, 1991b), but it is hard to justify why both tangible economic goods are traded at different costs. In this paper, I assume that within a city cluster, service goods are costly tradable while manufactured goods are freely tradable;
that is, service and manufactured goods are analogous to manufactured and agricultural good in Core-Periphery model. Due to modern transportation technology, the transportation cost for manufactured goods is largely reduced, and this paper looks at cities within a short distance so that the transportation cost is negligible compared to the service trade costs. The service goods are assumed to be costly tradable. The trade cost of each service good is the opportunity cost of traveling between the cities to consume the service. For example, a person who lives in City A travels to City B to see a music concert. We can interpret this as the person consumes the service variety from City B, and the trade cost is the opportunity cost of traveling between the Cities A and B.

People appreciate the varieties of service goods. $S$ is a nested CES function of the variety of service industry $S_j$

$$S = \left( \int_{1}^{n} S_j \frac{\phi-1}{\phi} dj \right)^{\frac{\phi}{\phi-1}}$$

Within each service industry $j$, there are service varieties $s_{ji}$:

$$S_j = \left( \int_{0}^{m_j} s_{ji} \frac{\sigma-1}{\sigma} di \right)^{\frac{\sigma}{\sigma-1}}$$

$\phi$ and $\sigma$ are the inter-industrial and intra-industrial elasticity of substitution. The intra-industry variety is always more substitutable than the inter-industry varieties, therefore $1 < \phi < \sigma$. It is also assumed that that $1 + \sigma = 2\phi$, which simplifies the mathematical solution without loss of generality.

Supply of the manufactured goods is of constant return to scale (CRS) and perfectly competitive. Usually, Core-Periphery models assume increase return to scale and monopolistic competition for the manufacturing sector. However, in this paper, I assume the trade cost of manufactured goods to be zero; with such an assumption, the price indices for the manufactured goods are location-invariant. As a result, the price index of the manufactured

\[3\text{This is to simplify the notation. With } 1 + \sigma \neq 2\phi, \text{ the solution can be attained nonetheless, which is shown in Equation 53 of Appendix A.2.}\]
goods does not affect people’s location choice within a city cluster. The CRS assumption of the manufacturing industry simplifies the model without affecting the major results. With the CRS technology, one unit of labor produces one unit of the manufactured goods, which is chosen as the numeraire good. Wage $W$ equals the price of the manufactured goods, which is one.

Supply of service goods is determined by an increasing return to scale technology and monopolistic competition à la Dixit and Stiglitz (1977). I further assume continuous quantity of inter-industries and intra-industry varieties. The inter-industries differ from each other at fixed cost. The industry with higher fixed cost exhibits a greater economy of scale and vice versa.

The labor engaged in the production of service variety $i$ in industry $j$ is

$$l_{ji} = j + \beta s_{ji}, \ j \in [1, +\infty) \quad (15)$$

Note that $j$ is the fixed cost of the production, and due to the assumption that each industry has a unique fixed cost, $j$ also serves as an index for each industry. Within an industry $j$, there are monopolistically competitive firms that make zero profit. Workers are homogeneous and have skills working in both two industries. Therefore, wages are equalized to be one in both manufacturing and service industries. So the fixed cost is $j$ in industry $j$, and the marginal cost is universally $\beta$ for all industries.

The price elasticity of each good is equal to the elasticity of substitution $\sigma$ in the case of continuous varieties and CES demand. Without loss of generality, set $\left(\frac{\sigma}{\sigma - 1}\right)\beta = 1$. The profit-maximizing price equals the constant markup of marginal cost:

$$p_{ji} = \left(\frac{\sigma}{\sigma - 1}\right)\beta w = 1 \quad (16)$$

All firms within each industry charge a price of 1, but because each industry has a different number of intra-industrial varieties, the price index for each industry varies and
depends on the total variety of that industry:

\[ P_j = (\int_0^{m_j} p_j^{1-\sigma} di)^{\frac{1}{1-\sigma}} = m_j^{\frac{1}{1-\sigma}} \]  

(17)

\( m_j \) is the total service variety in industry \( j \), and price index \( P_j \) is a decreasing function of \( m_j \). \( m_j \) is assumed to be a continuous quantity greater than 1; that is, the minimal number of firms in an industry is 1. Without this assumption, every city would supply an infinite number of industries with a minuscule number of firms in each industry, which is unrealistic. For instance, a city cannot supply half an airport, a quarter of an NBA team or 5% of a scientific research lab.

The trade cost of service goods is an iceberg cost at \( \tau^* > 1 \). It costs \( \tau^* \) unit of service good for the consumption of one unit. We can interpret the trade cost of each unit is \( \tau^* - 1 \), which is the opportunity cost of traveling between two cities.

1.2.3 The Autarky (Single-City) Equilibrium

**Definition 1** Single-city equilibrium is a collection of prices and quantities \( \{ P_S, P_H(r), P_M, S, H, M \} \) such that the commuters maximize welfare, the consumers maximize utility and the firms maximize profit.

Assume there is one city on a featureless plain, with total population \( L \). The wage rate equals the price of numeraire good. From the Equation (9), total nominal GDP of the city is \( 3L/2 \). Total expenditure on service goods is \( L/2 \).

The price index of the service sector is:

\[ P_s = (\int_0^{n} P_j^{1-\phi} di)^{\frac{1}{1-\phi}} = (\int_0^{n} m_j^{\frac{1}{1-\sigma}} dj)^{\frac{1}{1-\sigma}} \]  

(18)

This price index depends on total inter-industrial variety \( n \) and intra-industrial variety \( m_j \), which both are determined in the equilibrium. The price index of housing good is derived in equation (7):
Given a total population of a city, there exists a unique equilibrium where everyone chooses consumption and location to maximize its utility. The utility is determined by prices of housing, service goods, and manufacturing goods. Housing price is an increasing function of the total population and the price index of service goods is a decreasing function of the total population.

Note that because of free choice of location within a city, everyone has the same utility regardless of the location and commuting cost. We use the utility of the person at CBD to represent the whole population in the city. The indirect utility of the representative at CBD is:

\[ V^* = W \left( \frac{1}{27P_{CBD}P_S P_M} \right)^\frac{1}{3} \]  

The utility of each person can be normalized to (the price of manufactured goods is ignored, since it’s a constant):

\[ V = (P_{CBD} \times P_S)^{-1} \]  

The utility of living in a certain city boils down to the two price indices: housing price and service price index. Housing price is an increasing function of population, which represents the congestion cost. The service price index is a decreasing function of population, which represents the agglomeration effect: when people agglomerate, the higher demand base supports more service varieties, which lowers the service price index. The congestion and agglomeration benefits together determine the utility of the city.

The solution involves price index as a function of exogenous variables population \( L \) and other parameters. Let the total expenditure in service sector be \( E \) and the expenditure for industry \( j \) be \( E_j \). The total expenditure is the integral of the sub-expenditures \( E_j \):
\[ \int_1^n E_j dj = E \]  \hspace{1cm} (22)

Figure 1.5: The Determination of Vertical and Horizontal Varieties

Figure 1.5 shows the distribution of industrial varieties. The vertical industries range from 1 to \( n \). Within each industry \( j \in [1, n] \), there is an intra-industry variety \( m_j \), which is higher for lower ranked industries. Consumers spend relatively more on the lower-order industries, the reason being that low fixed costs induce more intra-industrial variety and, hence, lower price indices. Due to the substitution effect, consumers spend more on low-order service industries. This result is due to a marriage of monopolistic competition and hierarchical economies of scale.

The CES demand function and substitution effect entail:

\[ \frac{E_j}{E_k} = \left( \frac{P_j}{P_k} \right)^{1-\phi} = \left( \frac{m_j}{m_k} \right)^{\frac{1-\phi}{1-\sigma}} \]  \hspace{1cm} (23)

The quantity demanded of each variety is

\[ ^3 \text{In order to use a more intuition terminology, I refer the inter-industrial varieties and intra-industrial varieties to the vertical varieties and horizontal varieties.} \]
The zero profit condition of monopolistically competitive firms entails:

\[(p - \beta w)x_{ji} = jw\]  \hspace{1cm} (25)

Normalize the price and wage to be unity: \(p = w = 1\). We get:

\[x_{ji} = \frac{j}{1 - \beta}\]  \hspace{1cm} (26)

We interpret Equation (26) as the supply function. For all firms in industry \(j\) to be profit maximizing with free entry, the quantity of each firm supplied is \(x_{ji}\). Set the horizontal variety of highest ranked industry to be \(m_n = 1\). From equation (22) (23) (24) (26), we get:

\[\frac{n^2 \log n}{1 - \beta} = E\]  \hspace{1cm} (27)

\(n\) is monotonic function of expenditure \(E\), so by solving the inverse function, total vertical variety \(n\) is a function of total expenditure \(E\):

\[n = N(E; \phi, \sigma)\]  \hspace{1cm} (28)

The price index of service good depends on \(n\):

\[P_S = \left( \int_1^n m_j^{\frac{1 - \phi}{1 - \sigma}} dj \right)^{\frac{1}{1 - \phi}}\]

\[= [n \log(n)]^{\frac{1}{1 - \phi}} \quad \text{when} \quad 1 + \sigma = 2 \phi\]  \hspace{1cm} (29)

The indirect utility of a typical resident is:

\footnote{The detailed derivation is in Appendix A.2}
\[ V = (P_{CBD} \times P_S)^{-1} \]
\[ V = (C + 3L/2)^{-1}[n\log(n)]^{1/n} \]  

(30)

This indirect utility reflects the welfare of each individual in the city. As population increases, initially the utility increases with the agglomeration benefit dominating the congestion cost, but eventually, the congestion cost could increase faster due to the decreasing elasticity of land supply. Depending on the parameters, the utility is either a monotonically increasing function or a single peaked concave function.

**Lemma 1** The utility function is monotonic increasing function when the elasticity of substitution \( \phi \leq 1.5 \) and is single peaked concave function when \( \phi > 1.5 \).

*Proof in Appendix A.4*

When the utility function is a single-peaked concave function, the utility follows an inverted-U shape. In the beginning, when the population is low, the agglomeration effect, from the increasing variety of service goods, dominates the congestion cost. But there’s a decreasing marginal benefit of agglomeration compared to the congestion cost, and eventually the congestion cost dominates the agglomeration benefit. When the agglomeration benefits are high enough; that is, when the service elasticity of substitution is low enough, it is possible to have agglomeration effect dominate congestion cost perpetually. In that case, the city is always better off with more population.

Most of the urban literature accepts the assumption that utility follows an inverted-U shape utility function of population. In the numerical exercise section, I show that urban utility function can be a monotonically increasing function of population, and asymmetric-city-size equilibrium is still attainable.
1.2.4 The Two-City Model

Both cities locate on a featureless plain. The Core-Periphery models propose that cities were formed to serve the immobile agricultural population, and some are formed due to the geographical advantage such as being a portage city \cite{Bleakley and Lin 2012}. However, due to the nature of path dependence, cities today continue to exist despite the fact the agriculture population and geographical advantages are no longer relevant. Therefore, this paper does not argue the origins and formation of cities but focuses on the size distribution and evolution of existing cities.

Like Krugman \cite{1991b}, who only looks at two regions isolated from the outside world, I isolate and study a group of nearby cities in a city cluster. Within the city cluster, I study the size distribution of cities.

**Definition 2** A two-city equilibrium is a collection of prices and quantities for city $i \{ P^i_S, P^i_H, P^i_M, S^i, H^i, M^i \}$ and a population ratio between the two cities $x$, such that consumers maximize their utility and firms maximize their profit, with utilities equalized between the two cities.

Assume workers have intra-city free mobility and there is trade between the two cities. Service goods are traded with iceberg cost: $\tau^* > 1$. Let $\tau = (\tau^*)^{\phi - 1}$ \footnote{This is to simplify the following notations} $l_1$ and $l_2$ are the populations of City 1 and City 2, $n_1$ and $n_2$ be the number of vertical varieties of City 1 and City 2.

Due to the hierarchical economies of scale, the larger city produces a superset of vertical varieties over the smaller city. It is assumed that the smaller city only imports those varieties it doesn’t produce. In order to balance the trade, the smaller city exports manufactured goods back to the larger city.

Now consider two city equilibrium with inter-city trade. First, their congestion costs are determined by the populations of each city. Second, their price index of service goods is
determined by varieties they produce and, in the case of the smaller city, varieties it imports. The indirect utility for the two cities are:

\[
V_1 = (P_1^1 \times P_{CBD}^1)^{-1} \\
V_2 = (P_2^2 \times P_{CBD}^2)^{-1}
\]  

(31)  

(32)

The equilibrium requires a population ratio \(l_2/l_1\) such that the utilities are equalized between the two cities. It is assumed that \(l_2/l_1 < 1\), which means that City 1 is larger than City 2. The equilibrium is achieved when the utility ratio equals one: \(u_1/u_2 = 1\).

Let \(n_i\) be the total number of vertical varieties in City \(i\), with \(i \in \{1, 2\}\). We need to find the vertical varieties \(n_1\) and \(n_2\) each city produces given the city population \(l_2\) and \(l_1\).

Figure 1.6: Firm Distribution of the Two Cities

Figure 1.6 shows the expenditure distribution of the two cities. City 1 produces all the service industries City 2 produces, and therefore, City 2 “import” the varieties that are not produced locally: from \(n_2\) to \(n_1\). The darker grey areas stand for City 1 expenditure on the local service varieties and the lighter grey areas stand for the expenditure by City 2. Note that for City 1, there is a discontinuity at at vertical variety \(n_2\), because the demand from
City 2 increases the horizontal varieties $m_{n_2}$, which increases the local demand for varieties $i \in (n_2, n_1)$.

People in City 1 consumes all service varieties locally, while people in City 2 consume local varieties $i \in (1, n_2)$ and consume $i \in (n_2, n_1)$ from City 1. For given $l_1$ and $l_1$, the vertical variety $n_1$ and $n_2$ are determined such that the horizontal variety of the top ranked industries for City 1 and City 2 both equal to one: $m_{n_1} = m_{n_2} = 1$.

Given populations $l_1$ and $l_2$, with $l_1 > l_2$, there is a unique solution of $n_1$ and $n_2$. Because the wage equals to 1 and people's per capita income is 3/2, the per capita expenditure on service goods is $1/2$.[6] The total service expenditures of each city are $E^1 = l_1/2$ and $E^2 = l_2/2$. The solution of $n_1$ and $n_2$ are derived form the two nonlinear equations:[7]

$$n_1(n_1 - \tau n_2)\log\frac{n_1}{n_2} + (n_1 - \tau n_2)^2 \log n_2 - \frac{(1 - \beta)l_1}{2} = 0 \quad (33)$$

$$\tau n_1 n_2 \log\frac{n_1}{n_2} + n_2^2 \log n_2 - \frac{(1 - \beta)l_2}{2} = 0 \quad (34)$$

With the solution of vertical varieties $n_2$ and $n_1$, we can determine the utility level of both cities.

**Proposition 1** With $l_1$ fixed, positive growth in $l_2$ increase both $n_1$ and $n_2$ grow. With $l_2$ fixed, the positive growth in $l_1$ increase $n_1$ and decreases $n_2$.

*Proof in Appendix A.5*

This proposition states the inter-city interaction between the service employment of the large city and the neighboring city population. In the empirical section, I use the US County Business Pattern data to examine this prediction. The empirical results confirm the prediction of the model.

---

[6]It is derived in Equation (9)

[7]The derivation is in the Appendix A.3
With the solutions of $n_1$ and $n_2$, we can get the service price index for both city:

$$
P^1_s = (n_1 \log \frac{n_1}{n_2} + (n_1 - \tau n_2) \log n_2)^{\frac{1}{1-\phi}} 
$$

$$
P^2_s = (\tau n_1 \log \frac{n_1}{n_2} + n_2 \log n_2)^{\frac{1}{1-\phi}} 
$$

Due to free mobility between the two cities, an equilibrium is achieved when utilities of the two cities equalized:

$$
P^1_s \times P^1_{CBD} = P^2_s \times P^2_{CBD} 
$$

**Proposition 2** For a given total population $L > \frac{2B(\tau^* - 1)}{3}$, there is a unique solution for $l_1 > l_2$ such that the utilities are equalized between the two cities.

*Proof in Appendix A.3*

This proposition states that for a two-city model, as long as the total population is large enough, the only equilibrium is an asymmetric one where there is a large city that supplies all service varieties that are produced in the smaller city plus certain high-order varieties. In another word, the larger city produces a superset of service varieties over the smaller city. This theoretical finding is consistent with the empirical observation of the NAS rule and that large cities tend to be spaced apart with smaller cities organized around them (Hsu and Smith, 2014).

