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Three Essays in Transportation Economics

DISSERTATION

Submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

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by

Xiyan Wang

Dissertation Committee:
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DEDICATION

To

my parents and friends

in recognition of their support and love

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

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I would like to express my deepest appreciation to my principal advisor, Professor Jan Brueckner, for his guidance, encouragement, and continuous support. Without his guidance and persistent help, this dissertation would not have been possible. He always motivated my ideas and endeavors, gave fast and detailed feedback on my writings, and guided me into right directions whenever I was heading toward wrong directions. It was the greatest opportunity to meet him and write my academic papers under his supervision as it spurred my research throughout the years at UC Irvine. He has not just been a perfect academic advisor with his careful advice on every step of writing research papers but has become the mentor of my life by showing himself how my future life as a researcher must be like.

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ABSTRACT OF THE DISSERTATION

Three Essays in Transportation Economics

By

Xiyan Wang

Doctor of Philosophy in Economics

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Professor Jan Brueckner, Chair

This dissertation revolves around understanding the determination of transportation networks and service quality, as well as quantifying the impact of these decisions on social welfare.

The first chapter, “Subway Capitalization in Beijing: Theory and Evidence on the Variation of the Subway Proximity Premium”, discusses the heterogeneity of the urban transit capitalization effect and its policy implications. This chapter analyzes the relationship between community attributes and the subway home-price capitalization effect, asking whether the magnitude of the subway proximity premium is affected by neighborhood economic status and location. Using longitudinal data from Beijing, the chapter empirically estimates that decreasing a community’s distance to a subway station by 10% increases the housing price per square meter by 0.2%-0.9%. The chapter also shows that, subway capitalization effect is around 0.1%-0.2% lower for communities that charge a 1 Yuan higher property management fee. Moreover, the analysis also reveals that

the subway capitalization will decrease by around 0.08% as a community's distance to the CBD increases by 1 km.

The second chapter, "1-Hub, 2-Hub or Fully Connected Network? A Theoretical Analysis of the Optimality of Airline Network Structure", focuses on the determination of airline network structure, and provides a simple justification for the existence of the multi-hub networks. This chapter sets up a formal model to explore the optimality of multi-hub networks, with or without competition. It is shown that a single-hub or a fully connected network may not be the optimal network configuration, while a 2-hub configuration may be favored under certain circumstances. In addition, the chapter shows that competition can also affect an airline's optimal choice of network: a 2-hub network can be preferable if a competitor enters the market.

The third chapter "Service Competition in the Airline Industry: Schedule Robustness and Market Structure" investigates the relationship between airline's schedule robustness (how well can a schedule cope with a delay to a particular aircraft) and market structure. Recognizing that schedule robustness is an important factor affecting the flight on-time performance, the chapter shows that there exists service quality competition in the airline industry, as carriers adopt more robust flight schedules when competition heats up. Such results shed light on the debate on the magnitude of airport congestion tolls, and have great public policy implications.

Chapter 1

Subway Capitalization in Beijing:

Theory and Evidence on the Variation of the Subway Proximity Premium

1.1 Introduction

Building a fixed rail system like light rail or a subway is a costly investment for any metropolitan region. In Continental Europe, a fully-underground subway line costs anywhere between $110 million and $250 million per km, and in Beijing, subway construction costs are higher than one would expect given lower wages, as high as those of Europe. Fully-underground lines cost about $150 million per km.[1] An investment of such scale will have an enormous impact on millions of people's lives. For policy makers, part of the attraction of a rail-system investment

[1] These numbers come from calculations in the blog of "pedestrian observations". According to these calculations, the cost for Line 8 Phase 2 is $2.5 billion/17km, and the cost for Line 6 Phase 1 is $4.9 billion/30km.

would be the property value premium generated by such an investment. Thus, it is important for policy makers to know whether the investment can be paid off by capturing the home price premium through future taxation.

The value of a housing unit indicates how much people are willing to pay to live in it given the location and housing characteristics. In theory, if public transit allows people living nearby to travel faster and cheaper to their destinations, the value of the decreased travel time should also be reflected in home prices (Alonso, 1964; Mills, 1972; Hess and Almeida 2007). While a number of studies have empirically investigated the effect of rail station proximity on property values, this chapter focuses on investigating the possibility that such a capitalization effect varies with community attributes and station characteristics. The consideration of a heterogeneous proximity premium is crucial for local policymakers and real estate developers, who must plan for future construction of housing and subways.

A vast body of previous research estimates the impact of proximity to transit stations on land values. Bajic (1983) performed one of the earliest of these studies using a hedonic price regression model to measure the capitalization of the Toronto subway into residential property values. The most widely studied transit systems have been the BART system in San Francisco (Lee, 1973; Dornbusch, 1975; Baldassare et al., 1979) and the Washinton D.C. METRO (Damm et al., 1980; Aterkawi, 1991 ; Grass, 1992). Other major cities with rail transit like Chicago (McDonald and Osuji, 1995; McMillen and McDonald, 2004), Miami(Gatzlaff and Smith, 1993), Toronto (Dewees, 1976), Philadelphia (Boyce et al., 1976; Voith, 1993), Portland (Knaap et al., 2001), Atlanta (Nelson, 1992; Bowes and Ihlanfeldt, 2001; Immergluck, 2009), Minneapolis (Goetz et al., 2010) and New York City (Anas and Armstrong, 1993). Asian cities like Soeul (Bae et al., 2003) and Beijing (Zheng and Kahn, 2008) are also studied to some extent.

General consensus from the previous literature is that the accessibility benefit of living near transit leads to higher home values and rents in many cases (Wardrip, 2011). As for the magnitude of the impact, the price premium from being close to a transit station differs from case to case. Cervero et al. (2004) sets the range between 6% and 45%[2], while Duncan(2008) states that generalization is quite difficult and that it would be safe to assume that properties near stations sell at a 0% to 10% premium. However, in some cases no significant capitalization effect is observed (Lee, 1973; Gatzlaff and Smith, 1993) or even a negative effect is found (Dornbusch, 1973; Burkhardt, 1976). Possible reason for such mixed results could be that measures of crime and other negative externalities like noise and congestion are typically excluded from the property value equation, so that the direct capitalization effect from commuting benefit is underestimated due to these offsetting effects.

Various empirical works also reveal that, although rail proximity has a marginally positive impact on property value, the effects are not felt evenly throughout the system (Almeida, 2004). Hess and Almeida (2007) argue that for Buffalo NY, the premium homeowners will pay for station proximity is greater in high- than low-income neighborhoods. A similar conclusion was drawn by Gatzlaff and Smith (1993) and Bowes and Ihlanfeldt (2001). Interestingly, some other research shows the opposite conclusion: property values increase in low-income neighborhoods but decrease in high income neighborhoods in the case of Atlanta (Nelson, 1992). Using the Alonso-type urban setting assuming two traffic modes and two income groups, Sasaki (1990) shows that the slower traffic mode is usually used by people with lower income. Following this logic, one could reason that in the short run, building subway stations would raise nearby communities'

[2] According to Cervero (2004), the average housing value premiums associated with being near a station are 6.4% in Philadelphia, 6.7% in Boston, 10.6% in Portland, 17% in San Diego, 20% in Chicago, 24% in Dallas, and 45% in Santa Clara County.

housing value only if it is needed and used by those who live there (the low income group most likely). Hence, one explanation for the mixed results is a failure to account for attributes of nearby communities, i.e. the housing quality of the neighborhood (which may reflect the income level of the neighborhood), the distance from the house to the CBD (Bowes and Ihlanfeldt, 2001) and in some special cases, the efficiency of different types of rail transit lines. So the question this chapter is trying to answer is: Would the above mentioned attributes affect the magnitude of the capitalization effect, and if so, what is the underlying mechanism, and by how much can it affect the magnitude of capitalization?

The main contribution of this chapter is that it (1) answers the above question theoretically by utilizing a simple transportation mode-choice model (Anas and Moses, 1979; Brown, 1986; Sasaki, 1990) and (2) tests empirically using a panel data set how community attributes and the type of transit lines affect the magnitude of the capitalization effect caused by the proximity of the subway.

As the standard Alonso-type model assumes that everyone commutes by the same mode, such a statement may not be true for modern cities. Besides automobile, public transit is also rely heavily on in Asia cities. For example, 39.7% of the commuting in Beijing is completed using public transit.[3] Leroy and Sonstelie (1977) suggested that more than one transit mode should be included in the model in order to further explore the residential pattern of a city. They concluded that the introduction of the automobile before 1950s accounted for the resident pattern observed in most US cities. Similar Alonso-type models incorporating mode choice and income class are used in multiple analyses explaining urban land use (Anas, 1979), income's effect on location (Brown, 1985), and the effect of transportation improvement on welfare (Sasaki 1988). Moreover,

[3] Data source: 2011 Beijing Transportation Development Yearbook

Gin and Sonstelie(1992) assume two transportation modes (street car and walking) to prove that construction of a faster and more expensive transit mode will decentralize the high-income dwellers. However, none of the previous studies explores the possible causes of heterogeneous capitalization effect of transit improvements using the model.