The symmetric equilibrium is not attainable, because those high-order industries with high fixed costs can only locate in one city, the larger one. Because of consumer’s love for variety, the city with more service varieties tends to attract even more people, which further increases service varieties. This virtuous cycle prevents the formation of a symmetric equilibrium. The mechanism is further analyzed in the numerical section.
1.3 Numerical Exercise

The two-city model is not analytically solvable. Therefore, I use numerical methods to solve for the equilibrium and run numerical comparative statics to evaluate the effects of changing parameters on the size variation of the two cities.

1.3.1 Numerical Solutions

First let \( l_2/l_1 \) be exogenous population ratios between two cities, and let utility ratio to be \( u_2/u_1 \). The total population is \( L = l_1 + l_2 \). The utility ratio \( u_2/u_1 \) depends on allocation of populations \( l_1 \) and \( l_2 \) between the two cities. Utilities are determined by service varieties \( n_1 \) and \( n_2 \), which are solved from equations (33) and (34). The simulation computes the utility ratio as population ratio increases from 0 to 1.

Figure 1.7: The Utility Ratio As a Function of Population Ratio

Figure 1.7 shows the utility ratio between the cities as a function of the population ratio. When population ratio is \( l_2/l_1 \approx 0 \), utility ratio \( u_2/u_1 \) is far greater than 1. That is, when most of the population live in the large city, it is much more attractive to live in the smaller city. The intuition is that, in the smaller city, the congestion cost is relatively low and people enjoys the pecuniary externalities of high-order service varieties from the large city.
As people move from the larger to the smaller city, the utility ratio \( u_2/u_1 \) is decreasing. The reason is that the congestion costs between the two cities are gradually equalized, and the pecuniary externalities from the large city are decreasing.

When the population ratio is close to 1, \( l_2/l_1 \simeq 1 \), we can see the utility ratio is below one: \( u_2/u_1 < 1 \). That means, it is always more attractive to live in a slightly larger city. The intuition is that, when the populations between the two cities are close to 1, the congestion costs are indistinguishable, but the service varieties are much greater in the larger city. The service industries that require high economies of scale tend to locate in a larger city, even a slightly larger, for a larger market access; more local service varieties make it more attractive to live in. More service varieties and more population form a virtuous cycle that attracts the population into the larger city until the congestion costs equalizing the utilities between the two cities.

The numerical exercise shows that the two corner solutions are both non-stable, and the only stable equilibrium is the interior solution, where the utility ratio reaches unity. Further, Figure 1.7 shows the shift of the curve when the total population increases from 50 to 200. We can see that utility ratio curves is shifting to the right. The intersection points with the straight line shifts to the right. As total population increases for the two-city model, the equilibrium population ratio moves to the right; that is, there is a lightly convergent effect. The convergence or divergence hinge on the parameter \( \phi \). When \( \phi < 1.5 \), the agglomeration benefit perpetually dominating the congestion cost, total population growth causes urban divergence. When \( \phi \geq 1.5 \), population growth causes urban convergence. The numerical comparative statics is in Appendix D.3.

Next, I use a computation algorithm to find the unique equilibrium of the city sizes for the two-city model, and calculate the utility for residents in both cities. The computation algorithm is following: first, I assign numeric value to each parameter. Second, assign a population to each city. The ratio of the population \( l_2/l_1 \) increases from 0 to 1. Third, for each population allocation, plug into Equation (33) and (34) and solve for vertical varieties.
$n_1$ and $n_2$. Then plug into the utility function (35) and (36) to get $u_1$ and $u_2$. Last, when $u_1 < u_2$, it increases ratio $l_2/l_1$, and when $u_1 > u_2$, it decreases population ratio, till $u_1 \simeq u_2$ within tolerated small error. As predicted by Figure 1.7, the computation algorithm generates a unique solution where $u_1 = u_2$.

Next, I use the same algorithm with a larger total population and generate the result in the following figure:

Figure 1.8: The Equilibrium Sizes of Two Cities

![Equilibrium City Size Distribution](image)

Figure 1.8 shows a balanced growth process. The ratio of the two cities remains relatively stable despite repaid growth in total population. There is no particularly noticeable convergent or divergent trend. The city size distribution is stable over the time, a phenomenon noticed by Duranton (2007) who shows that the city size distribution remains stable over the time, despite rapid industrial churning.

**Discussion on the Optimal Urban Size**

According to Henderson’s (1974) theory, agglomeration benefits initially dominates the congestion cost, but eventually, the congestion cost dominates agglomeration benefit. This mechanism ensures the utility function of a city follows an inverted-U function of the total
population. If agglomeration benefit perpetually dominates the congestion cost, everyone will live in one and only one city. With Henderson's theory, one can conclude that cities are either in optimal size or over-sized. Because when a city is below the optimal size, it is not in a stable state. A positive perturbation increases utility and attracts even more people till a new equilibrium. In Henderson's theory, the optimal city sizes are achieved with the existence of land developers or local governments that internalize the positive externalities and agglomeration benefits.

In this model, however, there are pecuniary externalities from the large city to the surrounding cities. The utility of a city can be a monotonically increasing function of population, and asymmetric-size equilibrium is still attainable, which is shown in Figure 1.8. For a single city, there does not exist an optimal city size or a maximum point of the utility function. An increase in the number of cities does increase the overall welfare of each city in the city cluster.

### 1.3.2 Numerical Comparative Statics

**The Effect of Change in Trade Cost $\tau^*$**

The trade cost $\tau^*$ between the two cities plays a critical role in shaping the city sizes. The effect of the decline in inter-regional transportation cost has long been of interest among regional and urban economist. In this paper, we should interpret the trade cost in a different manner. In the NEG theory, the trade cost is the transportation cost of manufactured goods between cities, whereas, in this model, the trade cost is the inter-city opportunity cost of traveling. Infrastructure improvement like the high-speed train or self-driving car in the near future decreases the opportunity cost of inter-city travel, but not necessarily transportation cost of manufactured goods. Krugman (1991a) shows that a reduction in transportation cost could lead to regional divergence.

However, this model shows that a reduction of inter-city trade cost $\tau^*$ always leads to convergence of cities within a city cluster. The intuition is that the pecuniary externality of
the large city to the surrounding ones increases as the trade cost declines.

Figure 1.9: Urban Convergence With Reduction in Trade Costs

From Figure 1.9, one can see that as the iceberg trade cost decreases from 3 to 1.5, the equilibrium city sizes are converging and the utility of both cities increase.

The Effects of Changes in Other Parameters: $\phi$, $\sigma$, $\alpha_1$, $\eta$, and $C$

Figure D.4 illustrates the numerical comparative statics of changing model parameters. An increase in elasticity of substitution $\phi$ and $\sigma$ decreases the agglomeration benefits, and, therefore, decrease the appeal of the large city, which leads to urban convergence.

An increase of the share of service expenditure $\alpha_1$ leads to urban divergence. This a feasible trend in the future, because service is luxury goods. As people’s income increases, they spend more share of income on service goods. An increase in service expenditure share attracts more people to the larger cities, where consumers can enjoy a higher variety.

Congestion costs can be model putting a parameter in the commuting disutility term: $e^{-\eta r}$, where higher $\eta$ meaning higher congestion costs. Congestion cost $\eta$ can be reduced as the government invests more in commuting infrastructure like urban metro systems. Reduction in congestion costs increase welfare for both cities, and the larger city benefits more from the infrastructure investment. The reduction in congestion cost could lead to urban divergence.
Last, increases the opportunity cost of land usage $C$ raises the lower bounds of housing price, which hurts the smaller city and hence leads to urban divergence.

1.4 Numerical Evidence

1.4.1 Data

The dataset uses the urban definition of Core Based Statistical Areas (CBSA). A CBSA is a U.S. geographic area that consists of one or more counties (or equivalents) anchored by an urban center of at least 10,000 people plus adjacent counties that are socioeconomically tied to the urban center by commuting. In total, 1881 counties combine into 917 CBSAs, excluding the cities in Puerto Rico. All the data are observed at the county level and then aggregated into CBSAs.

The population data is from the US population census estimation. The census is conducted every ten years, and for the years between the decennial censuses, the Census Bureau issues estimates made using surveys and statistical models. I use the population estimates every two years from 1986 to 2014.

The employment data are from the County Business Pattern (CBP) data set, which records the employment information of each county from 1986 to 2014. For certain industries in some counties, the employment data are flagged to avoid disclosure of confidentiality. I use an estimate from the product of the average employ size class and the number of establishments, to replace the flags. There are two sets of industry codes. The first one is Standard Industrial Classification (SIC) Code, which is used from 1986 to 1996, and the second one is North American Industry Classification System (NAICS) codes, which is used from 1998 to 2014. I define the service industries as all but manufacturing, agricultural, mining, and administration industries.

The service industry is split into three categories, the high-order, middle-order, and low-order service industries. The high-order service industries are less common, and therefore there are fewer cities that supply them. For each service industry at the most refined level,
I count the number of hosting cities and rank the industries by the number of hosting cities. The high-order service industries are the ones with a smaller number of hosting cities, and the low-order service industries are ones with a larger number of hosting cities. The three categories of service industries are split in a way to keep each category with roughly similar total employment. Same methodologies are applied to the manufacturing industries.

1.4.2 The Baseline Estimation

This model generates a positive correlation between the nearby cities, as illustrated by the simulation, but the positive correlation is not surprising from the perspective of NEG theory, due to a market access story: when the neighboring cities experience positive population growth, there’s an increase of market access for the local manufacturing sector. The positive re-enforcement between the neighboring cities generates the positive co-movement of city growths. The NEG theory focuses on the traded manufactured goods, whereas my paper focuses on the inter-city interaction in the service industries. As such, my paper generates different prediction from the NEG theory. Since the dominant city in a city cluster supplies the high-order service varieties, there should be a positive correlation between the high-order service employment in a dominant city and the neighboring population, which is proven in Proposition 1. Polèse et al. (2004) made a similar argument that the decline of the Montreal as the top city Canada was due to the weakening of the service hinterland.

The baseline regression model is in the following:

\[ Serv_{it}^{T,H,M,L} = \beta_0 + \beta_1 pop_{it} + \beta_2 nb_{it} + (\beta_3 pop_{it} + \beta_4 nb_{it}) \times top_{i}^{100} + city_i + year_t + \epsilon_{it} \]  (38)

\[ Serv_{it} \] is the employment share of the service industries. \( T \) stands for total service as a percentage of total employment. \( H, M, L \) each respectively stands for the high-order, the middle-order, and the low-order employment as a percentage of the total employment.
$top_i^{100}$ is a dummy variable that indicates the largest city within a city cluster of 100 miles. For each city, I draw a circle of 100-mile radius, within which the largest city is indicated by 1 and the rest indicated by 0. Among 719 total cities, of which 68 are top cities within 100-mile city clusters. $pop_{it}$ and $nb_{it}$ are the logarithmic local population and neighboring population within 100 miles for city $i$ year $t$. $city_i$ and $year_t$ are individual and time fixed effects respectively.

The model predicts, as in Lemma 1, that there is a positive correlation between neighboring population and the high-order service employment for the largest city in a city cluster, but not for other cities. Therefore, the coefficient $\beta_4$ is predicted to be statistically positive. When there is an exogenous shock to the population growth for a certain city, it affects the service composition for the nearby larger cities.

1.4.3 Empirical Results

The following table summarizes four different regression results based on estimates of equation (38):

From Table 1.1, we can see that the coefficients on local urban population vary between $T$, $H$, $M$ and $L$. For the total service share $Service^T$, the coefficient on population is negative. The intuition is that manufacturing sector is still an important one that determines the rise and fall of cities. Especially for cities in the rust belt, population decline can be attributed to the secular decline of the manufacturing sector. The loss of population is correlated with loss of manufacturing employment, and, thus, is correlated with increasing service employment share.

The effect of local population on the high-order service employment share $Service^T$ is positive at 0.072, on the middle-order service $Service^M$ is negative at -0.043 and on the low-order service $Service^L$ is negative at -0.121. For non-dominant cities in the cluster, as the populations grow the percentage of employment is increasing for the high-order service industries, but not for low-order service industries. This is intuitive: as small cities grow the
Table 1.1: The Baseline Regression Results

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<tr>
<th></th>
<th>Service(^T)</th>
<th>Service(^H)</th>
<th>Service(^M)</th>
<th>Service(^L)</th>
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<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
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<td>(\log(\text{pop}))</td>
<td>(-0.051^{***})</td>
<td>(0.072^{***})</td>
<td>(-0.043^{***})</td>
<td>(-0.121^{***})</td>
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<td>((0.005))</td>
<td>((0.005))</td>
</tr>
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<td>(-0.002)</td>
<td>(-0.048^{***})</td>
<td>(0.023^{***})</td>
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<tr>
<td>(\log(\text{pop}) \times \text{top}^{100})</td>
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<td>(-0.096^{***})</td>
<td>(-0.086^{***})</td>
<td>(0.100^{***})</td>
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<tr>
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</tr>
</tbody>
</table>

Observations 13,485 13,485 13,485 13,485
R\(^2\) 0.536 0.093 0.134 0.576
Adjusted R\(^2\) 0.502 0.026 0.069 0.545

Note: \(*p<0.1; **p<0.05; ***p<0.01\)

population, there is an expansion in the high-order service industries. Therefore, there is more growth in the high-order service employments comparing to the low-order service. For the low-order service, there is an increasing return to scale effect at the city level. Consider, for example, that a city of 10,000 people has 1000 fast food servers and as the population doubles to 20,000, there will be more fast food servers, but probably not double the number of them. It is likely due to the fact that each employee serves more customers in more densely populated areas. The same applies to low-order services like gas stations and fast food restaurants; the service share of those low-ordered declines as populations grow.

The most interesting coefficient is \(\beta_4\), the coefficient on the interaction term of the neighboring population and the dummy variable indicating the top city. For the largest city in a city cluster, the positive growth of the neighboring population increases the high-order service employment, whereas such effect is weak for middle-order and insignificant for low-order
service employment. This is consistent with Lemma 1: for the largest city, as neighboring populations grow, there is a higher demand for high-order service goods and, thus, an increase in high-order service employment. The coefficient is at 0.116, which means that a one percent increase in the neighboring population leads to 0.116 percent increase in high-order service employment share, only for the largest city. Such effect attenuates for the middle-order and low-order service employment shares.

One caveat of using the dummy variable is that it only gives us the information on the largest city in a cluster. The second largest city Philadelphia within the New York urban cluster, for example, also supplies high-order service to the surrounding area. In the next regression, I use a continuous weight to denote the importance of a city within its city cluster. The continuous weight is defined as its percentage of population within the cluster as following

\[
\text{weight} = \frac{\text{city population}}{\text{total population of the cluster}}
\]

Table C.1 shows the effects are consistent with the case with the dummy variable. This regression shows that the larger a city is, the higher effects of growth in neighbor population on the high-order service employment share.

The existing Central Place models either emphasize on manufacturing industries (Tabuchi and Thisse, 2011) or makes no distinction between industries (Hsu, 2008; Christaller, 1933). However, this model argues that the central place mechanism is through the costly inter-city trade of the service industry and that the manufacturing industry does not exhibit the central place pattern, due to the relatively low trade costs.

In order to prove the difference between the two industries, I run the regressions with a comparison of the two. Table C.2 shows a comparison between service and manufacturing industry. The dependent variable is high-order, middle-order and low-order service
employment as a percentage of the total service employment. This specification shows the compositional change within the service industries. For the largest city, the positive growth in the neighboring cities increases the high-order service employment share of the total service. For the middle-order and low-order industries, the effects are insignificant and negative. Applying exactly the same methods to the manufacturing sector, the neighboring population has insignificant effects on the composition of the manufacturing industry, for the large cities. This comparison further confirms the difference between the two sectors, and that the service sector exhibits a central place pattern, not the manufacturing sector.

### 1.4.4 Alternative Estimates and Robustness

Additionally, the definition of a city cluster is an arbitrary one. To check the robustness, I run the regressions in city clusters with different distances of radius, ranging from 50 miles to 300 miles. The coefficients on the interaction between neighboring population and the weight of city in a city cluster are shown in Table 1.2. We can see from the following table that the coefficient for the high-order service employment share are significant at distances of 50 miles to 200 miles, and the significance ceases to exist for the distances beyond 250 miles. The effects of neighboring population on the high-order service employment initial increases and then decreases for distances greater than 100 miles. Notice that the weights of each city within a city cluster is decreasing when the distance is greater. Therefore, we should interpret the coefficient differently. The effect is most significant and robust at a distance of 100 miles.

In order to identify the causality effect of the neighboring population to the high-order service employment, I use the 2-year and 4-year lagged dependent variables in regression in Table C.3. The regression results are consistent. In Table C.4 to control the path dependency problem, I include the lagged dependent variable. The result shows that the lagged dependent variable absorbs much variation, but the effect of the neighboring population on the local high-order service employment is significant nonetheless.
Table 1.2: Regressions with Alternative Defining Distance of An Urban Cluster

<table>
<thead>
<tr>
<th>Service^T</th>
<th>Service^H</th>
<th>Service^M</th>
<th>Service^L</th>
</tr>
</thead>
<tbody>
<tr>
<td>β_4 : log(nb) × con</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>50 miles</td>
<td>-0.090***</td>
<td>0.025**</td>
<td>-0.017</td>
</tr>
<tr>
<td></td>
<td>(0.018)</td>
<td>(0.012)</td>
<td>(0.017)</td>
</tr>
<tr>
<td>100 miles</td>
<td>-0.010</td>
<td>0.173***</td>
<td>0.057**</td>
</tr>
<tr>
<td></td>
<td>(0.032)</td>
<td>(0.022)</td>
<td>(0.029)</td>
</tr>
<tr>
<td>150 miles</td>
<td>-0.033</td>
<td>0.147***</td>
<td>0.042</td>
</tr>
<tr>
<td></td>
<td>(0.048)</td>
<td>(0.034)</td>
<td>(0.044)</td>
</tr>
<tr>
<td>200 miles</td>
<td>-0.068</td>
<td>0.148***</td>
<td>-0.103*</td>
</tr>
<tr>
<td></td>
<td>(0.065)</td>
<td>(0.045)</td>
<td>(0.059)</td>
</tr>
<tr>
<td>250 miles</td>
<td>0.037</td>
<td>0.045</td>
<td>-0.228***</td>
</tr>
<tr>
<td></td>
<td>(0.069)</td>
<td>(0.048)</td>
<td>(0.063)</td>
</tr>
<tr>
<td>300 miles</td>
<td>0.162**</td>
<td>0.043</td>
<td>-0.213***</td>
</tr>
<tr>
<td></td>
<td>(0.077)</td>
<td>(0.054)</td>
<td>(0.069)</td>
</tr>
</tbody>
</table>

Note: The regressions follow the baseline model in Equation (38) using the continuous weights. β_4 is the coefficient for the interaction term.

1.5 Conclusion

This paper builds a general equilibrium model of urban hierarchy, with the service industries exhibiting a hierarchical pattern. It generates a unique equilibrium in a two-city model, with asymmetric city size equilibrium. It emphasizes the role of the service sector as a determinant of the urban hierarchy and offers empirical evidence that the service industries indeed exhibit the hierarchical pattern, but not for the manufacturing industries.

The large cities are more diverse because it tends to specialize in all service industries including ones of higher economies of scale, which serve both the local and neighboring populations. The smaller cities are less diverse because they do not offer large enough market access to the service industries of high returns to scale.

Using the NAS rule, this paper shows that the hierarchical pattern holds for the service sector, not for the manufacturing sector. In the empirical section, I use a panel data set to
confirm the dynamic interactions between the nearby cities: positive growth in neighboring population increases the high-order service employment in a large city, but not in small cities. Again such dynamic interactions only hold true for the service sector not for the manufacturing sector. The effect is most significant when the definitive radius of a city cluster is at around 100 to 200 miles.

This model shows that the utility of each resident can be a monotonically increasing function of the urban population, which differs from previous studies that assume an inverted-U shape utility function. On this basis, there exist no particular optimal size of a city and cities are not necessarily oversize. Hence, the policy implication is to reduce intra-city commuting and inter-city travel cost, or by increasing the number of cities that nearby the large cities. The optimal urban policy is the most cost-effective of the three, instead of simply downsizing urban populations by forming new cities.

In the general equilibrium, reduction in trade costs always benefits the smaller city, because high-order service goods can be more accessible to the consumers in smaller cities. However, in the Core-Periphery model, a reduction in trade costs could cause both convergence or divergence depending on the choice of parameters. In my model, the trade costs are the inter-city traveling opportunity costs and Core-Periphery model focuses on the transportation cost of the manufactured goods. Reduction in inter-city trade costs can enlarge the market access for high-order service industries in the large city, which improves social welfare in both cities.

A caveat of this model is the oversimplification the distances and topology within the city cluster. One potential extension is to look at a more complex structure of city clusters with more than two cities. With such a model, one can potentially explore the mechanism that generates Pareto city distribution in a Central Place setup. Agglomeration mechanism in this paper comes from people’s love for service consumption varieties. One natural extension is to generate agglomeration externalities from the increased intermediate inputs, à la Ethier (1982): the production is a CES function of intermediate service varieties. The larger city
has higher productivity is due to the sharing of intermediate service inputs.
Chapter 2

Do Political Disputes Make Foreign Cuisines Less Appealing? — Evidence From Chinese Online Data

2.1 Introduction

Do international conflicts and negative perceptions of a foreign country affect the domestic consumption of the associated economic goods? Many studies have tried to answer this question by looking at the effects on traded manufactured goods during a political conflict. Fuchs and Klann 2013 show that the Chinese government uses import reduction as punishment to countries that receive Dalai Lama visits. The authoritarian government has the ability to insert political influence on the state-owned corporations to boycott foreign imports, whereas, in democratic countries with market economies, the governments’ capacity to influence international trade decisions should be weaker. Nonetheless, it is shown that the deterioration of France-US political relations leads to reductions in bilateral trade [Michaels and Zhi (2010)]. Heilmann 2016 uses multiple political events to show that political tensions cause turbulence in bilateral trade. He further demonstrates that boycotts are more effective on consumers goods than on intermediate and capital goods, which is reasonable, considering consumers tend to make choices based on emotions. Such emotions would hurt the profit-maximizing motives for suppliers. Du et al. 2017 find that, in the case of China, the shocks in political relations have temporal effects on bilateral trades, and the negative effects are much more pronounced for state-owned enterprises (SOEs) than for private companies.

The aforementioned studies focus on the role of government and trading companies in the case of the boycott movements, but there are fewer studies on consumers’ actual boycott behavior during the time of political tension. One of such studies is by Pandya and Venkatesan 2016 who use samples of weekly supermarket sales to show that the US-France political tension in 2003 caused sale reduction of the French-sounding brands. Their paper
confirms the actual participation of the consumers in the events of political boycotts, and also demonstrates that the intensity of the boycotts correlates with the community characteristics: a supermarket with more American citizen consumers tends to boycott French-sounding brands more. Chavis and Leslie [2009] confirm this finding and show that there was a negative impact of Iraq war on the French wine sales in the United States. Such studies focus on consumer’s boycotts of the imported goods, which shows that consumers incorporate supplier’s nationalities into consumption choices.

Most of the existing studies, as far as I know, focus on manufactured goods, by identifying the effects on international trade and stock market performance of the associated firms. Some find contradictory results [Chavis and Leslie (2009); Ashenfelter et al. (2007)], and most find relatively small and short lived effects [Clerides et al. (2010); Michaels and Zhi (2010)]. In comparison, this paper finds significantly negative effects on non-traded service industry resulting from a political dispute, with the negative effects persisting for at least one year. This study also differs from the previous ones, in that the targeted Korean restaurants are mostly owned by Chinese businessmen. The target on Chinese-owned Korean restaurants contradicts the rationale of boycott as a rational movement to punish the foreign adversary. One can conclude that the Chinese taste for Korean foods is negatively affected in the face of negative propaganda against the Korean government.

This paper studies the Chinese consumer’s boycott of Korean restaurants during a period of political dispute caused by an American anti-missile defense system, Terminal High Altitude Area Defense (THAAD), being implemented in South Korea. It is the first paper that studies the political boycott on non-imported service industry that is associated with the foreign adversary and brings about a couple of new contributions to the literature. First, this paper studies consumer’s actual boycott of the foodservice industry, which takes up around

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8 These studies find, in the face of political tensions, 2.7% drop in Sino-Japan trade, 9% drop in French-US trade, 0.4% decline for French goods using scanned data and “modest and short-lived negative impact” on sale of US goods in Arabic countries. Most of the trade recovers next year. The consumption boycott peaks at the events and attenuates over weeks. There are studies that find a relatively large effect, for example, Heilman [2016] finds 18.8% drop of Denmark-Arab trade. That is likely to due to the relatively small trade volume between those countries.
10% of the total retailing industry in China. The food industry is relatively large compared to many previous studies that focus on one specialized industry, for example, automobile or wine. The negative impact is considerably larger and more persistent than previous findings, with 29% reduction in total consumption visits which lasts at least one year. Second, it identifies the intensive and extensive margin from the consumer boycott. The political tension not only causes consumers to visit Korean restaurant less but also it lowers the rate of business entrances for Korean restaurants by 54%. Third, I use a novel data set of online reviews to approximate the quantity of restaurants consumption visits. Using the additional information from the review site, this paper finds that the boycott is decreasing in review rating and the average price of Korean restaurants. Fourth, using the rating data, this paper finds that international dispute not only affects people’s consumption behaviors, but also affect their subjective quality judgment. Fifth, this study allows for geographical differential effects of the boycott. Economic openness intensifies people’s boycott effort.

The remainder of this article is organized into four sections. Section 2 briefly reviews the political dispute that took place between China and South Korea in 2016 and 2017. Section 3 describes the data set, and Section 4 outlines the baseline regression and findings. Section 5 concludes the paper and discuss the possible mechanisms of the negative impact.

2.2 Deterioration of the China-South Korea Relations

This paper uses recent political events in South Korea as an exogenous shock to the China-South Korea relations. THAAD is an American anti-ballistic missile defense system. It was reported that in early February 2016, the Korean government started to consult with the US military about the possibility of deploying the THAAD system. In July 2016 the Korean government announced that the THAAD system would be implemented in South Korea to counteract the nuclear threat from North Korea; the actual implementation started in March 2017. The Chinese government opposed the implementation of THAAD for national security concerns, even though the South Korean government insisted that the THAAD system only
targeted North Korea. The political relationship between the two countries worsened after the announcement of the anti-missile system and rapidly deteriorate in March 2017 when the Korean government started the implementation. Consequently, it was reported that the Chinese government took countervailing actions against Korea by restraining Chinese traveling visas to Korea and by restricting Korean celebrity performances in China. For the public, the event did not catch most people’s attention until March 2017, when the company Lotte, a South Korean conglomerate, agreed on a Korean government proposal to provide land for the installation of THAAD system. This then sparked boycotts movements against Lotte in China, which attracted extensive public attention. Some were even calling for comprehensive boycott for all Korea-related goods. These two key events are referred to as the announcement of THAAD and the Lotte-boycott in rest of the paper. On July 29th 2017, THAAD system was completed implemented.

Figure 2.10: The Daily News Simulcast Reporting of THAAD

The Chinese media gave in-depth reporting on the political disputes as the events unfolded. Figure 2.10 shows the reporting of THAAD from Chinese CCTV News Simulcast, the most watched TV news program in China. News Simulcast is a news program that reflects official positions of the Chinese government on a wide range of matters. It is broadcast 30 minutes everyday from 7 pm. Using the Chinese character counts of the THAAD related news from the news scripts, the figure captures relative reporting depth from 2016 to 2017. The reports most concentrated in mid-2016, when the THAAD was announced, and also in
early 2017, when the implementation started and the company Lotte cooperated with the Korean government. However, the news report differs from the attracted online attention.

Figure 2.11 shows the Weibo index, which reflects a trend of relative intensity of online attention. It started in July 2016 and got the most attention in early March 2017, when the Lotte-boycott event took place. It differs from the News Simulcast in that the relative intensity took place in early March 2017 in stead of July 2016. The online discussion and sharing is relative more on the Lotte-boycott event than the News Simulcast. This paper uses the both key events to identify the negative effects of political disputes.

Figure 2.11: The Media Index of THAAD using Chinese Media

The Weibo index reflects a trend of relative intensity of the Internet attention over the time. However, people cannot directly interpret the index in a meaningful way. To give a comprehensive view on the significance of the event, Figure D.5 shows the comparison of Google index between the keywords THAAD and Donald Trump. We can see that the attention received of the THAAD events are even comparable to the one of the 2017 US presidential election.

Contrast to the study by Pandya and Venkatesan[2016] who uses negative news mentioning

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9Weibo is a population Chinese social media, similar the twitter in the US.
as a continuous treatment, this paper uses before and after of the two pivotal dates, the announcement of THAAD in July 2016 and the Lotte-boycott in March 2017. It is similar to the study by Zhi et al. 2010, who use “pre-crisis” and “post-crisis” to identify negative political dispute effect. In this paper, I use a difference-in-differences method to identify the effects of political dispute using before and after the two key events.

2.3 Data

This paper uses a novel data set that is collected from the Chinese website dianping.com, which is a reviewing website of local businesses, similar to yelp.com in the United States. The scrapped online data gets increasing attention in recent years, and many economic and business studies have used the same data source from dianping.com [Wu et al. (2015); Zhang et al. (2015), and also from yelp Davis et al. (2017); Luca (2016)].

The data set contains longitudinal reviewing data of many restaurants. This paper uses the review counts to approximate the restaurant consumption visits. The key assumption, therefore, is that the chance for a typical consumer to leave a comment is persistent over different types of restaurants within the same time periods, regardless of the political dispute. For example, the chances of a consumer leaving a comment after a visit are the same for Korean and Japanese restaurants in the same week, not necessarily in different weeks. However, one concern about using the review data is that there is evidence that business owners have incentives to manipulate or, even, make up fake reviews to attract more customers Mayzlin et al. (2014). My argument is that as long as those fake reviews do not correlate types of restaurants, the fake reviews become noises. One more concern is that, for Korean restaurant owners make their effort to increase quality to prevent losing customers. In that regard, the negative shock might be underestimated. Nonetheless, we can think of the estimated negative shock as the lower bound of such negative effect.

One concern is that the political tension might cause consumers to be more reluctant to leave review on the site. This paper assumes such possibility away, because it is difficult to justify why consumers still want to go to Korean restaurants but being more reluctant to leave reviews. Even if this assumption is correct, this paper still identifies the change in consumer’s behavior.
The scrapped data contains about 40 million reviews for 22 thousand restaurants in the top 60 Chinese cities. Each restaurant observation contains information of rating, location, total number of reviews, and the exact time of each review. The review data is from January 2015 to March 2018, which covers the whole time span when the political events unfolded. In March 2018 the data were scrapped on dianping.com and only restaurants which existed in March 2018 are included in the data: restaurants which existed but were closed by the date the data were scrapped are not included in the data, which is a common shortcoming of most of the scrapped data.

The data set consists of five types of restaurants: Korean, Western, Southeastern, Japanese and Chinese. The Chinese type consists of a couple of local Chinese cuisines. Southeastern Asian and Japanese cuisines are considered close substitutes to Korean cuisine, since they are both neighboring Asian countries to China. Korean restaurants are the treated observations, and the Chinese restaurants are the control groups, which are assumed to have equal trends as Korean restaurants, if the political disputes had not happened. The control groups exclude the other three foreign restaurants because they are close substitutes for Korean restaurants, and they could experience increased visits due to boycotts on Korean restaurants, which violates the equal trend assumption, a necessary condition for difference-in-differences method.

Figure 2.12: The Equal Trend Assumption Between Korean and Chinese Restaurants
Figure 2.12 presents the equal trends of Korean, Japanese, and Chinese restaurant reviews. Before mid-2016, all three types have a resembling trend, but the gap between Korean and the other two types of restaurants slightly widened after the boycott events.

The negative boycott effect is slightly visible in the figure above, and it becomes more salient when I graph the ratio of Korean restaurant reviews to the total, shown in the next figure.

Figure 2.13: Time Trends of the dianping.com Review Counts

Figure 2.13 shows the total aggregated review counts and the ratio of Korean restaurant reviews as percentage of the total. The total review counts remain at around 150 thousand each week, and it declines slightly in mid-2016, possibly due to a declining popularity of the review site. The red line indicates the ratio of Korean restaurants reviews as a ratio of the total, and it declines in mid-2016; and the sharpest decline took place in March 2017. The ratio was above 12% before 2017, but after March 2017, the ratio persistently lingered around 9%. Eyeballing the graph, one can see a slight decline after the announcement of THAAD and a significant drop of the review counts for Korean restaurants at the Lotte-boycott event, compared to other types of restaurants. The next section uses a panel data and difference-in-differences model to identify the negative effects of the two events.
2.4 Empirical Model and Results

The empirical model uses difference-in-differences method of OLS and Poisson regressions. The dependent variables are restaurant visits, approximated by monthly review counts.\(^{11}\)

Due to the potential serial correlation for restaurants within the same city, the model could over-reject the null hypothesis, which is known as the Moulton problem.\(^{12}\) Moulton (1986).