The brief analytical section of the chapter shows that mode choice due to heterogeneous wages may cause a heterogeneous capitalization effect. The model also reveals that the capitalization effect is subject to change for houses at different location (the capitalization effect is smaller for houses farther away from the city center). In addition, houses with access to different types of transit may also experience different levels of the capitalization effect (the effect is higher for houses with access to faster transit lines). Using a subset of the aggregated data from the CPDB (China Property Data Base) for its empirical tests, this chapter is the first study to examine the subway proximity premium using longitudinal data. As longitudinal data is rarely used in similar empirical analyses, this dataset provides several advantages over the usual cross-sectional or before/after dataset: (1) a larger number of data points, which increases the efficiency of econometric analysis and (2)the use of repeated observations of the average home price for a large number of housing estates, which provides more information about how home prices have changed over time and makes it easier to establish a causal link by taking advantage of the data's time dimension.

1.2 The analytical model

1.2.1 The capitalization effect of public transit

As mentioned above, being close to a subway station can usually raise home prices through a capitalization effect. The goal of the analysis in this section is to explore the effect theoretically, analyzing the impact of income, home location and subway convenience on the magnitude of the capitalization effect. For simplicity, the analysis starts with the assumption that there is an open city with only one transit mode.

Let y denote full income of a resident in the city, and let x denote the distance a resident has to travel using the transit mode to get to the CBD. To get to this transit mode from home, residents incur an access cost T, and T increases as one lives farther away from the closest transit station. Let w denote the resident's hourly wage, and t denote the time spent commuting each mile on the transit mode, which reduces work hours. Thus the pre-tax income for a worker is: $y - wtx$. Note that the product wt can be interpreted as the time cost of commuting per mile. Besides the time cost, each resident also needs to pay a money cost per mile of commuting, which is denoted k. Thus the total commuting cost for each resident is $(wt + k)x + T$, and each resident faces the problem:

$$\max_{c,q} U(c, q) \qquad s.t. \quad c + rq = y - (wt + k)x - T$$

The resident chooses the amount of numeraire non-land good c and the consumption of land q, to maximize $U(c, q)$ subject to the budget constraint. The home price r adjusts so that the realized utility level is uniform across locations. Let the uniform utility level be u. Thus, to achieve equilibrium, the following two conditions must be satisfied:

$$\frac{U_q}{U_c} = r \tag{1.1}$$

$$U(y - (wt + k)x - rq - T, q) = u \tag{1.2}$$

The conditions determine r and q as functions of other parameters: x, w, k, y, t, T and u. Totally differentiating condition (1.2) with respect to T gives:

$$\frac{\partial r}{\partial T} = -\frac{1}{q} < 0 \tag{1.3}$$

From (1.3), the price will increase when T decreases, and $\left|\frac{\partial r}{\partial T}\right| > 0$ can be interpreted as the capitalization effect. In other word, compared with other locations, those closer to the transit station will experienced a higher price.

1.2.2 Heterogeneous capitalization effect

To investigate the question of heterogeneous capitalization effect imbedded in this model, assume instead that now besides choosing c and q , the residents of the city can choose the commuting mode m between the existing modes, car and $subway$. Each mode m has a corresponding inverse speed denoted by t_m, and a corresponding access cost denoted by T_m. The trade-off between travel speed and money cost per mile is now represented by the function $k = k(t_m)$, where $k'(t_m)<0$ and $k''(t_m)>0$, indicating that higher speed (lower t_m) is associated with higher money cost and that money cost falls at a decreasing rate as t_m increases. These two modes also satisfy $T_{car} = 0$ and $T_{subway} > 0$ since, unlike with the car mode (which has no access cost), people have to walk/take a feeder bus/drive to the closest subway station.

Further assume that the wages of the residents are heterogeneous. There are multiple wage groups, indexed by i, and each wage group i has a corresponding wage level denoted by w_i. If wage group i could have its ideal transportation mode, it would choose m (between car and $subway$) to minimize the total transit cost $[w_i t_m + k(t_m)]x + T_m$. Let M_i denote i's best mode. Formally, M_i is given by

$$M_i = argmin_{\{m=car,subway\}}[w_i t_m + k(t_m)]x + T_m \tag{1.4}$$

With the wage groups, the home price r and land consumption q now gain an i subscript. Then, extending (1.3), the following relationship can be established:

$$\frac{\partial r_i}{\partial T_m} = \begin{cases} -\frac{1}{q_i} & if\ m = M_i \\ 0 & if\ m \neq M_i \end{cases} \tag{1.5}$$

Equation (1.5) indicates that the capitalization effect for a certain transit mode m only exists for the income group whose best mode is m. To be more specific, being closer to a subway station ($T_{subway} \downarrow$) will only raise the home price paid by the wage group who are commuting by subway. Moreover, for the group of residents whose best mode is subway, the capitalization effect from subway proximity is not homogeneous if there is a variation of wage within the group[4]:

$$\frac{\partial^2 r_i}{\partial T_m \partial w_i} = \frac{1}{q_i^2}\frac{\partial q_i}{\partial w_i} > 0 \quad if\ m = M_i \tag{1.6}$$

Thus, the subway capitalization effect is smaller ($\left|\frac{\partial r_i}{\partial T_{subway}}\right|$ is less negative) for residents with higher wages. The intuitive explanation is that, with higher income leading to a larger q, a smaller decrease in the price per square meter reduces overall housing costs enough to compensate for worse subway access. Similarly, the capitalization effect may also differ depending on the home location, with q_i rising with distance x:

$$\frac{\partial^2 r_i}{\partial T_m \partial x_i} = \frac{1}{q_i^2}\frac{\partial q_i}{\partial x_i} > 0 \quad if\ m = M_i \tag{1.7}$$

---

[4] Note that $\frac{\partial q_i}{\partial w_i} > 0$ can be proved using the method provide by Brueckner (1987). First, totally differentiating (1.2) with respect to w yields $-U_c\left(tx + \frac{\partial r}{\partial w}q + \frac{\partial q}{\partial w}r\right) + U_q\frac{\partial q}{\partial w} = 0$, which yields $\frac{\partial r}{\partial w} = -\frac{tx}{q} < 0$ after substituting $\frac{U_q}{U_c} = r.$ Further note that since utility is constant, the increase in q corresponds to the substitution effect of the housing price decrease. Formally, it follows that $\frac{\partial q}{\partial w} = \eta\frac{\partial r}{\partial w} > 0$, where $\eta = \frac{\partial MRS}{\partial q}|_{utility=u}^{-1}$ is the slope of the appropriate income-compensated demand curve, and is a negative expression given the convexity of indifference curves ($MRS \equiv \frac{U_c}{U_q}$). By analogues, $\frac{\partial q_i}{\partial x_i}$ and $\frac{\partial q_i}{\partial t_m}$ can also be proved to be positive.

Thus, as x_i increases, the subway capitalization effect $\left|\frac{\partial r_i}{\partial T_s}\right|$ decreases, so that home prices farther away from the CBD are less sensitive to station proximity.

Similarly, $\frac{\partial^2 r_i}{\partial T_m \partial t_m} = \frac{1}{q_i^2}\frac{\partial q_i}{\partial t_m} > 0$ holds if $m = M_i$. Thus, a convenient subway line (a line with fewer transfers and thus a lower t_{subway}) will generate a larger capitalization effect than an inconvenient line. The intuitive explanations of these latter conclusions parallel the one above.

To summarize, the above theoretical analysis shows that subway proximity will induce higher home prices for the wage group using subways, and that this capitalization effect is smaller for better-off households within the group. The analysis also concludes that the subway proximity premium will decrease as a community's distance to the CBD increases, and that it is smaller when induced by an inconvenient subway line.

1.3 Hedonic Price Model

This section tests the predictions from Section 2 using an hedonic price model. Such a model offers a way to consistently estimate the relationship between prices and product attributes in a differentiated product market. The coefficients of the regression show the effect on the market price of increasing a particular product attribute while holding the other attributes fixed. From the consumer's perspective, the coefficient can be considered the implicit price of a certain attribute.

In this research, variables are measured for different housing estates i in different weeks t over a multi-year period. The semi-log hedonic price equation is:

$$log(P_{it}) = \alpha + \sum_k \beta_k S_{ikt} + \sum_l \gamma_l N_{ilt} + \sum_r \delta_r log(T_{rt}) + \epsilon_{it} \qquad (1.8)$$

The variation in home prices is explained as a function of structural characteristics (S), indexed by k, neighborhood characteristics (N), indexed by l, and subway-station proximity characteristics (T), indexed by r. The parameter vectors corresponding to S, N and T are β, γ and δ, while α is a constant.

This chapter adopts the assumption that ϵ_{it} is not iid within group i. Thus in the presence of clustered errors, pooled OLS estimates are still unbiased but standard errors may be wrong. Considering that the error terms may also be auto correlated across time, inferences made in Section 1.5 are based upon "Clustered errors". For simplicity, the empirical analysis in section 1.5 assumes that there is no spatial correlation between communities.

Section 1.5.2 adds interaction terms between the quality of the housing estate (an element of N) and subway proximity to the model, and in Section 1.5.3, the effect of distance to the CBD is captured by adding interaction terms and sub-sampling.

1.3.1 Subway system in Beijing

Beijing, the capital of China, is the second largest city in China and ranks in the first tier of Chinese cities in terms of economic development and the volume of urban construction. The municipality covers 16,410 km^2 and is composed of 18 urban districts and 2 counties. The total municipal population increased from 9 million in 1980 to 20.7 million in 2012. Beijing has also accommodated over 6 million migrants during the period. The transportation system needs to be expanded continuously to cope with the huge and growing number of residents and high population density, and Beijing's subway and light rail system has become more complex over the past ten years. Figure 1.1 shows a map of all the present Beijing subway lines.