The model avoids the Moulton problem by aggregating the restaurants by city and type. After aggregating by city and type, each observation contains total review counts within a month for a certain type of food in a city. For example, the aggregated review counts for all Japanese restaurants in Beijing is one observation, and the aggregated review counts for all Korean restaurant in Shanghai is another. In the baseline model, the data contains has 60 cities, 5 types of restaurant, 435 total cross sectional observations and 18,810 observations.

The baseline regression model is following:

\[
Counts_{it} = \beta_0 + \beta_1 Announcement_t \times \text{Korean}_i + \beta_2 Boycott_t \times \text{Korean}_i + \beta_3 Month_t \times \text{Type}_i + \alpha_i + \gamma_t + \epsilon_{it}
\]

where

- \(Counts_{it}\): Total review counts of observation \(i\) in month \(t\). Each observation is the total review counts for one type of restaurant in each city.

- \(\text{Korean}_i\): A dummy variable that indicate Restaurants that are tagged as Korean, or with Chinese character "韩式", meaning Korean Style, in the names.

- \(Announcement_t\): A time dummy variable for all time periods after the announcement of THAAD in July 2016.

- \(Boycott_t\): A time dummy variable that indicates the periods after the Lotte-boycott events.

\(^{11}\)The review counts are available in daily. The actual regressions use aggregated monthly review counts.

\(^{12}\)A popular way to solve the Moulton problem is to cluster the standard error. Aggregating the data by cities also solve the problem, due to the abundance of the observations. Also by doing so, it reduces the computational work.
\(Month_i \times Type_i\): The interaction term between month and type of restaurant. It captures the cyclical effect of each type of restaurant. For example, it could be that Korean cuisines are spicy in nature, and the consumption of Korean food declines in the summer months. By controlling same month in different year for each type of restaurant, it teases out the natural cyclical effects.

\(\alpha_i\): The individual fixed effect.

\(\gamma_t\): The time fixed effect.

Table 2.3 shows the regression results of 6 regressions. In addition to the baseline model, I control Japanese and Southwestern Asian restaurants (SEA), which are two close substitutes.

The first two columns are OLS regressions, with the dependent variable \(\text{log}(\text{Counts} + 1)\). There are many zero observations in the data set, due to the fact that some smaller cities do not supply certain types of foods. Adding 1 to the dependent variables solves the problem of logarithmic zeros.

The first column shows the OLS pooled regression, the announcement has insignificant effect, while the Lotte-boycott event has significantly negative effect. Compared to the domestic restaurants, the Korean restaurants experience \((e^{-0.498} - 1) \times 100\% = -39.2\%\) changes in visits.

In the second column, controlling individual, time fixed effect, and the cyclical effect, the announcement has significantly positive effect on the Korean restaurants, which is counter-intuitive. But my explanation is that first, in the beginning, when the South Korean government announce the THAAD project, the event received little public attention, which explains the non-negative result. Second, due to the abundance of zeros in the observation, adding 1 could cause biased results. This bias goes away in the Poisson regressions.\(^{13}\)

In the third and fourth columns, the Poisson regression generates some different results from the OLS. First, the coefficient on the announcement becomes significant at -0.299,

\(^{13}\)I tried deleting the ones with zero observations. The result shows that the coefficient became smaller at +0.056 but remained significant.
Table 2.3: Regression Results

<table>
<thead>
<tr>
<th></th>
<th>OLS</th>
<th>Poisson</th>
<th></th>
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<td></td>
<td>All Observations</td>
<td>All Observations</td>
<td>Pre-2016 Restaurants</td>
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<td></td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
<td>(6)</td>
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<td>−0.531***</td>
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<tr>
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<td>(0.056)</td>
<td>(0.001)</td>
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</tr>
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<td>Korean</td>
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</tr>
<tr>
<td>Japanese</td>
<td>0.576***</td>
<td>0.467***</td>
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<td>(0.073)</td>
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<td>(0.001)</td>
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<td>SEA</td>
<td>−0.182**</td>
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<td>−0.425***</td>
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<td>(0.001)</td>
<td>(0.001)</td>
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<td>Boycott</td>
<td>0.180***</td>
<td>−0.058***</td>
<td>−0.383***</td>
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<td>Announcement × Korean</td>
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<td>0.159***</td>
<td>−0.002</td>
<td>0.012***</td>
<td>−0.068***</td>
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<td>(0.132)</td>
<td>(0.059)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
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<tr>
<td>Announcement × Japanese</td>
<td>0.347***</td>
<td>0.350***</td>
<td>0.168***</td>
<td>0.186***</td>
<td>0.112***</td>
<td>0.129***</td>
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<td>(0.131)</td>
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<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
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<td>Announcement × SEA</td>
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<td>−0.004</td>
<td>0.028***</td>
<td>0.034***</td>
<td>−0.032***</td>
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<td></td>
<td>(0.145)</td>
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</tr>
<tr>
<td>Boycott × Korean</td>
<td>−0.498***</td>
<td>−0.516***</td>
<td>−0.345***</td>
<td>−0.354***</td>
<td>−0.199***</td>
<td>−0.204***</td>
</tr>
<tr>
<td></td>
<td>(0.142)</td>
<td>(0.061)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Boycott × Japanese</td>
<td>0.082</td>
<td>0.076</td>
<td>0.046***</td>
<td>0.036***</td>
<td>−0.003*</td>
<td>−0.015***</td>
</tr>
<tr>
<td></td>
<td>(0.141)</td>
<td>(0.061)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.002)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Boycott × SEA</td>
<td>0.011</td>
<td>0.009</td>
<td>−0.076***</td>
<td>−0.077***</td>
<td>−0.052***</td>
<td>−0.049***</td>
</tr>
<tr>
<td></td>
<td>(0.156)</td>
<td>(0.067)</td>
<td>(0.002)</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>Constant</td>
<td>5.164***</td>
<td>6.826***</td>
<td>7.447***</td>
<td>7.284***</td>
<td>7.535***</td>
<td>6.929***</td>
</tr>
<tr>
<td></td>
<td>(0.031)</td>
<td>(0.159)</td>
<td>(0.0003)</td>
<td>(0.004)</td>
<td>(0.0003)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>Individual Dummies</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Time Dummies</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Type:Month</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>18,810</td>
<td>18,810</td>
<td>18,810</td>
<td>18,810</td>
<td>17,594</td>
<td>17,594</td>
</tr>
<tr>
<td>R²</td>
<td>0.034</td>
<td>0.840</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.033</td>
<td>0.835</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: *p<0.1; **p<0.05; ***p<0.01
which is a more reasonable result by observing the Figure 2.13 in which after the announcement, total review counts experienced a visible decline. In the Poisson regression, the announcement has insignificant or weak effects on Korean restaurants, while it had positive significant effect on Japanese. The boycott effect on Korean restaurants is significant at -0.345, which translates to 29.17% reduction in visits.

One interesting result is that the Japanese restaurants experienced positive growth compared to the control groups. I interpret this result as the substitution effect, due to the fact that Japanese cuisine is considered a close substitute to Korean food. The Southeastern Asian restaurant experienced slight negative growth.

2.4.1 The Intensive and Extensive Margin

The total negative effect -29% can be partitioned into two parts: the intensive and extensive margin. The intensive margin is the negative effects on the pre-existing Korean restaurants before the occurrence of the political disputes, and the extensive margin is the relative reduction of entrances of Korean restaurants after the political events. From regression Table 2.3, the last two columns show the effects for Korean restaurants preexisting before 2016 and still existing when the data was scrapped. The coefficient on the Korean restaurants pre-existing in 2016 is -0.199 or -18%. The total reduction of 29% is partially explained by the decreased restaurant entries compared to other restaurants. The prospect of lower demand for Korean cuisine leads to lower entrances of Korean restaurants, which is shown in the next figure.

The data set contains review information for each restaurants from January 2015 to March 2018. I use the first review date as a proxy for the entrance date. Within the data set, there are total 21,977 restaurants, of which 10,886 are pre-existing before 2015. The rest are new entrances after 2015.

Figure 2.14 shows the total numbers of restaurant entrances from 2015 to 2018. It is estimated that there are roughly 40 new Chinese restaurants within each week, and the
Figure 2.14: The Time Trend of Total Restaurant Entrances

The number of entrances declined in the beginning of each year. That is likely due to the spring festival effect, because people tend to avoid starting new businesses during that time period. The red lines indicates the Korean restaurants entrance, and the blues lines for the Chinese restaurants. The ratio of the red lines to the blues lines are quite stable before 2017, and the Korean restaurant entrances experienced a sharp drop after the boycotts.

To run the regression on restaurant entrances, I aggregate the entrance data by the types of restaurants. Additionally I obtain a panel data with 5 cross-sectional observations and 1,470 total observations.

Table C.5 shows the effects on the restaurants entrances. The regression model is similar to the baseline model, except that the dependent variable is nationwide restaurant entrances for a type within a week. By doing this, it avoids zero observations, because many small cities have zero restaurant entries within a week. The Poisson regression gives two negative significant coefficients, $-0.265$ and $-0.78$, translating to 23% reduction of entrances after the announcement and 54% reduction after the Lotte-boycott event.

The effects on the Southeastern Asian foods are insignificant, and the effects on Japanese restaurants are inconsistent. The announcement of THAAD increases the entrances of Japanese restaurants, while the boycott decreases them. The two effects cancel out each other. Overall, it seems the boycott has weak effect on the two.
2.4.2 The Rating Effect, Price Effect, and Name Effect on the Boycotts

*Dianping.com* offers the rating and estimated cost of per capita consumption. Is there a differential boycott effect based on price and rating? Supposedly the high-quality restaurants with high ratings should have a more inelastic demand, which means the boycott effect tends to be weaker. This can be tested by the *dianping.com* data set, since the website offers information on both ratings and prices.

Due to the fact that each restaurant has one unique rating and average price, the regressions need to be run on the individual restaurant data, in stead of the aggregated city level data. Using the individual observation data, I estimate the differential effect of price and rating. Table C.6 shows the regression results that the price and quality have both moderating effects on the boycott. Consumers boycott less for the restaurants that are rated higher or charge higher price. The boycott inelasticity on rating is expected, considering it is difficult to boycott high-quality consumption since low-quality foods have more close substitutes. However, the price effect is less expected. Wouldn’t it be more convenient for people to boycott things that are more expensive, when everything else is equal? My speculation is that the price captures some quality that is not reflected in the rating. For example, a 7-star 100-dollar-meal probably is of higher quality than 7-star 5-dollar burger, because the price captures some quality that is not captured in rating.

In general, the perception of a foreign country is factored into the demand for foreign goods. Boycott behavior is motivated when the external national threats magnify the in-group and out-group distinction, and consumers choose to boycott foreign goods to reinforce their self-identity [Escalas and Bettman (2005)]. However the boycott motives are compromised by quality of foreign goods, and it is more convenient to boycott foreign goods that are perceived with lower quality.

A legitimate concern is that the prices are endogenous over the time. As the political

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14 Only the coefficients of the interest are reported to fit the page. In tables 2.4, C.6, and C.7 the following variables were included in the regression but, to fit the table on a page, not reported: Announcement, FDI ratios, Korean, Japanese, and Western.
tensions took place, in response, the Korean restaurants might want to lower their prices to attract more customers. I examine the data on the reported prices in appendix, and it shows prices do change over time, possible due to either the noisiness of the reported prices or the potential price endogeneity. The reported prices in the data set, the most frequently reported per-consumer price is 0, which is obviously a false report. So I exclude the obviously false reporting and focus on the reasonably reported prices from 10 to 600 yuan, which range from about 2 to 100 dollars. Figure \(D.6\) reports frequency of reported prices in the data set. We can see that most reported prices are between 10 and 200 yuan, and users like to report rounded up numbers.

To address the price endogeneity after the political events, in the 4th column of Table \(C.6\) I use data on the pre-existing restaurants before the political events. Further I only include the reported price before the boycott movement, because the prices reported afterward might be endogenous. Comparatively, the regressions shows some changes on the coefficients. The rating effect increases from 0.073 to 0.137, while the price effect changes from 0.0004 to -0.0005. For the pre-existing restaurants, the rating moderates the boycott even more, maybe because consumers cultivate brand loyalty for the long-existing and highly rated restaurants.

The regression also examines the name effect. Similar to the Pandya and Venkatesan's 2016 paper, where they use French sounding score to identify the level of Frenchness associated with the economic goods, this regression identifies effect of the Korean-sounding names on the boycott. In the data set, some Korean restaurants have a neutral name, while others have Korean-sounding names. I control those Korean restaurants with names that contains Chinese Characters "韩", which mean Korea. The coefficient turns out to be \(-0.107\), which translates into a 10% additional reduction compared to the neutral named Korean restaurants. However, the negative effect of the Korean sounding name is lower for preexisting restaurants at \(-0.055\).
2.4.3 The Boycott and Quality Judgment

As shown above, the political tension largely reduces consumption visits to Korean restaurants, but does it actually affect the consumer’s subjective quality judgment, revealed by their rating? I speculate two possible outcomes. First, it is possible that when consumers have a more negative perception of South Korean, they tend to rate the Korean cuisine lower because the appeal of Korean cuisine is deeply associated with the perception of the country. Second, it is also possible that consumers still go to Korean restaurants despite political disputes, as they tend to be the ones that like Korean cuisine more. Also the Korean restaurants that enter during the political tension tend to be the high-quality ones. The two positive selection effects may actually increase the rating.

Most of the related studies ignore the political tension on consumer’s subjective quality judgment. One study Shoham et al. (2006) uses survey data and argues that the animosity toward Arab uprising impacted Jewish people’s quality judgment of the Arabic goods and services. Due to data limitation, there is little study on political dispute on consumer’s subjective quality judgment on the boycotted goods. However, the online rating data reveals consumer’s subjective judgment, which enables to identify the political dispute effect.

The data set includes reviews and ratings of each restaurant. On dianping.com, for each review, the consumer leaves rating for three things: service, environment and flavor. Each category is rated with five levels: “bad”, “average”, “good”, “very good” and “excellent”. I assign the levels with value 1 to 5; therefore each consumption experience is rated from 3 to 15.

The regression results in Table C.7 aligns with the first speculation that political tension lowers peoples subjective quality judgment. Although different specification gives different results. When using the whole data sample, the political tension has insignificant effects for rating on Korean restaurants. When using the sub-sample of the pre-existing restaurants, the political tension has negative effects on ratings of Korean restaurants compared to other restaurants.
This finding is interesting in that the negative propaganda not only affect people’s consumption behavior, but also it lowers the costumer’s quality judgment.

Figure 2.15: The Rating Trend of the Restaurants

Figure 2.15 shows the trend of rating from 2015 to 2018. The rating of each restaurant ranges from 3 to 15, while the rating of aggregated restaurants ranges from 12.5 to 14. There is a cyclical effect of the Chinese restaurants ratings: the rating tend to be lower around the lunar new years. The first one uses the whole sample and the second one uses only the pre-existing restaurants before the political disputes. There is a slight difference between the two: in the second figure, the red line is relatively lower compared to the first figure. The subtle difference, despite small, changes significance of the regression results.

Table C.7 shows the regression results of both all observations and pre-existing restaurants. The three columns shows no significant results of the boycott, except the other foreign restaurants being rated higher than the Chinese restaurants. The last three columns
using pre-existing restaurants shows that comparing to all other types of restaurants, Korean restaurants experience 0.1 point reduction compared to all other restaurants, and the effect becomes 0.056 points when controlling the western restaurants. The contrast of the two can be explained by the selection effect: the Korean restaurant enters in the Chinese market despite of the political tension tend to be of higher quality. The pre-existing Korean restaurants experience drop in rating, while the new entries are selected to be higher quality. When combined, the two effects cancel out each other.

In Figure 2.16, it shows average rating for restaurants entered in a particular week over the time. The red and blue lines show that the average rating for restaurant entered before the political disputes are lower than the ones entered after, which confirms my conjecture of the selection effects.

2.4.4 Economic Openness and the Boycott

In this section, I examine the geographical cross-variation in the boycott effect. Pandya and Venkatesan 2016 show that political boycotts are strongly correlated with the consumer’s nationalist identity: regional with higher percentage of US citizens tend to experience more sale reduction in French-sounding goods. Their reasoning is that having US citizenship might heightens national identity and intensifies the boycott effort. In this section, I examine how
economic openness affect people’s boycott behaviors.