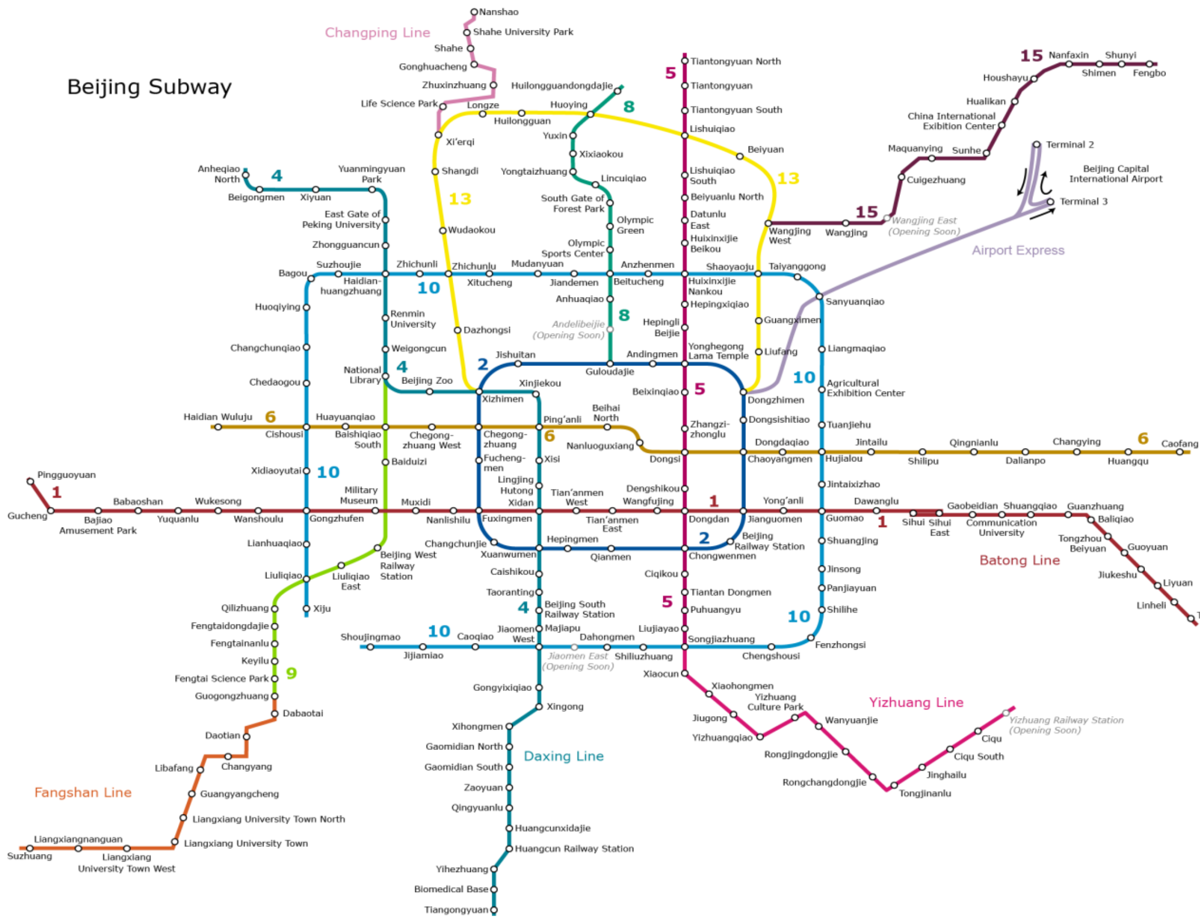


Figure 1.1 Beijing Subway Lines

During the period from 2002 to 2008, 638 billion Yuan had been spent on subway subsidies and subway construction.[5] Annual subsidies of about 2 billion Yuan are invested by the Beijing Municipal Government for subway operations. As a result, Beijing's subway service is provided at a flat fare of only 2 Yuan (USD $0.3) per ride with free transfer, except for the Airport Express. All but two of the subway's 16 lines have entered service since 2000 as the system has undergone rapid expansion, thus lowering transportation costs for residents of Beijing. The most recent expansion of the network came into effect on December 30, 2012 with the opening of Line 6 and extensions to Line 8 (Phase 2 southern section), Line 9 (northern section) and Line 10 (Phase 2). Table 1.1 gives detailed information on each line that was opened or expanded after 2007. After

[5] Data source: Chronicle Events of Beijing Subway: 2001-2004.

all these expansions, the existing network still cannot adequately meet the city's mass transit needs, and extensive expansion plans call for 19 lines to be in operation by 2015.

Table 1.1 Subway Lines Opened and Extended after 2007

Lines	Opened	Newest Extension	Length(km)
Line5	2007	-	27.6
Line10	2008	2012	54.8
Line8	2008	2012	22.0
Line4	2009	2010	28.2
Line15	2010	2011	30.2
Changping Line	2010	-	21.24
Daxing Line	2010	-	21.7
Fangshan Line	2010	2011	24.79
Yizhuang Line	2010	-	23.3
Line9	2011	2012	16.5
Line 6	2012	-	30.4

1.3.2 Spatial locations of Beijing

The Beijing Administrative Area consists of 18 districts, with 8 of them considered by the municipal government as the "inner 8 districts". While most other papers examine the effect of subway construction within these 8 inner districts (Zheng and Kahn, 2013), the subway system in Beijing now reaches many of the suburban areas of Beijing, and the effect of such infrastructure may be different between inner city and suburban areas. Thus, it is necessary to include more districts in the research. In the dataset, an additional 5 suburban districts are included, for a total of 13 districts (Dongcheng, Xicheng, Chongwen, Xuanwu, Chaoyang, Haidina, Fengtai, Shijingshan, Tonzhou, Shunyi, Mentougou, Huairou, Fangshan).

Below the district level, the fundamental administrative level in Beijing is the Jiedao (subdistrict). Jiedaos are responsible for minor services such as garbage collection, but they are also in charge of multiple Xiaoqus (communities). Every community has a community committee, and every committee administers the dwellings in that community.[6] A community in China is normally a housing estate that has a population of 7000 to 15000 and an area of about 10 acres. These estates are usually built by a single contractor with only a few styles of house or building design, so that they tend to be uniform in appearance. Housing within these housing estates has similar floor space, heating type, number of bathrooms and other characteristics.

Distance from the CBD played a big role in the model of Section 2. Zheng and Kahn(2008) argue that Tiananmen Square is the only CBD of Beijing. However, according to the Beijing CBDs Administrative Committee, there are two distinct CBDs in Beijing. The main CBD is about 7 kilometers to the east of Tiananmen Square, sandwiched between the 3rd Ring Road and the 4th Ring Road, as depicted in Figure 1.2. The second CBD is located to the west of Tiananmen Square on Financial Street. About 53% of tertiary-industry employees in the municipal area commuted to Beijing's two CBDs in 2008. With about 20% of the tertiary-industry workers commuting to the Financial Street district, and about 30% of the working force commuting to main CBD (Z. Yang et.al 2008). Besides the two CBDs, Zhongguancun Science Park (ZSP) is another employment center, to which 47% of the municipality's workers commuted during the year 2009 (H, Duan, 2008).

[6] Data source: Law of the Urban Residents Committees of the Peoples Republic of China.

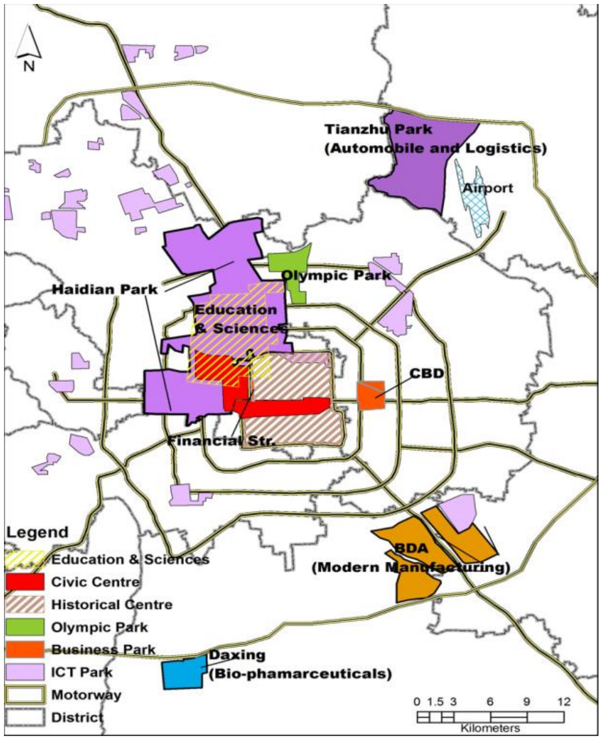


Figure 1.2 Spatial Location of Beijing

Note. Retrieved from "Beijing" by Z. Yang, J. Cai, H. Ottens, and R.Sliuzas, 2008, Cities, volume 31, p. 491-506.

As made clear in the theoretical analysis, the capitalization effects of different subway lines may differ because of differences in convenience. Zheng and Kahn (2008) categorize subways into city subways and suburban subways, and they find different capitalization effects for the two types of subways using cross-sectional data from new housing projects in Beijing (there were only 4 lines during their sample period). In addition, Zheng and Kahn (2013) examine both the start-up effect and the completion effect of subway construction.[7] They find that the start-up effect is only marginally significant, but that the completion effect is significant and that the coefficient is consistent with their analysis in 2008: a 10% increase in distance to a subway station lowers home prices by 1.4%. They also find an insignificant announcement effect for un-built subways.[8] These results indicate that in Beijing, the capitalization effect is minimal for places where subway

[7] The start-up effect measures the capitalization effect of subway stations that are still under construction. The completion effect measures the capitalization effect of subway stations that are already in use.

[8] The announcement effect measures the capitalization effect of subway stations that are planned by the municipality but are not yet under construction.

stations are undergoing planning and construction. Only when the real construction has been finished does a location experience significant home price appreciation.

This study divides the subway lines into 3 different groups according to their level of convenience. Some subway lines can get people to the CBDs and ZSP without a transfer, yet some suburb subway lines can only transport suburban dwellers to CBDs and ZSP with multiple transfers. Subway lines that go through CBDs or ZSP are denoted as subway group A. Lines directly connected to subway group A are denoted as subway group B. Lines directly connected to subway group B are denoted as subway group C. Table 1.2 shows the detailed classification of the subway lines.

Using GIS software, the CBDs (including ZSP), all the subway stations and housing estates in the data set are geocoded, and the geographical distances between the estates and the stations of a certain subway group are calculated. The geographical distances between the estates and the closest CBDs are also calculated. [9] Since the subway system in Beijing has been expanding with amazing speed since 2007, it is worth noticing that for some housing estates, distance to the closest subway group (A/B/C) may dwindle over time as new subway lines open. Thus, the variables measuring subway proximity are not time invariant.

Table 1.2 Subway Groups

Subway group A	Subway Group B	Subway Group C
Line1 Line2 Line10 Line 6	Line 9 Line4 Line 5 Line 8 Line 13 Line Yizhaung Line Batong	Line Fangshan Line Changping Line 15

[9] Here distance is measured from the center of the estates. Most of the communities are relatively small (with a diameter smaller than 200m, so that they can be considered as a point on the map, with residents spending similar time to get to the subway station. For extremely huge housing estate (like the case of *Tiantongyuan*), developers always arrange shuttle buses to travel within the community so that residents can be transported to the gates of the community. Thus people living in the same community can have similar access to subway regardless of their residential location within the community.

Other public goods should also be included in the hedonic price model, including the housing estate's access to hospitals, gardens, core schools of all levels and business subcenters. Hospitals in China are organized according to a 3-tier system with highest grade of 3. Grade 3 (Tertiary) hospitals top the list as comprehensive or general hospitals at the city, provincial or national level, with a bed capacity exceeding 500. Further, based on the level of service provision, size, medical technology, medical equipment, and management and medical quality, these three grades are further subdivided into three subsidiary levels: A, B and C. [10] With the completion of the medical insurance system, city dwellers' valuation of proximity to hospitals with better service is rising. Hence, the capitalization of close medical services should be accounted for in the hedonic price model, and proximity to a 3A hospital is included to measure this attribute.

In Beijing, six years in primary school and three years in middle school are required under compulsory education. For each school district, there are several core middle schools and primary schools while the rest are common schools. Core schools have better funding and better faculties. Students studying in core schools not only have a better chance at higher quality education than other schools, but they may also be privileged when choosing a high school and even a university. Hence, proximity to core middle schools, core high schools and core primary schools is measured and included in the model.

Proximity to core universities is also measured and included in the model. By living close to a university, residents can have access to the available working opportunities. University areas also provide their residents with better a neighborhood and a tranquil atmosphere, including high quality amenities and cultural events.

[10] Wikipedia: classification of Chinese hospitals

Recognizing that some amenities like shopping centers and restaurants may cluster near the subway stations, proximity to sub-business centers and shopping malls are also controlled for. An advantage of studying capitalization effects in Beijing is that the location of schools, hospitals, parks, universities and most of the subway stations are exogenously determined, because of the former planning economy and path dependency. Most of these public goods were built by the Central Government or local government without much consideration of the market forces and demand (with the exception of a few suburban lines).

It is mentioned in many studies that, because of nuisance effects from negative externalities like noise, homes located too close to above-ground heavy rail lines and some light rail lines sell at a discount relative to homes a bit further away (Landis et al. 1995; Bowes and Ihlanfeldt 2001; Chen et al. 1998; Lewis-Workman and Brod 1997; Goetz et al. 2010). In Beijing, most urban rail transit lines[11] are underground, and thus no noise externalities are imposed on nearby residence. Similarly, almost all subway stations do not provide park-and-ride service so that congestion is not likely to be caused by subway stations. Just to be cautious, variables indicating if a community is very close to a subway station or an above ground light rail station are also created and included in the model.

1.4 Data

1.4.1 Data sources

It is difficult to obtain micro level household data within a Chinese city. The National Bureau of Statistics of China conducted two waves of a large-scale survey in Chinese cities in 2007 and 2010,

[11] Above ground light rail lines are Line 13, Line Batong, part of Line Yizhuang, Line Changping and Line Fangshan. All of them are suburban lines.

but the Bureau refuses to release micro household data for confidentiality reasons, only releasing zone-level data on the condition of a close collaborative relationship with the researcher. Without access to such data, this chapter is based on an original community-level dataset from "Home price Web" (FangjiaWang). As one of the most popular searching tool used by property buyers and sellers, the Web provides information based on the CPDB (China Property Data Base). The CPDB data covers basic characteristics and prices of 50 million housing properties in 300 cities and 300,000 communities in China, and is so far the biggest and most detailed dataset available. The sample used in this chapter includes 251,239 observations, which include weekly average resale prices in 907 housing estates from 12/02/2007 to 03/24/2013 (277 weeks). The spatial distribution of the 907 housing estates is shown in Figure 1.3. They spread evenly throughout the inner city but are clustered in the suburban areas. As was mentioned earlier, housing in these communities is mostly homogenous. Thus using community-level data will not induce significant bias.

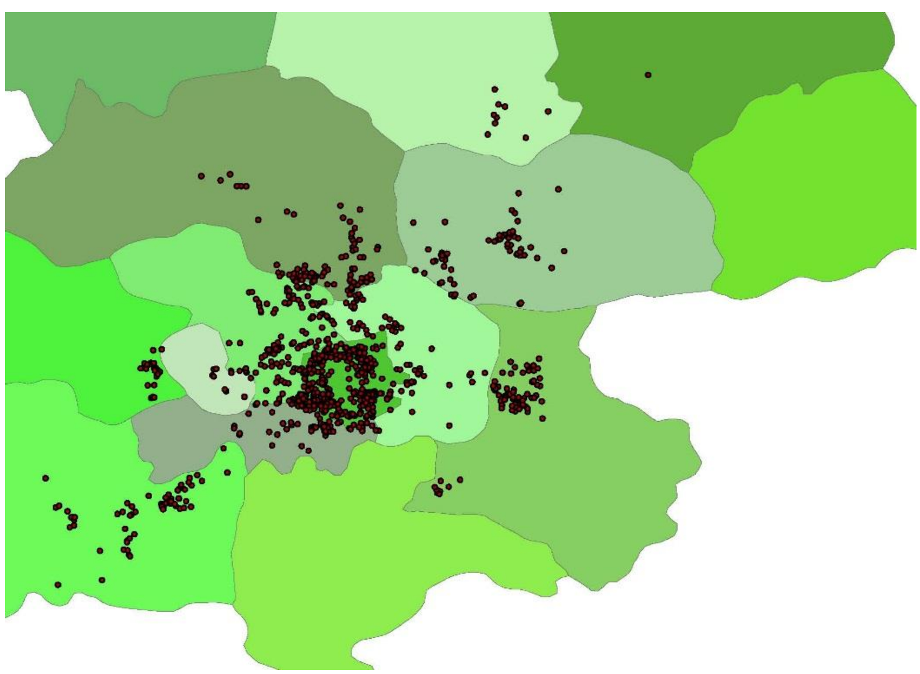


Figure 1.3 The Location of 907 Housing Estates in Beijing

All the housing estates in the dataset consist of condominiums, the most typical housing type in Beijing. As of 2013, about 95% of the communities in Beijing consist of condominiums[12], and the few single-family home communities are usually located outside the inner 8 districts, their major purpose being for vacation houses and retirement homes. Since some housing estates were built later than the initial sample week, the dataset is unbalanced, with data missing at random (MAR). Table 1.3 shows the number of housing estates within categories corresponding to the number of observations per housing estate. 626 out of 907 housing estates in the dataset have been observed more than 250 times, which means that most of the housing estates in the dataset were built before 2008.

Table 1.3 Number of Observations per Community

Number of Observations	Number of Communities
$9<n\leq 50$	21
$50<n\leq 100$	165
$100<n\leq 150$	21
$150<n\leq 200$	91
$200<n\leq 250$	75
$250<n\leq 277$	625

As known to all, land is owned by the state in Chinese cities, yet after the land market reforms, land markets in Beijing started to emerge in 1992. But using home prices for new projects, as in previous papers, may be problematic since the prices are influenced by government supply decisions. On the other hand, the resale markets for condominiums are not subject to governmental supply regulation so that the resale prices only reflect the characteristics of the community and can be used to better identify the capitalization effects.