There are two possible outcomes. First, the more economic open regional might be less nationalistic. Study shows that in China, the nationalistic view is negative correlated with economic openness \cite{Lan and Li 2015}. Therefore, regions with more economic openness could experience less boycott movement. Second, on the other hand, people in more economic open regions tend to be more educated and informed with the international political disputes, and therefore, they might boycott Korean restaurants more. Another reason is it is easier for people in economic open regions to find other foreign restaurant to substitute Korea restaurants, due to the fact in larger cities it is relatively easier to find foreign and rare cuisines \cite{Schiff 2014}, which makes the demand for Korean cuisine more elastic.

I use the FDI/GDP ratio as the proxy to economic openness. The data is from China City Statistical Yearbook, which consists city-level GDP and FDI. I use the top 60 largest Chinese cities. The mean of FDI ratio is 0.026 and the standard deviation is 0.018.

In the regression, I interact the FDI ratio with Korean restaurants and after the Boycott: \( \text{Korean} \times \text{Boycott} \times \text{FDI} \). I also control the average income which positively correlate with the FDI ratio. The empirical evidence aligns with the second conjecture that economic openness intensify the negative effects of the political tensions.

Table 2.4: Economic Openness and Boycott

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Boycott x Korean x FDI Ratio</td>
<td>-4.308*** (0.061)</td>
<td>-5.115*** (0.065)</td>
</tr>
<tr>
<td>Boycott x Japanese x FDI Ratio</td>
<td>-1.518*** (0.056)</td>
<td></td>
</tr>
<tr>
<td>Boycott x Western x FDI Ratio</td>
<td>-3.300*** (0.052)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>18,506</td>
<td>18,506</td>
</tr>
</tbody>
</table>

*Note: \( \ast p < 0.1; \ast \ast p < 0.05; \ast \ast \ast p < 0.01 \)

Notice that the Japanese and Western restaurants both experience drop after the boycott event. My explanation is that there is a relative higher increase of demand for foreign foods
in more economically closed cities. The economically open cities tend to have more saturated market for foreign restaurants, compared to the less economically opened cities.

This result contrasts with Pandya and Venkatesan’s 2016 result, in that their founding confirms that national identity intensifies the boycott effort, while this paper finds that economically open regions experience more reduction of the boycotted goods. Meanwhile studies show that nationalism is negatively correlated with economic openess. Lan and Li (2015)Zhang and He (2014). This finding suggests that besides nationalism, there is something else that impact people’s boycott behaviors. For example, in economically open cities, people tend to be more aware of the international disputes, and they have more elastic demand for Korean cuisine compared to people in less economically open cities.

2.5 Discussion and Conclusion

In a globalized world today, political disputes between countries likely result in calling for boycott of the foreign adversary. Regarding the question of whether or not consumers actually participate in the boycott, many studies either find short lived effects, contradictory effects, or small effects on the manufactured goods. This paper looks at people’s boycott action on the non-traded service industry, and it finds significantly negative effects that last at least more than one year. This study contributes to the literature that it identifies the intensive and extensive margin. China-South Korea political disputes not only causes Chinese to consume Korea foods 20% less for pre-existing restaurants, but also negatively impacts the Korean restaurant entrances. It also finds that the negative effects are moderated when the restaurants are rated or priced higher, whereas a Korean-sounding name intensifies the negative effects.

\[15\] The duration of the boycott can be seen from Figure 2.13. The negative effect is persistent at least for one year. In order to ensure this result, I run regression with dummies of every two-month. The result is in Table C.8. “Boycott2” stands for 2 month after the boycott movement, and so on. Those are switch-on dummies that overlap with each other. We should interpret the coefficient by adding on to the previous ones. For example, the in regression (4), the effect of Boycott2 should be (-0.381+0.07) = -0.311. We can see that for OLS, there’s weak difference between the months after the boycott movement. For the Poisson regressions, the effects are different, but the scales are small. And there’s no particular attenuation nor intensifying trend over the time.
The paper also finds that the social media has a larger effect on the consumer’s action than the traditional TV news. Figure 2.10 shows that most of the THAAD mentions are in the second half of 2016, whereas the intensity of boycott was more severe after the Lotte-boycott event in March 2017. The boycott movement is more positively correlated with online attention, instead of the traditional type of TV news and government propaganda.

This paper also contribute to the literature in that it identifies negative effect on people’s subjective quality judgment in the events of political disputes, and it shows that economic openness actually intensifies the boycott effort.

There are two potential mechanisms for the negative impacts. First, the conventional interpretation is that the international dispute activates the public calling for consumers’ boycott, in order to punish the foreign adversary. Consumers respond to the public’s calling and participate in the boycott of the associated goods, by doing so they reinforce their own identity. The second mechanism is that Chinese people’s perception of South Korea deteriorates as they are exposed to negative news that portray South Korea as an unfriendly country. Even though most of the Korean restaurants are owned by Chinese, the appeal of Korean foods declined due to the fact people now associate the country with more negative views. A study by Shoham et al. 2006 uses the Arab uprising in Israel to show that animosity toward Arabs not only negatively impacted Jewish people’s willingness to pay, but also the quality judgment of the Arabic goods and services. Their study identifies both people’s action and perceptions. The cognitive dissonance theory Festinger (1962) supports the contention that negative perception of South Korea might cause people to believe that Korean foods are less appealing.

The two mechanisms are indistinguishable in that they both result in the reduction of consumption of the associated economics goods. However, I want to argue that the latter

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16 The owners of the restaurants can be identified from the certificate the restaurant uploaded online. From the names of the owners, one can identify the nationality of the restaurant owners. It will be interesting to look at the differential effects on the Chinese owned and Korean owned restaurants for future works.

17 The cognitive dissonance theory argues that there is a tendency for individuals to seek consistency among their beliefs. When there is an inconsistency between attitudes or behaviors, something must change to eliminate the dissonance.
could be an important mechanism in our case, for three reasons. First, empirically I find that political disputes not only affect people’s consumption action but also their subjective quality judgment. Second, the negative impacts persist long after the peak of calling for boycotts. Third, the fact that most of the Korean restaurants are owned by local Chinese contradicts the purpose of the boycott, which is to punish the foreign adversary. Therefore this paper argues that the negative impact is likely due to the reduction in appeal of Korean foods associated with the negative reports. The calling for boycott is temporary, while the negative perceptions persist.
Chapter 3

Human Capital Accumulation, Urbanization and Endogenous Growth

3.1 Introduction

Massive internal migration from the agricultural sector towards the urban sector is a salient economic phenomenon in many developing countries. For the first time in human history, there are more people living in the cities than in the rural areas [Glaeser and Xiong (2017)]. Most of the internal migration takes place in the developing countries, with or without industrialization [Gollin et al. (2016)]. Urbanization is a necessary process for a country achieving fast and sustainable growth, as there is a strong positive correlation between the urbanization rate and the income level [Zhang and Shunfeng (2003)]. Some economic historians even use urbanization rates to approximate income levels when the income data is not available [Nunn and Qian (2011)].

Figure 3.17: The Urbanization Rate Over the Years

Figure 3.17 shows the rapid urbanization for China, India, and the world average since 1960. The world has achieved more than 50% urbanization rate in recent years. There are many studies that model internal migration and the urbanization process.
Lewis's seminal work on the dual economy assumes inelastic supply of cheap labor from the agricultural sector, which suppresses the labor wage in the city. Absorbing the surplus labor, the urban sector expands relative to the whole economy. Harris and Todaro focus on explaining the noticeable existence of the unemployed and the informal sector. They argue that the existence of minimum wage laws impedes labor market clearance, resulting in unemployment. In the equilibrium, the expected incomes are equalized between the rural and the urban sector. In the work by Bond et al. (2015), they find that the reduction of trade costs mitigates the migration barriers, which promotes urbanization and economic development.

In a recent study, Liao et al. separate the Chinese internal migration process into work-based and education-based. They use Chinese data to calibrate the model and conduct policy experiments with the model. Lucas looks at the internal migrants as people shifting from the traditional sector to a modern sector. In the modern sector, people spend some time on accumulating human capital. His unique assumption is that people migrate to maximize their life earnings, as they expect to spend some time accumulating human capital in the city and become productive. Lucas’ model integrates rural-urban migration into the endogenous growth literature. My paper builds on similar assumptions, but in an OLG setting. Additionally I assume heterogeneous talent and the coexistence of the formal and informal sectors. The OLG model has certain advantages over infinitely-lived model in Lucas’ model. The OLG model only assumes rational expectation in a finite horizon for a given generation, which is a more reasonable assumption than an infinitely lived agent with a perfect foresight. In addition, the model is compatible with analysis of the role of government in facilitating the urbanization process.

This paper contributes to the literatures in a couple of ways. First it constructs a dual economy model that incorporates education as one of the motivations for internal migration. After all, most of the educational resources are located in the cities, especially for developing countries like China. Second, the model resonates with Harris
and Todaro \cite{1970} in analyzing the formal and informal sectors. In this model, the formal sector requires human capital and education, whereas the informal sector requires only labor. Third, this paper conducts simulations, which feature continuous internal migration, growth in average human capital and share of educated population. Fourth, following the endogenous growth tradition \cite{Romer1990, Lucas1988}, the social optimal path differs from the market solution. A benevolent planner would force a greater share of population to get education due to the positive externalities from the human capital. The rest of the paper is organized as follows: Section 2 presents the theoretical model. Section 3 conducts model simulation, and section 4 offers discussion and concludes the paper.

### 3.2 The Model

The model features overlapping generations in the context of a dual economy. There are two sectors that produce the same products, similar to dual economy models by Hansen and Prescott \cite{2002} and Lucas \cite{2004}. I formulate a dynamic equilibrium arising from people’s rational expectation and optimization within their life time. My model differs from Hansen and Prescott’s work \cite{2002} in that, instead of assuming the exogenous growth of technology, I assume that the modern sector experiences growth due to people’s decisions of accumulating human capital.

#### 3.2.1 The Urban Sector

The urban sector uses modern capital and technology that are complementary to human capital, while the production in rural sector requires no human capital. Cities offer opportunities to accumulate human capital, in the form of tertiary education, on job training, or any form of gaining experience and skills. Formal education, such as attending college, is one way to accumulate human capital, but it can be in any forms of learning and acquiring skills. For example, if some one starts a business in the city and eventually fails, we can interpret that as someone gaining real life experience and paying the cost of a failed business.
That's how one would generally intuitively interpret human capital in this model. However, in what follows, I refer the “human capital accumulation” as “going to school”, although this does not have to be confined to formal education only.

Each worker in each period is endowed with one unit of time and efficiency labor. They work two periods; only in the first period can they accumulate human capital. If people choose not to get educated, they work in both periods with one unit of effective labor. If they choose to get educated, they forgo one unit of labor in the first period and work as a skilled labor with effective labor $H_{t+1} > 1$ in the next period.

The model assumes that accumulating human capital depends on individuals’ realization of talent $s \sim f(s)$ and their parents’ human capital $H_t$: $H_{t+1} = H_t \delta s + 1$. Parameter $\delta$ is the effectiveness of education, which can be interpreted as the educational infrastructure in the economy. Since human capital is an intangible asset, it cannot be directly inherited from parents. However offspring’s human capital should be indirectly and positively affected by the parent’s education. This setting makes certain that an individual’s decision of human capital accumulation depends on the parent’s education $H_{t+1}$, the education infrastructure $\delta$ and the randomly realized talent $s$.

The talent distribution is given by:

$$f(s) = \frac{1}{\phi s}; s \in [1, e^\phi]$$

where $\phi$ is a distribution parameter. When $\phi$ is larger, the distribution is more dispersed. In the simulation, $\phi$ should be properly chosen to represent how dispersed the talent distribution is. When the distribution is more dispersed, individuals’ education decision is more affected by the realized talent, and vice versa. In the simulations below, I shall chose $\phi$ so as to represent a realistic distribution of talent as proxied with labor-market income differentials.

Let $u$ denote the time they spend on education. Assume the interest rate is $R = 1 + r$, so the total discounted income for a typical worker is:
$U = u\bar{H}_t^\gamma + \frac{[(1 - u)H_t\delta s + 1]\bar{H}_{t+1}^{\gamma}}{R}$

(40)

where $\bar{H}_t^\gamma$ is the average human capital in the time period $t$. The average human capital affects the overall income level, which is a standard endogenous growth assumption Lucas (1988). Since the social return to human capital accumulation is greater than the private return, the market solution is sub-optimal.

This model assumes away credit constraints and interest rate is exogenous. Each worker tries to maximize the discounted value of life time income by choosing the value of $u$. Because the return from schooling is a linear function of talent, they choose whether or not to go to school full time. Hence $u$ only takes on two values: 0 or 1. Whenever accumulating human capital brings higher expected life income, $u$ equals to 1. The condition for choosing to get educated is given by:

$$\frac{H_t\delta s}{R} \bar{H}_{t+1}^\gamma \geq \bar{H}_t^\gamma$$

(41)

When taken as a strict equality, equation (3) pins down the talent cutoff, or the talent lower bound of people who go to school $s$:

$$s \geq \frac{R}{H_t\delta}(\frac{\bar{H}_t}{\bar{H}_{t+1}})^\gamma \equiv s$$

(42)

When the realized talents are higher than the cutoff $s$, individuals choose to accumulate human capital full time. Otherwise, they choose not to. The talent cutoff is a decreasing function of one’s parents’ education $H_t$: when someone is born to a more educated parent, she is more likely to receive education. This can be interpreted as the integerational human capital transfer Currie and Moretti (2003).

Expected human capital of the young depends on her parent’s education $H_t$:

18The exogenous interest rate can be attained with an assumption of a small and open economy. The first assumption ensures people can make best decision of education attainment without worrying of credit constraints.
\[ E(H_{t+1} \mid H_t) = \int_{s}^{e^\phi} H_t \delta s f(s) ds + \int_{1}^{e^\phi} f(s) ds \] (43)

\[ = \int_{s}^{e^\phi} H_t \delta s \frac{1}{\phi s} ds + 1 \]
\[ = \frac{1}{\phi} H_t \delta (e^\phi - \bar{s}) + 1 \]
\[ = \frac{1}{\phi} [H_t \delta e^\phi - R(\frac{H_t}{H_{t+1}})^\gamma] + 1 \]

Equation (5) states that the expected education for an offspring with a parent of education \( H_t \) is a weighted average of two cases: the expected human capital when she draws \( s \) above \( \bar{s} \) and the other case where her expected human capital is 1.

It is shown that each individual’s expected human capital turns out to be a linear function of their parent’s education. When the parent’s education is higher, the offspring tends to have higher education. Individually it is still uncertain and up to chance. If an offspring draws a low level of talent, she is likely to have lower human capital despite having a highly educated parent. The total population is continuously distributed and is assumed to be one. Therefore due to the law of large numbers, average human capital for the next generation is exactly at the expected average human capital. Taking the integral with respect to \( H_t \) gives the value of \( \bar{H}_{t+1} \):

\[ \bar{H}_{t+1} = \int E(H_{t+1} \mid H_t)dF_t(H_t) \]
\[ = \frac{1}{\phi} [H_t \delta e^\phi - R(\frac{H_t}{H_{t+1}})^\gamma] + 1 \] (44)

Equation (6) generates a linear relation between the average human capital of the two generations. Human capital growth depends on the distribution parameter \( \phi \), the education infrastructure \( \delta \), and the interest rate \( R \). Higher \( \phi \) and higher \( \delta \) both increase the growth.
rate. In the long run, the growth rate of average human capital equals to \( \frac{\delta e^\phi}{\phi} \). Higher interest rate \( R \) reduces the human capital growth, which is intuitive: when the opportunity cost is higher one is less likely to accumulate human capital. The model’s advantage is that there is a linear relationship between inter-generational average human capital \( \bar{H}_{t+1} \) and \( \bar{H}_t \), despite heterogeneous talents and inherited family educational backgrounds. This setup avoids the unrealistic assumption of perfect foresight in the infinite future, instead assume rational expectation within individual’s life time. The growth process described above applies to the urban sector.

Individuals choose education level based on their parents’ education \( H_t \), education infrastructure \( \delta \) and realized talent \( s \). For a dual-economy model, the migration process should be smooth and gradual. The gradual migration requires an equilibrium force that balances the attractiveness between the two sectors. In Lewis’s model [1954], the over-supply of labor depresses the labor market in the cities. In Harris and Todaro’s [1970] work, the equilibrium comes from equalization of the expected income due to possibility of unemployment in the urban sector. By contrast, in my model, as more people migrate, the rural productivity increases due to a higher land-labor ratio (Hansen and Prescott 2002). I now turn to a description of the dynamics that apply in the rural sector and the migration flows that would stem on that basis between the rural and urban sectors.