[12] Unlike western counties where single family houses are the dominant type of housing, major Asian cities mainly consists of condominiums where both the poor and rich live.

1.4.2 Data Cleaning

The housing price data cover 13 districts in Beijing. But since the Mentougou and Huairou districts are far away from the CBDs and from subway stations, these two districts were dropped. After these deletions, the dataset contains 870 housing estates and a total of 240,990 observations. If a housing estate is 10 or more kilometers away from the nearest subway station on 3/12/2013, then this housing estate is assumed to be too far away from subway lines to be affected by them (threshold values of 5km and 2km are also applied to the sample to test for robustness). 17 housing estates meet this criterion and are deleted, leaving 853 housing estates and 236,281 observations. Among these 853 housing estates, some were built after the start of the sample period (later than 12/02/2007), so that there are missing values for these housing estates. Deletion of observations that contain missing value leaves an unbalanced panel data with 182,646 observations. A list and the descriptive statistics of the variables are presented in Table A1 in the appendix.

1.5 Results

1.5.1 How do subway lines affect home prices?

The first set of home price regressions is presented in Table 1.4. A housing estate fixed effect is included, with all time-invariant variables excluded from the model. While capturing some community characteristics that are observable, community-level fixed effects capture all unobserved housing estate characteristics. For example, whether or not the housing estate belongs to a popular school district is not specified. According to Beijing News, the price of a home located in an extremely popular school district is at least 10 thousand Yuan higher per square meter than that of a nearby home not located in a popular school district. Similarly, the dataset does not include information about whether or not the property was built by a state-owned enterprise (SOE)[13]. Even though SOE and non-SOE developers produce similar products, SOE developers may sell their commodity housing units at a price discount, although Zheng and Kahn (2013) argue that such discounts are insignificant. In subsequent regressions, fixed effects are replaced by measured community characteristics.

Table 1.4 shows the results of the community fixed-effect model. Column (1) uses all the data and assumes that subway lines in each group all affect the home price. In column (2), (3) and (4), only the closest subway station is assumed to matter. With home prices only affected by the closest subway station, the sample can be divided into three groups: housing estates closest to subway groups A, B, C, respectively. Recall that since new construction means that subway access varies with time, its effect can be estimated despite the presence of fixed effects.

Nearly 95% of the variation in the log of home prices is explained by the fixed effect model. This compares favorably to similar models previously estimated in the literature. Moreover, estimated coefficients are generally statistical significant and with the expected signs. As expected, the home price decreases as distance to the nearest subway station increases. For people whose closest station allows them commute to the CBD without a subway transfer (using subway group A lines), the home price decreases by 0.38% when distance to the subway station increases by 10%. Similarly, for people whose closest station allows them commute to the CBD with one subway transfer (using subway group B lines), the home price decreases by 0.08% when distance to the closest subway group B station increases by 10%, an effect that is not statistically significant. For people whose closest station allows them commute to the CBD with more than one subway

[13] State-owned enterprises are projects in which the state is the largest shareholder.

transfer (using subway group C lines), the home price decreases by 0.2% when distance increases by 10%.

Table 1.4 Fixed Effect Capitalization of Subway Proximity
(all samples are within 10km of a subway station)

Dependent Variable: Log(Price)	(1) Pooled	(2) Subway Group A	(3) Subway Group B	(4) Subway Group C
Log(Distance to Subway Group A)	-0.0286***	-0.0382***		
	(0.00355)	(0.0104)		
Log(Distance to Subway Group B)	-0.00123		-0.00831	
	(0.00201)		(0.0167)	
Log(Distance to Subway Group B)	-0.00348			-0.0213***
	(0.00475)			(0.00501)
Year 2008	-0.0396***	-0.0289***	-0.0439***	
	(0.00553)	(0.00687)	(0.00482)	
Year 2009	0.106***	0.121***	0.0928***	
	(0.0194)	(0.00848)	(0.00766)	
Year 2010	0.542***	0.553***	0.526***	-0.112***
	(0.00860)	(0.00920)	(0.0104)	(0.0113)
Year 2011	0.637***	0.677***	0.629***	-0.102***
	(0.0127)	(0.0102)	(0.0101)	(0.0101)
Year 2012	0.666***	0.726***	0.659***	-0.113***
	(0.0153)	(0.0109)	(0.0109)	(0.00748)
Year 2013	0.827***	0.900***	0.829***	
	(0.0172)	(0.0129)	(0.0128)	
Constant	9.533***	9.677***	9.407***	9.772***
	(0.0217)	(0.00840)	(0.00937)	(0.00650)
Observations	182,646	90,250	88,612	15,826
R-squared	0.943	0.942	0.940	0.962

Standard errors in parentheses, and *** denotes a p value smaller than 0.01, ** denotes a p value smaller than 0.05, * denotes a p value smaller than 0.1. Similar regressions including indicators of being too close to the stations or light rail stations are run, yet the coefficients are statistically insignificant thus results are not shown here. Same strategy and results applies to other regressions. The same regressions with samples within 5km of the closest subway station are reported in the Appendix.

This conclusion is similar to that of Zheng and Kahn (2008): the older subway lines that run through the CBDs have a higher capitalization effect than the newly built subway lines and suburban lines. But in their regression, all observations are pooled in one regression. However, estimating the hedonic price model this way may be less appropriate since a far-away subway station from another subway group may have no effect on home prices, so that adding it to the model may underestimate the actual capitalization effect. Comparing the pooled results from column (1) and those from columns (2), (3) and (4), the capitalization effects are higher after observations are grouped according to the dwellers' best commuting choice, which confirms the above statement.

1.5.2 Does the capitalization effect depend on the quality of the housing estate?

As is mentioned in the introduction, this chapter aims to explore the heterogeneity of capitalization effects with respect to community attributes. The property management fee of each housing estate is utilized to measure the quality of the housing. The property management fee is a service fee charged by the property management department of a housing estate. The fee covers expenses like parking management, janitor's wages and equipment, the maintenance of public facilities of the residential area, gardening and necessary renovations. The property management fee can be considered an indicator of the "quality" of the housing estate that cannot be captured by measured characteristics, reflecting instead cleanliness, public facilities or even the taste and design philosophy of the properties.

Now that we are to include a time invariant variable (property management fee) into the model, the community-level fixed effect can no longer be used, and other time invariant control variables should also be included for a better fitting model. After controlling for neighborhood characteristics, structural characteristics, district fixed effects and time fixed effects, Table 1.5 shows regression results that reveal the effect of income on subway capitalization. Because of lack of data, few physical housing attributes are included in the model. Note that all of the housing estates are condominium and are quite similar in building structure, internal space and decoration.

In addition, the dependent variable is the price per square meter. Hence omitting physical housing attributes should not bias the results significantly.

Without community fixed effects, the absolute value of the coefficients of subway proximity are higher than those in the previous section. As expected, all the coefficients of the interaction terms are significantly positive, so that comparing a housing estate with another one that charges a 1 Yuan higher property management fee, the latter estate's home price is less sensitive to subway proximity. This finding implies that high-quality housing estates have a lower subway capitalization effect per square meter than low-quality housing estates, which according to the theory in Section 1.2, could be caused by the fact that with higher wage leading to larger house, so that a smaller decrease in the price per square meter reduces overall housing costs enough to compensate for worse subway access. Hence, the home prices of such communities are affected with lower magnitude by subway proximity.

On average, the capitalization effect is about 0.9%, 0.37% and 0.25% respectively for a home with a zero property management fee in housing estate groups A, B and C. It is also worth noticing that, as the convenience level of the subway group decreases, the capitalization effect also decreases, just as predicted in section 1.2.

According to the coefficients of the interaction terms in regressions (1) to (10), if a home in housing estate group A has a property management fee of approximately 4 Yuan, and then the capitalization effect of its nearby subway lines would decrease to zero. Similarly, if a home in housing estate group B charges a property management fee about 3 Yuan, then the capitalization effect of its nearest Subway group B station would be zero. The same can be said about a home in housing estate group C if it charges a property management fee of 1 Yuan.

As depicted in Figure 1.4, the property management fee for the 907 housing estates in the dataset ranges from 0 to 12 Yuan per square meter per month, with an average of 2 Yuan per square meter per month. Thus, for a house with an area of 100 square meters, property management fee can range between 0 to 1200 yuan per month. For an average employee earning around 5200[14] Yuan per month, the property management fee can be a burden if he/she is to live in a high-quality community with the fee as high as 800 Yuan. While the property management fee can be quite substantial, it is reasonable to believe that a resident will choose to live in communities whose property management fee is commensurate with his or her income[15]. Hence, without access to community level income data[16], the result that the coefficients of the interaction terms between the property management fee and subway proximity measures are positive suggests that those who live in high-quality communities (probably people with higher wages) experience a smaller capitalization effect compared to those who live in low-quality communities (probably people with lower wages). Thus, to some extent, the empirical results confirm the theory in Section 1.2.

[14] Statistics on the average income of Beijing residents in 2012 come from National Bureau of Statistics of PRC.

[15] Further justification of the positive relationship between income and housing quality/management fee is provided in the appendix.

[16] Household or even Jiedao level income data is difficult to come by. Even though the official statistics bureau has already collected nearly 20 years of survey data on households, they have not been made available to researchers.

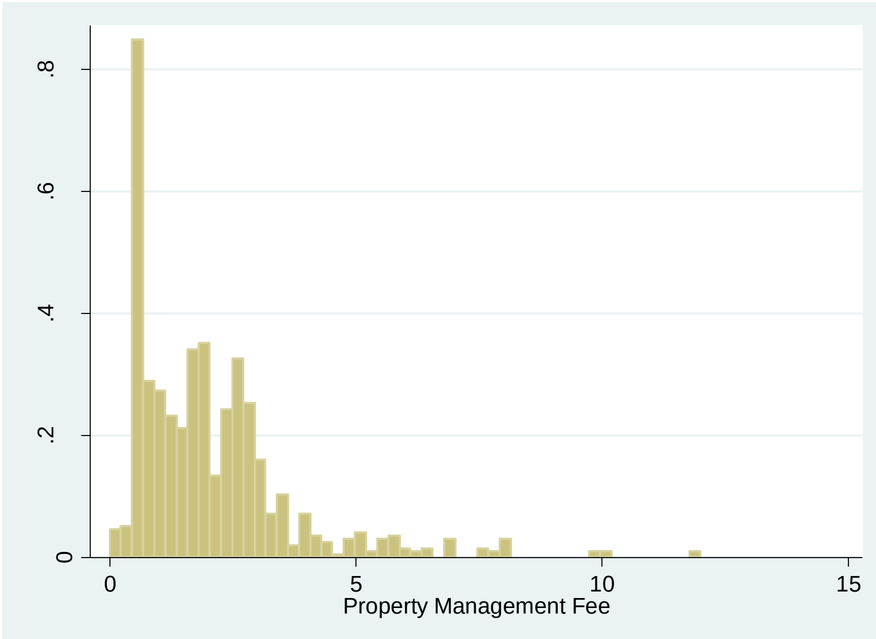


Figure 1.4 Histogram of property management fee

Table 1.5 also shows that communities using subway group A have significant negative price gradients with respect to the distance from all levels of core schools. Interestingly, the regressions show no evidence to support that the distances from business centers affect the home price of these communities (distance to the subway station is all that matters). The regressions in column (3) and (7) show that the home prices of communities using subway group B increases as their distances to core primary school, university, business center and sub-center decreases. Similarly, column (4) and (8) show that for communities using subway group C, home prices increases if the distance to the closest university, hospital and garden decreases. The regressions also show that the home price is lower if the property is constructed earlier.

The land area of the community has almost a zero effect on the home price (per square meter). On the other hand, the floor area ratio has a significant influence on the home price for all communities. If the floor area ratio increases by 1, the home price will decrease by 0.1%, 0.19% and 0.29% for a community commuting using subway group A, B and C lines, respectively. As for the greening rate (the ratio of greenery area and land area) , a 10% increase in the rate will increase the home price by 2.8% for communities using subway group A, but the greening ratio have little effect on home price of communities using subway group B or C. The results show that the signs of the coefficients for distance to a hospital and distance to the nearest public garden are both positive for communities using subway group A and B. This unexpected effect can be perhaps explained by the strong correlation between distance to a business center and the other two covariates. In unreported regressions, three dummy variables were created indicating proximity to a hospital, a business sub-center and parks to replace the continuous variables. These results in show that being close to a park or business sub-center (within 500m) will raise the home price by 1.3% and 6%, respectively. On the other hand, being close to a hospital will decrease the home price by 2.1%, probably because of negative externalities brought by hospitals (like traffic jams and noise).

Table 1.5 Hedonic Estimation of the Interaction between Capitalization Effect of Subway and Housing Quality (all samples are within 10km of a subway station)

VARIABLES	(1) Pooled	(2) Subway Group A	(3) Subway Group B	(4) Subway Group C	(7) Pooled	(8) Subway Group A	(9) Subway Group B	(10) Subway Group C
Log(Distance to Subway Group A)	-0.046***	-0.095***			-0.041***	-0.089***		
	(0.014)	(0.019)			(0.014)	(0.019)		
Log(Distance to Subway Group B)	-0.029**		-0.037**		-0.028*		-0.036**	
	(0.015)		(0.016)		(0.014)		(0.016)	
Log(Distance to Subway Group B)	-0.0033			-0.025	0.012			-0.027
	(0.0061)			(0.019)	(0.0085)			(0.019)
Prop manage fee	0.016*	0.045***	0.036***	0.029	0.018**	0.045***	0.036***	0.029
	(0.0089)	(0.0091)	(0.011)	(0.018)	(0.0088)	(0.0091)	(0.011)	(0.018)
Log(Distance to A) * Fee	-0.0050	0.021***			-0.0047	0.020**		
	(0.0056)	(0.0078)			(0.0055)	(0.0078)		
Log(Distance to B)* Fee	0.024***		0.013*		0.023***		0.013*	
	(0.0066)		(0.0072)		(0.0065)		(0.0072)	
Log(Distance to C)* Fee	0.0059***			0.029***	0.0056***			0.029***
	(0.0016)			(0.011)	(0.0016)			(0.011)
Land area	-1.8e-08	1.2e-08	-7.5e-08	6.7e-10	-1.6e-08	1.2e-08	-7.5e-08	1.7e-09
	(1.9e-08)	(4.5e-08)	(4.6e-08)	(2.2e-08)	(1.9e-08)	(4.4e-08)	(4.6e-08)	(2.2e-08)
Floor area ratio	-0.014***	-0.010*	-0.019**	-0.029	-0.014***	-0.010*	-0.020**	-0.028
	(0.0050)	(0.0052)	(0.0091)	(0.020)	(0.0050)	(0.0052)	(0.0091)	(0.020)
Greening ratio	0.15	0.28**	0.085	0.30	0.15	0.29**	0.085	0.30
	(0.11)	(0.14)	(0.15)	(0.19)	(0.11)	(0.14)	(0.15)	(0.19)
Time_of_Constru	0.000011***	0.000019***	9.0e-06*	1.4e-06	0.000011***	0.000019***	8.9e-06*	1.4e-06
	(3.6e-06)	(5.1e-06)	(5.0e-06)	(7.8e-06)	(3.5e-06)	(5.0e-06)	(5.0e-06)	(7.8e-06)
Distance to Hospital	0.016**	0.030**	0.014	-0.11***	0.014*	0.030**	0.013	-0.11***
	(0.0075)	(0.015)	(0.0085)	(0.036)	(0.0074)	(0.015)	(0.0086)	(0.036)
Distance to Park	0.015*	-0.0022	0.026**	-0.042***	0.014*	-0.0020	0.025**	-0.042***
	(0.0078)	(0.011)	(0.010)	(0.015)	(0.0078)	(0.011)	(0.010)	(0.015)
Distance to Business District	-0.018***	-0.0055	-0.018**	0.080**	-0.015**	-0.0062	-0.017**	0.080**
	(0.0066)	(0.012)	(0.0079)	(0.035)	(0.0066)	(0.012)	(0.0079)	(0.035)
Distance to High School	-0.012***	-0.041***	-0.0072	0.0012	-0.013***	-0.041***	-0.0073	0.0013
	(0.0043)	(0.0074)	(0.0065)	(0.0059)	(0.0043)	(0.0074)	(0.0065)	(0.0059)

VARIABLES	(1) Pooled	(2) Subway Group A	(3) Subway Group B	(4) Subway Group C	(7) Pooled	(8) Subway Group A	(9) Subway Group B	(10) Subway Group C
Distance to Primary School	-0.016***	-0.028***	-0.024***	-0.0065	-0.015***	-0.028***	-0.024***	-0.0064
	(0.0053)	(0.0099)	(0.0061)	(0.0091)	(0.0053)	(0.0099)	(0.0061)	(0.0092)
Distance to CBD	0.0069	0.0066	0.00065	0.088**	0.0057	0.0067	0.00019	0.088**
	(0.0077)	(0.013)	(0.0095)	(0.035)	(0.0077)	(0.013)	(0.0095)	(0.035)
Distance to University	-0.021***	-0.012	-0.023**	-0.044***	-0.022***	-0.013	-0.023**	-0.044***
	(0.0081)	(0.0097)	(0.0091)	(0.015)	(0.0081)	(0.0097)	(0.0092)	(0.015)
District Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	No	No	No	No
Week Fixed Effect	No	No	No	No	Yes	Yes	Yes	Yes
R-squared	0.819	0.827	0.794	0.741	0.834	0.845	0.811	0.753

Robust Standard errors in parentheses, and *** denotes a p value smaller than 0.01, ** denotes a p value smaller than 0.05, * denotes a p value smaller than 0.1. Regressions are clustered at community level. For simplicity, fixed effect coefficients for each regression are not reported. The same regressions with samples within 5km of the closest subway station are reported in the Appendix.

1.5.3 Does the capitalization effect depend on distance to the CBDs?

According to the conclusion drawn in Section 1.2, communities far from the CBDs may experience a lower capitalization effect. This argument is tested by introducing an interaction term between distance to CBDs and distance to subway stations. In Table 1.6 column (1) assumes that home prices are not only affected by the closest subway station, but that they can also be affected by other subway lines, so that all the observations are used. Columns (2), (3) and (4) assume that the home price can only be affected by the closest subway lines.