### 3.2.2 The Rural Sector

The production in the rural sector is assumed to be a Cobb-Douglas function of land and labor only. Land is assumed to be equally owned by everyone in the rural area, and so land rents are equally distributed back to everyone.

\[
Y = AL^\alpha T^{1-\alpha}
\]  

The total factor productivity term, \( A \), represents agricultural technology relative to that of the urban sector. Higher \( A \) gives higher relative productivity compared to the urban sector.
sector. As labor leaves the rural sector, the marginal product of land increases; and thus the
opportunity cost of migration increases. This insures continuous nature of internal migration
and urbanization.

For rural individuals, the expected incomes are equalized between the rural and urban
sector in the equilibrium. In the case of Harris and Todaro[1970] they assume the equalization
is due to unemployment in the urban sector. Even though the urban job pays higher,
possibility of unemployment lowers the expected income. This model assumes the same
equalization of expected income, but the uncertainty comes from realized talents.

Before a rural individual leaves for the city, she only observes her talent distribution and,
thus, expected urban income. She realizes her learning ability upon arrival at the city. Based
on her realized talent, she makes the decision whether or not to accumulate human capital.
This set up is similar to the work by Behrens et al.’s[2014] sorting model, where they assume
people draw their random lucks upon arrival in the city. Their model sorts the talented to
the large cities and the less talented to smaller cities. In contrast, my model does not sort
the population into different areas, because the people are homogeneous before leaving, and
the realization of talent only occurs after arrival in the city.

3.3 Model Simulation

The model above does not generate a closed form solution, therefore I next use a computer
to simulate the internal migration process from 10% to 80%. For each generation, a share of
rural population choose migration. In each period, the expected life-time incomes are equal-
ized between the two sectors. When people stay in the rural sector, they get a guaranteed
income, and when they choose to migrate, they get an expected income based on their talent
distribution.

In order to properly simulate the urbanization process, I assume the parameter $\phi$ to be
3 which gives a reasonable dispersion for the talent distribution. Interest rate $R$ is 2, which
translates to around 1.035 yearly interest rate over 20 years. The long run average human
capital growth rate is determined by \( \frac{\delta e^w}{\phi} \), which is set to 2 as well. Therefore, \( \delta \) needs to be around 0.29. The labor income share \( \alpha \) is 0.7, and total land \( T \) and relative agricultural technology \( A \) are both set to be 1.

Figure 3.18 shows the result and the flow of internal migration. The simulation results show that migration peaks in the first three generations, and total urbanization rate approaches to 80% as the economy achieves high income. During the process, the average human capital increases as a result of people accumulating human capital. Due to higher average human capital, the ability cutoff for human capital accumulation decreases, resulting in more percentage of population in the formal sector with education.

Figure 3.18: Simulation of Urbanization and Internal Migration

Figure 3.19 shows that an increasing percentage of population chooses to get educated as average human capital increases. The increasing average human capital is accompanied by internal migration and the urbanization process.

As the economy becomes more urbanized, the percentage of population that chooses to accumulate human capital increases. The average human capital experiences a steady increase. This model generates a comprehensive perspective of economic development. In reality, the growth of a developing country is often accompanied by continuous rapid urbanization, an increasing share of the educated population, and a continuous increase of average human capital.
3.4 Discussion and Extensions

Lucas [2004] argues that the internal migration decision is characterized by maximizing life earnings. I build an OLG model in the spirit of Lucas [2004] yet avoid the unrealistic assumption of perfect foresight of a representative agent that lives indefinitely. In addition, I assume heterogeneous talent draws and coexistence of the formal and informal sectors.

The OLG nature of this model makes it possible to be compatible with the public and urban literatures. There are a number of possible extensions for this model.

First, this model could potentially examine the optimal endogenous growth path for a benevolent planner. A benevolent planner who cares more about the future generations would invest disproportionately more in the urban sector, which increases the potential future growth rate. This urban bias depends on different weights that the benevolent planner may put on each generation. The Lucas model [2004] is unfit for such analysis, because there is only one infinitely live generation, and therefore there are no trade-offs between generations.

Second, this endogenous growth model could be combined with the urban economics literature. When there are massive migrants into the urban sector, there is a congestion problem, driving up housing rents and demand for urban infrastructure. Rapidly rising housing rents and lacking in urban infrastructure are often observed in many developing countries. Governments face fiscal constraints when offering urban infrastructure investment.
The dilemma is that in order to afford more urban infrastructure investment, governments have to tax the formal sector which distorts the human capital accumulation motives, hurting the long economic growth.

Third, this model could look at the effects of different political systems on the endogenous growth path. One could compare two political systems: a centralized power system and a decentralized power system. Under the decentralized power system, the government wants to distribute the economic resources more equally in the economy. In the centralized power system, it may want to locate economic resources to the urban sector where the ruler can raise more taxes. The two different political systems may cause the diverge of the two endogenous growth paths. The Lucas model offers no space for the role of the government. Once the government changes policy, the infinitely live agent changes the permanent optimal path, which makes the model intractable.

Fourth, this an endogenous growth model. Following the endogenous growth tradition that the private solutions tend to be sub-optimal Romer (1990); Lucas (1988), due to that the social return of human capital is greater than the private return. A social optimal growth path can be solved for. In the social optimal, the talent cutoff $s^* \leq s$. That is, a benevolent planner would encourage more people to accumulate human capital than the market solution.
References


Christaller, W., *Central Places in Southern Germany* 1933.


A Appendix of Chapter 1

A.1 Derivation of $P_{CBD} = IL + C$

Given income $I$, people choose location $r$ and consumption of $H$, $S$ and $M$ to maximize their utility:

$$\text{maximize}_{r,H,S,M} U^* = e^{-r} H^\frac{1}{3} S^\frac{1}{3} M^\frac{1}{3}$$

Subject to $HP_H + SP_S + MP_M = I$

The share of expenditure on each good is constant at 1/3. Free mobility ensures utility equalize for all people in one city:

$$\bar{V} = e^{-r} W\left(\frac{1}{3P_H(r)}\right)^{\frac{1}{3}}\left(\frac{1}{3P_S}\right)^{\frac{1}{3}}\left(\frac{1}{3P_M}\right)^{\frac{1}{3}}$$

The housing price is such that keeps this indirect utility as a constant with respect to variable $r$. The housing price at location $r$ is:

$$P_H(r) = P_{CBD} e^{-3r} \geq C$$

$C$ is the marginal cost of housing unit. It is assumed that a large of number of competitive real estate developers supply housing units whenever the housing price is above $C$. So there is physical boundary of the size $R \equiv \frac{1}{3} \ln \frac{P_{CBD}}{C}$.

Each location exists one unit of land and supplies one unit of housing good. The housing demand for each person at location $r$ is

$$H(r) = \frac{I}{3P_{CBD}e^{-3r}}$$
The population density at location \( r \) is

\[
L(r) = \frac{1}{H(r)} = \frac{3P_{CBD}e^{-3r}}{I}
\]

Taking the integral of population density from 0 to \( R \) gives us the total population \( L \):

\[
\int_0^R L(r)dr = \left[-\frac{P_{CBD}e^{-3r}}{I}\right]_0^R = L
\]

\[
[-\frac{P_{CBD}e^{-3R}}{I}] - [-\frac{P_{CBD}e^0}{I}] = L
\]

\[
P_{CBD} - P_{CBD}e^{-3\times3\ln\frac{B}{PCBD}} = IL
\]

\[
P_{CBD}(1 - e^{\ln\frac{B}{PCBD}}) = IL
\]

\[
P_{CBD}(1 - \frac{B}{PCBD}) = IL
\]

\[
P_{CBD} = IL + C
\]

A.2 The Solution of Single-City Equilibrium

\[
\int_1^n E_j dj = E \quad (46)
\]

\[
\frac{E_j}{E_k} = \left(\frac{P_j}{P_k}\right)^{1-\phi} = \left(\frac{m_j}{m_k}\right)^{1-\phi} \quad (47)
\]

\[
x_{ji} = \frac{E_j}{m_j} \quad (48)
\]

\[
x_{ji} = \frac{j}{1-\beta} \quad (49)
\]

Given total expenditure \( E \), we need to solve the intra-industry variety \( m_j \) for each industry \( j \). Let \( E_j \) be the total expenditure in industry \( j \).

The zero profit condition entails:

\[
(p_{ji} - \beta w)s_{ji} = jw
\]

Price and wage both equal to one. The zero profit condition gives us the quantity supplied


from each firm:

\[ s_{ji} = \frac{j}{1 - \beta} = \frac{E_j}{m_j} \]

This equation gives us the relation between the expenditure \( E_j \) and intra-industry variety \( m_j \), which derived from the supply side:

\[ E_j = \frac{j \times m_j}{1 - \beta} \quad (50) \]

From the CES function of the demand side, we have:

\[ \frac{E_n}{E_j} = \left( \frac{P_n}{P_j} \right)^{1 - \phi} = \left( \frac{m_n}{m_j} \right)^{\frac{1 - \phi}{\sigma}} \]

This gives us another relation between the expenditure \( E_j \) and intra-industry variety \( m_j \):

\[ E_j = E_n \left( \frac{m_j}{m_n} \right)^{\frac{1 - \phi}{\sigma}} = \frac{n}{1 - \beta} m_j^{\frac{1 - \phi}{\sigma}} \quad (51) \]

From the two equations of (50) and (51), the inter-industry variety \( m_j \) is determined:

\[ m_j = \left( \frac{j}{n} \right)^{\frac{1 - \sigma}{\sigma - \phi}} \]

Use the \( m_j \) to plug back into the equation (50) or (51), we can find the expenditure for each industry \( E_j \)

\[ E_j = \left( \frac{1}{n} \right)^{\frac{1 - \sigma}{\sigma - \phi}} \frac{j^{\frac{1 - \sigma}{\sigma - \phi} + 1}}{1 - \beta} \quad (52) \]

Integration of \( E_j \) with respect to industries, when \( 1 + \sigma \neq 2\phi \) :

\[ E = \int_1^n E_j \, dj = \frac{1}{\left( \frac{1 - \sigma}{\sigma - \phi} + 2 \right)(1 - \beta)} \left( n^2 - n^{-\frac{1 - \sigma}{\sigma - \phi}} \right) \quad (53) \]

When \( 1 + \sigma = 2\phi \):
\[ E_j = \frac{n^2}{(1 - \beta)j} \]

Integration of \( E_j \) with respect to mass of industry:

\[ E = \int_1^n E_j dj = \frac{n^2 \log n}{1 - \beta} \]

Invert the monotonic function gives us the total industry variety \( n \)

\[ n = N(E; \phi) \]

### A.3 The Solution of Two-City Model

Let \( E_j \) to be the total expenditure by two cities on industry \( j \) and \( E_j^i \) be the expenditure of city \( i \) on industry \( j \). Let \( m^i_j \) to be the variety of industry \( j \) in city \( i \), \( x^i_j \) be to the quantity produced of industry \( j \) in city \( i \)

We know that:

\[ m^1_{n_1} = m^2_{n_2} = 1 \]

By zero-profit condition we have:

\[ x^i_j = \frac{E_j}{m_j} = \frac{i}{1 - \beta} \]

Because \( m^1_{n_1} = 1 \), we have:
\[ E_{n_1} = \frac{n_1}{1 - \beta} \]
\[ E_{n_1}^2 = \frac{n_2 \tau}{1 - \beta} \]
\[ E_{n_2}^2 = \frac{n_2}{1 - \beta} \]
\[ E_{n_1}^1 = \frac{n_1 - n_2 \tau}{1 - \beta} \]

Let \( i_+ \in (n_2, n_1) \) and \( i- \in (1, n_2) \).

We have:

\[ \frac{E_{n_1}^1}{E_{i_+}^1} = \left( \frac{m_{n_1}}{m_{i_+}} \right)^{\frac{1-\phi}{1-\sigma}} = \left( \frac{1}{m_{i_+}} \right)^{\frac{1-\phi}{1-\sigma}} \]

The demand function:

\[ E_{i_+}^1 = E_{n_1}^1 m_{i_+}^{\frac{1-\phi}{1-\sigma}} = \frac{n_1 - n_2 \tau}{1 - \beta} m_{i_+}^{\frac{1-\phi}{1-\sigma}} \]

The supply function:

\[ E_{i_+}^1 = \left( \frac{n_1 - n_2 \tau}{n_1} \right) E_i = \left( \frac{n_1 - n_2 \tau}{n_1} \right) i_+ \times m_{i_+} \]

Supply equals demand:

\[ m_{i_+} = \left( \frac{i_+}{n_1} \right)^{\frac{1-\sigma}{1-\phi}} \quad (54) \]

Take (54) into the demand or supply function, and assume \( 1 + \sigma = 2\phi \) we get:
Next we look at $i_- \in (1, n_2)$. The demand function:

$$E_{i_-}^1 = E_{n_1}^{1} m_{i_-}^{\frac{1}{1-\sigma}} = \frac{n_1 - n_2 \tau}{1-\beta} \frac{i_-^{\frac{1}{1-\phi}}}{m_{i_-}^{\frac{1}{1-\sigma}}} = \frac{n_1(n_1 - n_2 \tau)}{(1-\beta)i_-}$$

The supply function:

$$E_{i_-}^2 = \frac{n_2 \tau}{n_1^{\frac{1}{1-\phi}}} \frac{i_-^{\frac{1}{1-\sigma}}}{(1-\beta)} = \frac{n_1 n_2 \tau}{(1-\beta)i_-}$$

Supply equals demand:

$$m_{i_-} = \left(\frac{i_-}{n_1 - n_2 \tau}\right)^{\frac{1-\sigma}{1-\phi}} = \left(\frac{i_-}{n_1 - n_2 \tau}\right)^{-2}$$

$$E_{i_-}^1 = \frac{1}{(n_1 - n_2 \tau)^{\frac{1-\sigma}{1-\phi}}} \frac{i_-^{-1}}{(1-\beta)} = \frac{(n_1 - n_2 \tau)^2}{(1-\beta)i_-}$$

The four expenditure functions:
Take the integral of the expenditures from each city:

\[
E^1_{i_+} = \frac{n_1(n_1 - n_2 \tau)}{(1 - \beta)i_+}
\]
\[
E^2_{i_+} = \frac{n_1 n_2 \tau}{(1 - \beta)i_+}
\]
\[
E^1_{i_-} = \frac{(n_1 - n_2 \tau)^2}{(1 - \beta)i_-}
\]
\[
E^2_{i_-} = \frac{n_2^2}{(1 - \beta)i_-}
\]

It simplifies to:

\[
l_1 \frac{1}{2} (1 - \beta) = n_1(n_1 - n_2 \tau) \log \frac{n_1}{n_2} + (n_1 - n_2 \tau)^2 \log n_2
\]
\[
l_2 \frac{1}{2} (1 - \beta) = n_1 n_2 \tau \log \frac{n_1}{n_2} + n_2^2 \log n_2
\]

The solution of the two nonlinear equations \( n_1 \) and \( n_2 \) determine the price indices of the service good in two cities. \( P^1_S \) and \( P^2_S \) represent the service indices for City 1 and City 2:
\[ P_S^1 = \left( \int_{n_2}^{n_1} \frac{1-\phi}{m_{i+}} + \int_0^{n_2} \frac{1-\phi}{m_{i-}} di \right)^{\frac{1}{1-\phi}} \]
\[ = [n_1 \log \frac{n_1}{n_2} + (n_1 - n_2 \tau) \log n_2]^{\frac{1}{1-\phi}} \]
\[ P_S^2 = \left( \int_{n_2}^{n_1} \tau \frac{1-\phi}{m_{i+}} di + \int_0^{n_2} \frac{1-\phi}{m_{i-}} \right)^{\frac{1}{1-\phi}} \]
\[ = (\tau n_1 \log \frac{n_1}{n_2} + n_2 \log n_2)^{\frac{1}{1-\phi}} \]

A.4 The Proof of Lemma 1

Total expenditure on the service industry is:
\[ E = \frac{L}{2} \]

The relation between the expenditure and total variety \( n \) is:
\[ E = \frac{n^2 \log n}{1 - \beta} \]

Let \( \epsilon_n \) to be the elasticity of total variety \( n \) with respect to \( L \).
\[ \epsilon_n = (2 + \frac{1}{\log n})^{-1} \]
\[ \lim_{L \to \infty} \epsilon_n = \frac{1}{2} \]

The utility function is
\[ V = (C + \frac{3}{2}L)^{-\frac{1}{1}} [\log(n)]^{\frac{1}{1-\phi-1}} \]

Let \( \epsilon \) to be the elasticity of utility function with respect to \( L \).
\[
\epsilon = (-1) \times \frac{3L}{C + \frac{3}{2}L} + (\epsilon_n + \frac{1}{\log n}) \times \frac{1}{\phi - 1}
\]

\[
\lim_{L \to \infty} \epsilon = -1 + (\frac{1}{2} + 0) \frac{1}{\phi - 1} 
\]

As the population goes to the infinite, the elasticity of utility is always positive when:

\[
\lim_{L \to \infty} \epsilon = -1 + (\frac{1}{2} + 0) \frac{1}{\phi - 1} \geq 0 
\]

\[
\phi \leq \frac{3}{2} 
\]

When \(\phi \leq \frac{3}{2}\), the utility function is a monotonically increasing function of population \(L\).