The coefficients of the interaction terms are significantly positive in columns (2) and (3), but significantly negative in column (4). Thus, for a housing estate using subway group A or B, and that is 1 km farther away from CBD, the capitalization effect of its nearest subway station is smaller compared to that of a housing estate closer to the center. For housing estates using subway group A, the capitalization effect decreases the fastest: with each extra 1km from the CBD, the capitalization effect decreases by 0.08%. For a housing estates using subway group B, the capitalization effect decreases somewhat slower: the rate of decreasing capitalization is 0.06% per km away from CBD. For housing estates using subway group C, the effect of distance to the CBDs on the subway proximity premium has the opposite sign: with each extra 1 km from the CBD, the capitalization effect increases by 0.09%. Thus, the empirical analysis shows that the capitalization effects of convenient subway lines decrease as distance to the CBDs increases, which is consistent with the theoretical analysis in Section 1.2.

Table 1.6 Hedonic Estimation of the Interaction between Capitalization Effect of Subway and Distance to CBDs. (All samples are within 10km of the closest subway station)

VARIABLES	(1) Pooled	(2) Subway Group A	(3) Subway Group B	(4) Subway Group C
Log(Distance to Subway Group A)	-0.12***	-0.084***		
	(0.020)	(0.024)		
Log(Distance to Subway Group B)	0.050**		-0.075***	
	(0.020)		(0.024)	
Log(Distance to Subway Group B)	-0.015**			0.28***
	(0.0072)			(0.054)
Log(Distance to A)*Distance to CBD	0.012***	0.0097***		
	(0.0023)	(0.0037)		
Log(Distance to B)*Distance to CBD	-0.0032*		0.0056***	
	(0.0019)		(0.0020)	
Log(Distance to C)*Distance to CBD	0.0013***			-0.0093***
	(0.00026)			(0.0018)
District Fixed Effect	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Observations	170,978	83,793	84,136	14,583
R-squared	0.805	0.816	0.789	0.736

Robust standard errors in parentheses, and *** denotes a p value smaller than 0.01. ** denotes a p value smaller than 0.05. * denotes a p value smaller than 0.1. District and yearly fixed effects are both controlled for in the above regressions. Other variables included in the model include: land area, floor area ratio, time of construction, distance to nearest hospital, park, sub-CBD, CBD, core high school, core university, prime school. The signs of the coefficients are consistent with the results reported in Table 5. For simplicity, fixed effect coefficients for each regression are not reported. The same regressions with samples within 5km of the closest subway station are reported in the Appendix.

1.6 Conclusion

This chapter has shown that house-price capitalization of proximity to a subway station depends on the convenience level of the subway line and on community characteristics like housing quality and location. The capitalization effect is higher for communities using convenient subway lines (those directly connected to the CBDs) and lower for inconvenient subway lines (those requiring transfers to reach the CBDs). In addition, the capitalization effect decreases as the quality of housing in the community increases, as increasing property management fee at a community by 1 Yuan reduces subway capitalization effect by approximately 0.1%~0.2%. The effect also decreases for communities located farther away from the CBDs, as communities 1km farther from the CBD experience around 0.08% lower subway capitalization effect.

The research suggests that when policy makers seek to achieve faster, frequent transit service that makes the CBDs more accessible, they should also implement strategies to preserve affordable housing near subway stations so that the rising prices caused by the new transit will not harm the low income families, whose dwellings will be affected most. In the short-run, homeowners can benefit from the capitalization effects, but in the long run, longstanding residents may no longer be able to afford rising rents and property taxes that will be levied in the future. Without such steps, locations that have the highest subway proximity premium (communities that are close to the CBDs or have access to convenient subways) may no longer be affordable for many working families.

Appendix 1:

Table A.1.1 Variables and Descriptive Statistics

Variable	Description	Mean	Std.dev
Panel 1. Structural Characteristics			
price	The average price per square meter of the housing estate, by housing estate/week (Yuan per square meter)	22671.15	12340.86
Land area	Total land area of the housing estate	159458.1	354287
Floor area ratio	Floor area ratio of the housing estate	2.48	1.58
Prop manage fee	Property management fee per month per square meter	1.99	1.63
Greening ratio	Greening ratio of the housing estste	0.35	0.91
Time_constru	Time of construction	NA	NA
Panel 2. Neighborhood Characteristics			
Distance to Park	A housing estate's distance to the closest park	4.72	5.84
Distance to Highschool	A housing estate's distance to the closest core high school	4.63	4.59
Distance to Middle School	A housing estate's distance to the closest core middle school	4.54	4.45
Distance to Hospital	A housing estate's distance to the closest 3A hospital	5.52	7.64
Distance to Primary school	A housing estate's distance to the closest core primary school	6.94	7.73
Distance to CBD	A housing estate's distance to the closest CBD	11.4	10.07
Distance to Business district	A housing estate's distance to the closest business subcenter	9.00	9.37
Distance to University	A housing estate's distance to the closest 985(core) university	8.41	9.34
Dongcheng	Binary, 1=housing estate is located in Dongcheng District	0.081	0.274
Xicheng	Binary, 1=housing estate is located in Xicheng District	0.087	0.282
Xuanwu	Binary, 1=housing estate is located in Xuanwu District	0.088	0.284
Haidian	Binary, 1=housing estate is located in Haidian District	0.111	0.315
Chaoyang	Binary, 1=housing estate is located in Chaoyang District	0.087	0.282
Fengtai	Binary, 1=housing estate is located in Fengtai District	0.087	0.282
Mentougou	Binary, 1=housing estate is located	0.031	0.173

	in Mentougou District		
Shijingshan	Binary, 1=housing estate is located in Shijingshan District	0.011	0.104
Fangshan	Binary, 1=housing estate is located in Fangshan District	0.072	0.260
Tongzhou	Binary, 1=housing estate is located in Tongzhou District	0.157	0.364
Shunyi	Binary, 1=housing estate is located in Shunyi District	0.076	0.265
Changping	Binary, 1=housing estate is located in Changping District	0.090	0.288
Huairou	Binary, 1=housing estate is located in Huairou District	0.010	0.099
Year 2008	Binary, 1=year 2008	0.170	0.375
Year 2009	Binary, 1=year 2009	0.173	0.378
Year 2010	Binary, 1=year 2010	0.173	0.378
Year 2011	Binary, 1=year 2011	0.173	0.378
Year 2012	Binary, 1=year 2012	0.173	0.378
Year 2013	Binary, 1=year 2013	0.054	0.226
Panel 3. Subway station Proximity			
Log(Distance to Subway Group A)	A housing estate's log distance to the closest group A subway station	7.485	8.914
Log(Distance to Subway Group B)	A housing estate's log distance to the closest group B subway station	6.510	8.860
Log(Distance to Subway Group C)	A housing estate's log distance to the closet group C subway station	61.192	44.351
Panel 4. Interaction Terms			
Distance to A * Fee	Interaction between property management fee and Log(Distance to Subway Group A)	NA	
Distance to B* Fee	Interaction between property management fee and Log(Distance to Subway Group B)	NA	
Distance to C * Fee	Interaction between property management fee and Log(Distance to Subway Group C)	NA	
Log(Distance to A) * Distance to CBD	Interaction between Distance to CBD and Log(Distance to Subway Group A)	NA	
Log(Distance to B)* Distance to CBD	Interaction between Distance to CBD and Log(Distance to Subway Group B)	NA	
Log(Distance to C) * Distance to CBD	Interaction between Distance to CBD and Log(Distance to Subway Group C)	NA	

Justification for the positive correlation between housing quality and income

Data are collected on district-average GDP per capita and district average property management fees for 4 megacities in China. Simple scatter plots and correlation coefficients (Table 6) show a significant positive correlation between income per capita and the property management fee.

Table A.1. 2 Correlation between GDP per capita and Property Management Fee

Megacities	Beijing	Shanghai	Guangzhou	Chongqing
Correlation Coefficient	0.705	0.604	0.562	0.692

Table A.1.3 Fixed Effect Capitalization of Subway Proximity
(all samples are within 5km of a subway station)

Dependent Variable: ln_price	(1) Pooled	(2) Subway Group A	(3) Subway Group B	(4) Subway Group C
Log(Distance to Subway Group A)	-0.0205***	-0.0382***		
	(0.000993)	(0.00202)		
Log(Distance to Subway Group B)	-0.00403***		-0.0161***	
	(0.00136)		(0.00358)	
Log(Distance to Subway Group B)	-0.0266***			
	(0.000745)			
Year 2008	-0.0381***	-0.0266***	-0.0436***	
	(0.00163)	(0.00229)	(0.00217)	
Year 2009	0.105***	0.121***	0.0892***	
	(0.00164)	(0.00228)	(0.00222)	
Year 2010	0.540***	0.551***	0.535***	
	(0.00168)	(0.00230)	(0.00226)	
Year 2011	0.599***	0.676***	0.636***	0.0123***
	(0.00242)	(0.00228)	(0.00224)	(0.00383)
Year 2012	0.632***	0.725***	0.667***	0.00264
	(0.00243)	(0.00230)	(0.00224)	(0.00384)
Year 2013	0.798***	0.901***	0.838***	0.130***
	(0.00265)	(0.00278)	(0.00268)	(0.00412)
Constant	9.683***	9.735***	9.446***	9.706***
	(0.00387)	(0.00201)	(0.00187)	(0.00366)
Observations	159,332	82,804	76,088	12,070
R-squared	0.935	0.918	0.935	0.956

Robust standard errors in parentheses, and *** denotes a p value smaller than 0.01, ** denotes a p value smaller than 0.05, * denotes a p value smaller than 0.1. Similar regressions including indicators of being too close to the stations or light rail stations are run, yet the coefficients are statistically insignificant thus results are not shown here. The same regressions with samples within 2km of the closest subway station yield similar results and the results can be offered upon request.