And when \(\phi > \frac{3}{2}\), the utility function is a single peaked concave function.

### A.5 The Proof of Proposition 1

For given \(l_2\) and \(l_1\), \(n_2\) and \(n_1\) are determined by the following nonlinear equations:

\[
F_1: n_1(n_1 - \tau n_2)\log \frac{n_1}{n_2} + (n_1 - \tau n_2)^2\log n_2 - \frac{(1 - \beta)l_1}{2} = 0 \tag{55}
\]

\[
F_2: \tau n_1 n_2 \log \frac{n_1}{n_2} + n_2^2 \log n_2 - \frac{(1 - \beta)l_2}{2} = 0 \tag{56}
\]

Let \(F_{1n_1} = \frac{\partial F_1}{\partial n_1} \), \(F_{1n_2} = \frac{\partial F_1}{\partial n_2} \), \(F_{2n_1} = \frac{\partial F_2}{\partial n_1} \), \(F_{2n_2} = \frac{\partial F_2}{\partial n_2} \), \(F_{1l_1} = \frac{\partial F_1}{\partial l_1} \), \(F_{1l_2} = \frac{\partial F_1}{\partial l_2} \), \(F_{2l_1} = \frac{\partial F_2}{\partial l_1} \), and \(F_{2l_2} = \frac{\partial F_2}{\partial l_2} \). Take the partial derivatives and we get:
\[ F_{1n_1} = (2n_1 - \tau n_2) \log \frac{n_1}{n_2} + (1 + 2 \log n_2)(n_1 - \tau n_2) > 0 \]
\[ F_{1n_2} = -n \tau \log \frac{n_1}{n_2} - \frac{n_1(n_1 \tau n_2)}{n_2} - 2 \tau (n_1 - \tau n_2) \log n_2 + (n_1 - \tau n_2)^2 \frac{1}{n_2} < 0 \]
\[ F_{2n_1} = \tau \log \frac{n_1}{n_2} + \tau n_2 > 0 \]
\[ F_{2n_2} = \tau n_1 (\log \frac{n_1}{n_2} - 1) + n_2 (2 \log n_2 + 1) > 0 \]
\[ F_{l_1} = -\frac{1 - \beta}{2} < 0 \]
\[ F_{l_2} = 0 \]
\[ F_{2l_1} = 0 \]
\[ F_{2l_2} = -\frac{1 - \beta}{2} < 0 \]

The determinant of the matrix is positive:
\[ \begin{vmatrix} F_{1n_1} & F_{1n_2} \\ F_{2n_1} & F_{2n_2} \end{vmatrix} = F_{1n_1} \times F_{2n_2} - F_{1n_2} \times F_{2n_1} > 0 \]
Using the Cramer’s rule, we can find the partial derivatives:

\[
\begin{align*}
\frac{dn_1}{dl_1} &= \frac{\begin{vmatrix} -F_1l_1 & F_{1n_2} \\ -F_2l_1 & F_{2n_2} \\ F_{1n_1} & F_{1n_2} \\ F_{2n_1} & F_{2n_2} \end{vmatrix}}{\begin{vmatrix} F_{1n_1} & F_{1n_2} \\ F_{2n_1} & F_{2n_2} \end{vmatrix}} > 0 \\
\frac{dn_2}{dl_1} &= \frac{\begin{vmatrix} -F_1l_2 & F_{1n_2} \\ -F_2l_2 & F_{2n_2} \\ F_{1n_1} & F_{1n_2} \\ F_{2n_1} & F_{2n_2} \end{vmatrix}}{\begin{vmatrix} F_{1n_1} & F_{1n_2} \\ F_{2n_1} & F_{2n_2} \end{vmatrix}} < 0 \\
\frac{dn_1}{dl_2} &= \frac{\begin{vmatrix} F_{1n_1} & -F_1l_1 \\ F_{2n_1} & -F_2l_1 \\ F_{1n_1} & F_{1n_2} \\ F_{2n_1} & F_{2n_2} \end{vmatrix}}{\begin{vmatrix} F_{1n_1} & F_{1n_2} \\ F_{2n_1} & F_{2n_2} \end{vmatrix}} > 0 \\
\frac{dn_2}{dl_2} &= \frac{\begin{vmatrix} F_{1n_1} & -F_1l_2 \\ F_{2n_1} & -F_2l_2 \\ F_{1n_1} & F_{1n_2} \\ F_{2n_1} & F_{2n_2} \end{vmatrix}}{\begin{vmatrix} F_{1n_1} & F_{1n_2} \\ F_{2n_1} & F_{2n_2} \end{vmatrix}} > 0
\end{align*}
\]

A.6 The Proof of Proposition 2

The find the equilibrium we need to find the population ratio \( x = \frac{l_2}{l_1} \) such that the utility is equalized between the two cities.

The utility ratio

\[
\frac{U_2}{U_1} = \frac{P_1^1 \times P_{CBD}^1}{P_2^2 \times P_{CBD}^2} = \frac{(n_1 \log \frac{n_1}{n_2} + (n_1 - n_2) \log n_2) \frac{1}{\tau} \times (C + \frac{3}{2} l_1)}{(\tau n_1 \log \frac{n_1}{n_2} + n_2 \log n_2) \frac{1}{\tau} \times (C + \frac{3}{2} l_2)}
\]

First let the ratio \( x \) to be a very small number, in which case most of population lives in the large city. \( n_2 \approx 1 \). This gives us :

\[
\lim_{x \to 0} \frac{U_2}{U_1} = \lim_{x \to 0} \frac{(n_1 \log n_1) \frac{1}{\tau} \times (C + \frac{3}{2} l_1)}{(\tau n_1 \log n_1) \frac{1}{\tau} \times C} = \frac{\tau \frac{1}{\tau} C + \frac{3}{2} L}{C}
\]

When \( L > \frac{2C(\tau \frac{1}{\tau} - 1)}{3} \), the limit when \( x = \frac{l_2}{l_1} \) goes to zero is great then one:
\[ \lim_{x \to 0} \frac{U_2}{U_1} > 1 \] (57)

The \( n_1 \) and \( n_2 \) are determined by

\[
\frac{l_1(1 - \beta)}{2} = n_1(n_1 - n_2\tau)\log\frac{n_1}{n_2} + (n_1 - n_2\tau)^2\log n_2
\]

\[
\frac{l_2(1 - \beta)}{2} = n_1n_2\tau\log\frac{n_1}{n_2} + n_2^2\log n_2
\]

The service price indices for the cities are:

\[
P_1^S = \left( \int_{n_2}^{n_1} m_{i_+} \frac{1}{1-\phi} \, di + \int_1^{n_2} m_{i_-} \frac{1}{1-\phi} \, di \right) \frac{1}{1-\phi} = \left[ n_1\log\frac{n_1}{n_2} + (n_1 - n_2\tau)\log n_2 \right] \frac{1}{1-\phi}
\]

\[
P_2^S = \left( \int_{n_2}^{n_1} \tau m_{i_+} \frac{1}{1-\phi} \, di + \int_1^{n_2} m_{i_-} \frac{1}{1-\phi} \, di \right) \frac{1}{1-\phi} = \left( \tau n_1\log\frac{n_1}{n_2} + n_2\log n_2 \right) \frac{1}{1-\phi}
\]

From the equations above we can get:

\[
\frac{U_2}{U_1} = \frac{[n_1\log\frac{n_1}{n_2} + (n_1 - n_2\tau)\log n_2] \frac{1}{1-\phi} \times (C + \frac{3}{2}l_1)}{[\tau n_1\log\frac{n_1}{n_2} + n_2\log n_2] \frac{1}{1-\phi} \times (C + \frac{3}{2}l_2)} = \frac{\frac{l_1(1 - \beta)}{2(n_1 - n_2\tau)}}{\frac{l_2(1 - \beta)}{2n_2}} \times \frac{C + \frac{3}{2}l_2}{C + \frac{3}{2}l_1}
\]

When the ratio \( x \) goes to one, the populations in two cities become almost equalized.

\[
\lim_{x \to 0} \frac{U_2}{U_1} = \left( \frac{n_2}{n_1 - \tau n_2} \right) \frac{1}{1-\phi} \times 1 < 1
\] (58)

The utility ratio \( \frac{U_2}{U_1} \) is a monotonically decreasing function as \( x = \frac{l_1}{l_2} \) increases. With the
equations (57) and (58), we can conclude there is a unique solution.
B Appendix of Chapter 2

Price Variance Over Time

In the following table, I check the price variance before and after the boycott movement. I report the percentage of Korean restaurants deviating price less than 2% and 5% compared to that of the non-Korean restaurants. Due to the fact that the reported prices are quite noisy, I restrain the data set to the observation with more 50 reported prices, which gives us 15,156 total restaurants. I am using both average and median reported prices in the following table:

<table>
<thead>
<tr>
<th></th>
<th>Average Price</th>
<th>Median Price</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Less than 2%</td>
<td>Less than 5%</td>
</tr>
<tr>
<td>Korean</td>
<td>0.147</td>
<td>0.351</td>
</tr>
<tr>
<td>Non-Korean</td>
<td>0.129</td>
<td>0.318</td>
</tr>
</tbody>
</table>

The table above shows that before and after the political tensions, Korean restaurants actually deviate the price less compared to the non-Korean restaurants. However, due to the noisiness or potential endogeneity of the price, the price change is quite large. Therefore, in the regression Table C.6 for the 3rd and 4th columns, I use only the reported prices before the political events.
Table C.1: The Regression With Continuous Weights

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Service&lt;sup&gt;T&lt;/sup&gt;</th>
<th>Service&lt;sup&gt;H&lt;/sup&gt;</th>
<th>Service&lt;sup&gt;M&lt;/sup&gt;</th>
<th>Service&lt;sup&gt;L&lt;/sup&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>log(pop)</td>
<td>−0.071***</td>
<td>0.052***</td>
<td>−0.041***</td>
<td>−0.140***</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(0.006)</td>
<td>(0.008)</td>
<td>(0.008)</td>
</tr>
<tr>
<td>log(nb)</td>
<td>0.098***</td>
<td>0.015**</td>
<td>−0.044***</td>
<td>0.054***</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.006)</td>
<td>(0.009)</td>
<td>(0.009)</td>
</tr>
<tr>
<td>log(pop) × con</td>
<td>−0.128***</td>
<td>−0.148***</td>
<td>−0.100***</td>
<td>−0.083***</td>
</tr>
<tr>
<td></td>
<td>(0.027)</td>
<td>(0.019)</td>
<td>(0.025)</td>
<td>(0.025)</td>
</tr>
<tr>
<td>log(nb) × con</td>
<td>−0.010</td>
<td>0.173***</td>
<td>0.057**</td>
<td>0.064**</td>
</tr>
<tr>
<td></td>
<td>(0.032)</td>
<td>(0.022)</td>
<td>(0.029)</td>
<td>(0.029)</td>
</tr>
</tbody>
</table>

Observations | 13,485 | 13,485 | 13,485 | 13,485 |
R<sup>2</sup>  | 0.540  | 0.094  | 0.134  | 0.574  |
Adjusted R<sup>2</sup> | 0.506  | 0.027  | 0.069  | 0.543  |

Note: *p<0.1; **p<0.05; ***p<0.01
Table C.2: The Compositional Change: Comparison between Service and Manufacturing Industries

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>$Service^T$ Employment</th>
<th>$Service^H$ Employment</th>
<th>$Service^M$ Employment</th>
<th>$Service^L$ Employment</th>
</tr>
</thead>
<tbody>
<tr>
<td>log(pop)</td>
<td>$-0.051^{***}$</td>
<td>$0.116^{***}$</td>
<td>$-0.011^*$</td>
<td>$-0.105^{***}$</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.005)</td>
<td>(0.006)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>log(nb)</td>
<td>$0.053^{***}$</td>
<td>$0.016^{***}$</td>
<td>$-0.055^{***}$</td>
<td>$0.039^{***}$</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.006)</td>
<td>(0.007)</td>
<td>(0.007)</td>
</tr>
<tr>
<td>log(pop) × top</td>
<td>$0.060^{***}$</td>
<td>$-0.073^{***}$</td>
<td>$-0.079^{***}$</td>
<td>$0.152^{***}$</td>
</tr>
<tr>
<td></td>
<td>(0.019)</td>
<td>(0.016)</td>
<td>(0.019)</td>
<td>(0.018)</td>
</tr>
<tr>
<td>log(nb) × top</td>
<td>$-0.103^{***}$</td>
<td>$0.050^{**}$</td>
<td>$0.016$</td>
<td>$-0.067^{***}$</td>
</tr>
<tr>
<td></td>
<td>(0.025)</td>
<td>(0.021)</td>
<td>(0.025)</td>
<td>(0.024)</td>
</tr>
</tbody>
</table>

Observations 13,485 13,485 13,485 13,485
R² 0.536 0.200 0.352 0.533
Adjusted R² 0.502 0.141 0.304 0.498

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>$Manu^T$ Employment</th>
<th>$Manu^H$ Employment</th>
<th>$Manu^M$ Employment</th>
<th>$Manu^L$ Employment</th>
</tr>
</thead>
<tbody>
<tr>
<td>log(pop)</td>
<td>$0.056^{***}$</td>
<td>$0.101^{***}$</td>
<td>$0.036^{*}$</td>
<td>$-0.137^{***}$</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.014)</td>
<td>(0.014)</td>
<td>(0.014)</td>
</tr>
<tr>
<td>log(nb)</td>
<td>$-0.035^{***}$</td>
<td>$-0.036^{**}$</td>
<td>$-0.065^{***}$</td>
<td>$0.101^{***}$</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(0.018)</td>
<td>(0.018)</td>
<td>(0.018)</td>
</tr>
<tr>
<td>log(pop) × top</td>
<td>$-0.055^{***}$</td>
<td>$-0.082^*$</td>
<td>$0.019$</td>
<td>$0.063$</td>
</tr>
<tr>
<td></td>
<td>(0.021)</td>
<td>(0.045)</td>
<td>(0.047)</td>
<td>(0.046)</td>
</tr>
<tr>
<td>log(nb) × top</td>
<td>$0.102^{***}$</td>
<td>$0.052$</td>
<td>$-0.064$</td>
<td>$0.012$</td>
</tr>
<tr>
<td></td>
<td>(0.028)</td>
<td>(0.059)</td>
<td>(0.061)</td>
<td>(0.061)</td>
</tr>
</tbody>
</table>

Observations 13,455 13,455 13,455 13,455
R² 0.445 0.400 0.058 0.234
Adjusted R² 0.404 0.356 −0.012 0.178

Note: *p<0.1; **p<0.05; ***p<0.01
Table C.3: The Regression with 2-Year and 4-Year Lagged Independent Variables

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Service</th>
<th>Service-H</th>
<th>Service-M</th>
<th>Service-L</th>
</tr>
</thead>
<tbody>
<tr>
<td>lag.log(pop)</td>
<td>$-0.033^{***}$</td>
<td>0.079$^{***}$</td>
<td>$-0.042^{***}$</td>
<td>$-0.102^{***}$</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.004)</td>
<td>(0.006)</td>
<td>(0.006)</td>
</tr>
<tr>
<td>lag.log(nb)</td>
<td>0.042$^{***}$</td>
<td>-0.002</td>
<td>$-0.049^{***}$</td>
<td>0.015$^{**}$</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(0.005)</td>
<td>(0.007)</td>
<td>(0.007)</td>
</tr>
<tr>
<td>lag.log(pop) × top</td>
<td>0.047$^{**}$</td>
<td>-0.107$^{***}$</td>
<td>$-0.082^{***}$</td>
<td>0.092$^{***}$</td>
</tr>
<tr>
<td></td>
<td>(0.020)</td>
<td>(0.014)</td>
<td>(0.019)</td>
<td>(0.018)</td>
</tr>
<tr>
<td>lag.log(nb) × top</td>
<td>$-0.098^{***}$</td>
<td>0.118$^{***}$</td>
<td>0.042$^*$</td>
<td>0.040$^{*}$</td>
</tr>
<tr>
<td></td>
<td>(0.026)</td>
<td>(0.018)</td>
<td>(0.025)</td>
<td>(0.024)</td>
</tr>
</tbody>
</table>

Observations 12,586 12,586 12,586 12,586
R$^2$ 0.501 0.082 0.137 0.605
Adjusted R$^2$ 0.462 0.009 0.068 0.574

Note: $^{*}p<0.1; ^{**}p<0.05; ^{***}p<0.01$

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Service</th>
<th>Service-H</th>
<th>Service-M</th>
<th>Service-L</th>
</tr>
</thead>
<tbody>
<tr>
<td>lag2.log(pop)</td>
<td>$-0.020^{***}$</td>
<td>0.079$^{***}$</td>
<td>$-0.037^{***}$</td>
<td>$-0.081^{***}$</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.004)</td>
<td>(0.006)</td>
<td>(0.006)</td>
</tr>
<tr>
<td>lag2.log(nb)</td>
<td>0.034$^{***}$</td>
<td>-0.002</td>
<td>$-0.044^{***}$</td>
<td>0.014$^{*}$</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(0.006)</td>
<td>(0.008)</td>
<td>(0.008)</td>
</tr>
<tr>
<td>lag2.log(pop) × top</td>
<td>0.038$^{*}$</td>
<td>-0.108$^{***}$</td>
<td>$-0.080^{***}$</td>
<td>0.084$^{***}$</td>
</tr>
<tr>
<td></td>
<td>(0.021)</td>
<td>(0.015)</td>
<td>(0.020)</td>
<td>(0.019)</td>
</tr>
<tr>
<td>lag2.log(nb) × top</td>
<td>$-0.094^{***}$</td>
<td>0.118$^{***}$</td>
<td>0.031</td>
<td>0.044$^{*}$</td>
</tr>
<tr>
<td></td>
<td>(0.027)</td>
<td>(0.020)</td>
<td>(0.026)</td>
<td>(0.025)</td>
</tr>
</tbody>
</table>

Observations 11,687 11,687 11,687 11,687
R$^2$ 0.473 0.086 0.142 0.639
Adjusted R$^2$ 0.427 0.008 0.069 0.608

Note: $^{*}p<0.1; ^{**}p<0.05; ^{***}p<0.01$
### Table C.4: The Regression with Control of the Lagged Dependent Variables

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Service(^T)</th>
<th>Service(^H)</th>
<th>Service(^M)</th>
<th>Service(^L)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>(\text{log}(\text{pop}))</td>
<td>(-0.002)</td>
<td>(0.030^{**})</td>
<td>(-0.018^{***})</td>
<td>(-0.019^{***})</td>
</tr>
<tr>
<td></td>
<td>((0.004))</td>
<td>((0.003))</td>
<td>((0.005))</td>
<td>((0.004))</td>
</tr>
<tr>
<td>(\text{log}(\text{nb}))</td>
<td>(0.001)</td>
<td>(-0.0002)</td>
<td>(-0.024^{***})</td>
<td>(-0.003)</td>
</tr>
<tr>
<td></td>
<td>((0.005))</td>
<td>((0.004))</td>
<td>((0.006))</td>
<td>((0.005))</td>
</tr>
<tr>
<td>(\text{lag.Service}^{T})</td>
<td>(0.725^{***})</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>((0.006))</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(\text{lag.Service}^{H})</td>
<td></td>
<td>(0.619^{***})</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>((0.007))</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(\text{lag.Service}^{M})</td>
<td></td>
<td></td>
<td>(0.604^{***})</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>((0.007))</td>
<td></td>
</tr>
<tr>
<td>(\text{lag.Service}^{L})</td>
<td></td>
<td></td>
<td></td>
<td>(0.669^{***})</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>((0.007))</td>
</tr>
<tr>
<td>(\text{log}(\text{pop}) \times \text{top})</td>
<td>(0.008)</td>
<td>(-0.046^{***})</td>
<td>(-0.028^{*})</td>
<td>(0.027^{**})</td>
</tr>
<tr>
<td></td>
<td>((0.014))</td>
<td>((0.011))</td>
<td>((0.015))</td>
<td>((0.014))</td>
</tr>
<tr>
<td>(\text{log}(\text{nb}) \times \text{top})</td>
<td>(-0.028)</td>
<td>(0.047^{***})</td>
<td>(0.017)</td>
<td>(0.037^{**})</td>
</tr>
<tr>
<td></td>
<td>((0.019))</td>
<td>((0.015))</td>
<td>((0.020))</td>
<td>((0.018))</td>
</tr>
<tr>
<td>Observations</td>
<td>12,586</td>
<td>12,586</td>
<td>12,586</td>
<td>12,586</td>
</tr>
<tr>
<td>R(^2)</td>
<td>0.769</td>
<td>0.442</td>
<td>0.468</td>
<td>0.794</td>
</tr>
<tr>
<td>Adjusted R(^2)</td>
<td>0.751</td>
<td>0.397</td>
<td>0.425</td>
<td>0.778</td>
</tr>
<tr>
<td>F Statistic (df = 31; 11656)</td>
<td>(1,253.040^{***})</td>
<td>(297.362^{***})</td>
<td>(330.629^{***})</td>
<td>(1,448.617^{***})</td>
</tr>
</tbody>
</table>

**Note:**
- \(*p<0.1\)
- \(**p<0.05\)
- \(**^{*}p<0.01\)
Table C.5: The Entrance Regression

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent variable:</strong></td>
<td>Number of Entrance</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Announcement</td>
<td>-0.047</td>
<td>(0.035)</td>
<td></td>
</tr>
<tr>
<td>Korean</td>
<td>0.348***</td>
<td>0.348***</td>
<td>0.348***</td>
</tr>
<tr>
<td></td>
<td>(0.043)</td>
<td>(0.043)</td>
<td>(0.043)</td>
</tr>
<tr>
<td>Japanese</td>
<td>0.177***</td>
<td>0.177***</td>
<td>0.177***</td>
</tr>
<tr>
<td></td>
<td>(0.035)</td>
<td>(0.035)</td>
<td>(0.035)</td>
</tr>
<tr>
<td>SEA</td>
<td>-0.677***</td>
<td>-0.677***</td>
<td>-0.677***</td>
</tr>
<tr>
<td></td>
<td>(0.066)</td>
<td>(0.066)</td>
<td>(0.066)</td>
</tr>
<tr>
<td>Boycott</td>
<td>-0.043</td>
<td>(0.040)</td>
<td></td>
</tr>
<tr>
<td>Announcement × Korean</td>
<td>-0.265***</td>
<td>-0.265***</td>
<td>-0.265***</td>
</tr>
<tr>
<td></td>
<td>(0.081)</td>
<td>(0.081)</td>
<td>(0.081)</td>
</tr>
<tr>
<td>Announcement × Japanese</td>
<td>0.216***</td>
<td>0.216***</td>
<td>0.216***</td>
</tr>
<tr>
<td></td>
<td>(0.059)</td>
<td>(0.059)</td>
<td>(0.059)</td>
</tr>
<tr>
<td>Announcement × SEA</td>
<td>0.019</td>
<td>0.019</td>
<td>0.019</td>
</tr>
<tr>
<td></td>
<td>(0.115)</td>
<td>(0.115)</td>
<td>(0.115)</td>
</tr>
<tr>
<td>Boycott × Korean</td>
<td>-0.780***</td>
<td>-0.780***</td>
<td>-0.780***</td>
</tr>
<tr>
<td></td>
<td>(0.113)</td>
<td>(0.113)</td>
<td>(0.113)</td>
</tr>
<tr>
<td>Boycott × Japanese</td>
<td>-0.200***</td>
<td>-0.200***</td>
<td>-0.200***</td>
</tr>
<tr>
<td></td>
<td>(0.067)</td>
<td>(0.067)</td>
<td>(0.067)</td>
</tr>
<tr>
<td>Boycott × SEA</td>
<td>-0.092</td>
<td>-0.092</td>
<td>-0.092</td>
</tr>
<tr>
<td></td>
<td>(0.132)</td>
<td>(0.132)</td>
<td>(0.132)</td>
</tr>
<tr>
<td>Constant</td>
<td>1.962***</td>
<td>1.899***</td>
<td>1.221***</td>
</tr>
<tr>
<td></td>
<td>(0.020)</td>
<td>(0.119)</td>
<td>(0.133)</td>
</tr>
</tbody>
</table>

Other characteristics: | No | No | Yes |
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Individual Dummies</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time Dummies</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>1,470</td>
<td>1,470</td>
<td>1,470</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-6,072.978</td>
<td>-5,623.477</td>
<td>-3,268.994</td>
</tr>
<tr>
<td>Akaike Inf. Crit.</td>
<td>12,175.960</td>
<td>11,564.950</td>
<td>6,865.988</td>
</tr>
</tbody>
</table>

*Note:*  
*p<0.1; **p<0.05; ***p<0.01*
Table C.6: Regression Results: the Effects of Price, Quality, and Name

<table>
<thead>
<tr>
<th></th>
<th>Dependent Variables: Review Counts</th>
<th>All Observations</th>
<th>All Observations</th>
<th>Pre-2016</th>
<th>Pre-2016</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>Korean</td>
<td>0.303***</td>
<td>−0.866***</td>
<td>0.247***</td>
<td>−0.544***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.018)</td>
<td>(0.001)</td>
<td>(0.019)</td>
<td></td>
</tr>
<tr>
<td>K-name</td>
<td>−0.142***</td>
<td>−0.097***</td>
<td>−0.174***</td>
<td>−0.138***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td></td>
</tr>
<tr>
<td>Boycott × Korean</td>
<td>−0.350***</td>
<td>−0.999***</td>
<td>−0.286***</td>
<td>−1.412***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.030)</td>
<td>(0.002)</td>
<td>(0.033)</td>
<td></td>
</tr>
<tr>
<td>Boycott × Rating</td>
<td>−0.071***</td>
<td></td>
<td></td>
<td>−0.115***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td></td>
<td></td>
<td>(0.001)</td>
<td></td>
</tr>
<tr>
<td>Korean × Rating</td>
<td>0.090***</td>
<td></td>
<td></td>
<td>0.049***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td></td>
<td></td>
<td>(0.002)</td>
<td></td>
</tr>
<tr>
<td>Korean × Price</td>
<td>0.005***</td>
<td></td>
<td></td>
<td>0.005***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00003)</td>
<td></td>
<td></td>
<td>(0.00003)</td>
<td></td>
</tr>
<tr>
<td>Boycott × K-name</td>
<td>−0.107***</td>
<td>−0.095***</td>
<td>−0.064***</td>
<td>−0.055***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td></td>
</tr>
<tr>
<td>Boycott × Korean × Rating</td>
<td>0.073***</td>
<td></td>
<td></td>
<td>0.137***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td></td>
<td></td>
<td>(0.004)</td>
<td></td>
</tr>
<tr>
<td>Boycott × Korean × Price</td>
<td>0.0004***</td>
<td></td>
<td></td>
<td>−0.0005***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00004)</td>
<td></td>
<td></td>
<td>(0.00004)</td>
<td></td>
</tr>
</tbody>
</table>

Observations: 536,925 536,925 456,100 456,100
Log Likelihood: −16,338,919.000 −16,295,058.000 −13,148,993.000 −13,106,679.000
Akaike Inf. Crit.: 32,677,901.000 32,590,190.000 26,298,049.000 26,213,431.000

Note: *p<0.1; **p<0.05; ***p<0.01
Table C.7: The Regression on Rating

<table>
<thead>
<tr>
<th></th>
<th>All</th>
<th>The Pre-existing</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td><strong>Boycott × Korean</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>−0.040</td>
<td>−0.040</td>
</tr>
<tr>
<td></td>
<td>(0.027)</td>
<td>(0.027)</td>
</tr>
<tr>
<td><strong>Boycott × Southeastern</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>−0.006</td>
<td>0.057*</td>
</tr>
<tr>
<td></td>
<td>(0.032)</td>
<td>(0.032)</td>
</tr>
<tr>
<td><strong>Boycott × Japanese</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.006</td>
<td>0.069**</td>
</tr>
<tr>
<td></td>
<td>(0.027)</td>
<td>(0.028)</td>
</tr>
<tr>
<td><strong>Boycott × Western</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.225***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.028)</td>
<td></td>
</tr>
</tbody>
</table>

| Individual Dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| Time Dummies       | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations       | 72,527 | 72,527 | 72,527 | 54,724 | 54,724 | 54,724 |
| R²                  | 0.172 | 0.172 | 0.172 | 0.178 | 0.178 | 0.179 |
| Adjusted R²        | 0.164 | 0.164 | 0.165 | 0.170 | 0.170 | 0.171 |

*Note:* *p<0.1; **p<0.05; ***p<0.01
Table C.8: Regression Results within Different Months

<table>
<thead>
<tr>
<th></th>
<th>OLS All Observations (1)</th>
<th>OLS All Observations (2)</th>
<th>Poisson All Observations (3)</th>
<th>Poisson Pre-2016 Observations (4)</th>
<th>Poisson Pre-2016 Observations (5)</th>
<th>Poisson Pre-2016 Observations (6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Boycott</td>
<td>-0.036 (0.104)</td>
<td>-0.141*** (0.001)</td>
<td>-0.316*** (0.002)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Boycott2</td>
<td>0.139 (0.132)</td>
<td>0.013*** (0.002)</td>
<td>-0.046*** (0.002)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Boycott4</td>
<td>0.177 (0.132)</td>
<td>0.092*** (0.002)</td>
<td>0.043*** (0.002)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Boycott6</td>
<td>-0.022 (0.132)</td>
<td>0.023*** (0.002)</td>
<td>-0.063*** (0.002)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Boycott8</td>
<td>-0.021 (0.114)</td>
<td>-0.006*** (0.001)</td>
<td>-0.084*** (0.002)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Announcement×Korean</td>
<td>0.143 (0.132)</td>
<td>0.120* (0.062)</td>
<td>-0.002 (0.002)</td>
<td>0.016*** (0.002)</td>
<td>-0.068*** (0.002)</td>
<td>-0.050*** (0.002)</td>
</tr>
<tr>
<td>Boycott×Korean</td>
<td>-0.339 (0.246)</td>
<td>-0.320** (0.127)</td>
<td>-0.321*** (0.004)</td>
<td>-0.381*** (0.004)</td>
<td>-0.250*** (0.004)</td>
<td>-0.308*** (0.005)</td>
</tr>
<tr>
<td>Boycott2×Korean</td>
<td>-0.056 (0.311)</td>
<td>-0.024 (0.158)</td>
<td>0.016*** (0.005)</td>
<td>0.070*** (0.005)</td>
<td>0.028*** (0.006)</td>
<td>0.089*** (0.006)</td>
</tr>
<tr>
<td>Boycott4×Korean</td>
<td>-0.066 (0.311)</td>
<td>-0.096 (0.161)</td>
<td>0.020*** (0.004)</td>
<td>0.046*** (0.005)</td>
<td>0.038*** (0.006)</td>
<td>0.053*** (0.006)</td>
</tr>
<tr>
<td>Boycott6×Korean</td>
<td>-0.119 (0.311)</td>
<td>-0.196 (0.158)</td>
<td>-0.089*** (0.004)</td>
<td>-0.084*** (0.005)</td>
<td>-0.030*** (0.006)</td>
<td>-0.024*** (0.006)</td>
</tr>
<tr>
<td>Boycott8×Korean</td>
<td>-0.029 (0.270)</td>
<td>0.046 (0.135)</td>
<td>-0.015*** (0.004)</td>
<td>-0.067*** (0.004)</td>
<td>0.056*** (0.005)</td>
<td>0.001 (0.006)</td>
</tr>
<tr>
<td>Constant</td>
<td>5.164*** (0.031)</td>
<td>6.829*** (0.159)</td>
<td>7.447*** (0.0003)</td>
<td>7.285*** (0.004)</td>
<td>7.535*** (0.0003)</td>
<td>6.931*** (0.005)</td>
</tr>
</tbody>
</table>

Individual Dummies: No Yes
Time Dummies: No Yes
Type:Month: No Yes
Observations: 18,810 18,810 18,810 18,810 17,594 17,594
R²: 0.035 0.841
Adjusted R²: 0.033 0.835

Note: *p<0.1; **p<0.05; ***p<0.01
D Figures

Figure D.1: The Zipf’s Law for Urban Clusters
Figure D.2: The NAS Rule for City Cluster Around Detroit, New York, and Houston
Figure D.3: Numerical Comparative Statics with Changing Population

\( \phi = 1.3, \tau^* = 3, B = 5 \)

\( \phi = 1.5, \tau^* = 3, B = 5 \)

\( \phi = 1.6, \tau^* = 3, B = 5 \)
Figure D.4: Numerical Comparative Statics with Changing $\phi$, $\sigma$, $\eta$ and $C$
Figure D.5: A Comparison of Google Search Index for THAAD and Donald Trump

Figure D.6: The Most Frequently Reported Prices