Table A.1.4 Hedonic Estimation of the Interaction between Capitalization Effect of Subway and Housing Quality (all samples are within 5km of a subway station)

VARIABLES	(1) Pooled	(2) Subway Group A	(3) Subway Group B	(4) Subway Group C	(7) Pooled	(8) Subway Group A	(9) Subway Group B	(10) Subway Group C
Log(Distance to Subway Group A)	-0.044***	-0.070***			-0.038***	-0.063***		
	(0.014)	(0.021)			(0.014)	(0.021)		
Log(Distance to Subway Group B)	-0.042***		-0.074***		-0.042***		-0.071***	
	(0.014)		(0.023)		(0.014)		(0.023)	
Log(Distance to Subway Group B)	-0.020**			-0.028	0.0040			-0.028
	(0.010)			(0.031)	(0.015)			(0.031)
Prop manage fee	0.0095	0.041***	0.037***	0.030	0.010	0.040***	0.036***	0.029
	(0.011)	(0.0093)	(0.013)	(0.023)	(0.011)	(0.0093)	(0.013)	(0.023)
Log(Distance to A)*Fee	0.00053	0.016*			0.00025	0.016*		
	(0.0055)	(0.0094)			(0.0055)	(0.0095)		
Log(Distance to B)*Fee	0.024***		0.026**		0.024***		0.025**	
	(0.0068)		(0.012)		(0.0068)		(0.012)	
Log(Distance to C)*Fee	0.0069***			0.036**	0.0067**			0.036**
	(0.0026)			(0.016)	(0.0026)			(0.016)
Land area	-1.4e-08	1.8e-09	-3.3e-08	-2.6e-08*	-1.4e-08	4.1e-09	-3.6e-08	-2.5e-08*
	(2.1e-08)	(4.9e-08)	(4.9e-08)	(1.4e-08)	(2.1e-08)	(4.8e-08)	(4.8e-08)	(1.4e-08)
Floor area ratio	-0.015***	-0.011**	-0.024***	-0.058***	-0.015***	-0.011**	-0.025***	-0.057***
	(0.0049)	(0.0052)	(0.0085)	(0.018)	(0.0049)	(0.0053)	(0.0085)	(0.018)
Greening ratio	0.17	0.26*	0.16	0.044	0.17	0.26*	0.16	0.044
	(0.10)	(0.15)	(0.14)	(0.29)	(0.10)	(0.15)	(0.14)	(0.29)
Time_of_Constru	0.000013***	0.000023***	0.000014***	9.3e-06	0.000013***	0.000023***	0.000014***	9.1e-06
	(3.5e-06)	(5.0e-06)	(5.1e-06)	(8.9e-06)	(3.5e-06)	(5.0e-06)	(5.1e-06)	(8.9e-06)
Distance to Hospital	0.013	0.022	-0.00036	-0.10***	0.013	0.021	-0.00027	-0.10***
	(0.0079)	(0.016)	(0.011)	(0.038)	(0.0079)	(0.016)	(0.011)	(0.039)
Distance to Park	0.019**	-0.0075	0.021*	-0.029	0.018*	-0.0085	0.020*	-0.029*
	(0.0093)	(0.015)	(0.012)	(0.018)	(0.0092)	(0.015)	(0.012)	(0.018)
Distance to Business District	-0.020***	-0.014	-0.022**	0.079**	-0.019***	-0.015	-0.022**	0.079**
	(0.0065)	(0.012)	(0.0089)	(0.037)	(0.0066)	(0.012)	(0.0089)	(0.037)

Distance to High School	-0.018***	-0.042***	-0.010	0.016	-0.020***	-0.041***	-0.011	0.016
	(0.0049)	(0.011)	(0.0085)	(0.012)	(0.0050)	(0.011)	(0.0085)	(0.012)
Distance to Primary School	-0.024***	-0.042***	-0.041***	-0.0077	-0.025***	-0.043***	-0.041***	-0.0078
	(0.0058)	(0.011)	(0.0069)	(0.012)	(0.0058)	(0.011)	(0.0069)	(0.012)
Distance to CBD	0.0055	0.012	0.0015	0.052	0.0062	0.012	0.0014	0.052
	(0.0075)	(0.013)	(0.010)	(0.034)	(0.0075)	(0.013)	(0.011)	(0.034)
Distance to University	-0.0077	-0.016*	-0.00061	-0.0094	-0.0084	-0.017*	0.000068	-0.0094
	(0.0061)	(0.0098)	(0.0079)	(0.017)	(0.0062)	(0.0098)	(0.0079)	(0.017)
District Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	No	No	No	No
Week Fixed Effect	No	No	No	No	Yes	Yes	Yes	Yes
Observations	149,245	77,274	72,045	11,048	149,245	77,274	72,045	11,048
R-squared	0.802	0.761	0.810	0.780	0.820	0.784	0.828	0.794

Robust Standard errors in parentheses, and *** denotes a p value smaller than 0.01, ** denotes a p value smaller than 0.05, * denotes a p value smaller than 0.1. Regressions are clustered at community level. For simplicity, fixed effect coefficients for each regression are not reported. The same regressions with samples within 5km and 2km of the closest subway station are reported in the Appendix. The same regressions with samples within 2km of the closest subway station yield similar results and the results can be offered upon request.

Table A.1.5 Hedonic Estimation of the Interaction between Capitalization Effect of Subway and Distance to CBDs. (All samples are within 5km of the closest subway station)

Dependent Variable: log(Price)	(1) Pooled	(2) Subway Group A	(3) Subway Group B	(4) Subway Group C
Log(Distance to Subway Group A)	-0.12***	-0.086***		
	(0.020)	(0.033)		
Log(Distance to Subway Group B)	0.045**		-0.054**	
	(0.021)		(0.024)	
Log(Distance to Subway Group B)	-0.015*			0.31***
	(0.0085)			(0.064)
Log(Distance to A)*Distance to CBD	0.013***	0.012**		
	(0.0025)	(0.0050)		
Log(Distance to B)*Distance to CBD	-0.0040*		0.0032	
	(0.0020)		(0.0021)	
Log(Distance to C)*Distance to CBD	0.0011			-0.011***
	(0.00091)			(0.0023)
Observations	149,245	77,274	72,045	11,048
R-squared	0.789	0.749	0.805	0.735

Robust standard errors in parentheses, and *** denotes a p value smaller than 0.01, ** denotes a p value smaller than 0.05, * denotes a p value smaller than 0.1. District and yearly fixed effects are both controlled for in the above regressions. Other variables included in the model include: land area, floor area ratio, time of construction, distance to nearest hospital, park, sub-CBD, CBD, core high school, core university, prime school. The signs of the coefficients are consistent with the results reported in Table 6. For simplicity, fixed effect coefficients for each regression are not reported. The same regressions with samples within 2km of the closest subway station yield similar results and the results can be offered upon request.

Chapter 2

1-Hub, 2-Hub or Fully Connected Network?

A Theoretical Analysis of the Optimality of Airline Network Structure

2. 1 Introduction

The Hub-and-spoke (HS) network has been the focus of airline network studies since US airline deregulation. Abundant literature exists on airline networks, and the cost and demand conditions of an airline are the main determinants of network choice. Using linear marginal cost functions ($MC = 1 - \theta Q$), most theoretical work relies on a high value of returns-to-density parameter θ to guarantee optimality of the HS network (Q is traffic). Empirically, the existence of substantial economies of density has been confirmed in a number of papers (Caves el al. 1984, Brueckner et al. 1992 and Brueckner and Spiller 1994). Moreover, studies on consolidation and dehubbing in the US and European airline industry have provided empirical support for the optimality of the single-hub solution (Burghouwt and De wit 2005; Dennis 1994; Redondi et al. 2012). As a number of theoretical studies have pointed out, each additional hub in the network reduces the cornerstone of the hub strategy, density economies. Moreover, additional hubs also incur complexity costs (Düdden 2006; Wojahn 2001a&b). Pels et al. (2000) investigate the optimality of HS versus FC networks and show that, although economies of density are important, it does not guarantee optimality of the HS network. However, much of the prior work is confined only to comparing 1-Hub network (1H) to point-to-point or fully connected (FC) configurations.

The arguments that a single-hub network or an FC network may be the optimal solution do not explain the reality where the multi-hub network structure is popularly adopted by most of today's airlines. Studies advance several arguments trying to explain the existence of multi-hub networks. In network simulation studies, Geodeking (2010) and Adler and Berechman (2001) argue that multi-hub networks with an effective geographical division tend to create the best opportunities for airlines to generate profits. Additionally, a single-hub network that disregards the dispersion of the spoke cities may result in great inconvenience for the passengers, as stated by O'Kelly (1998, p.177), thus affecting the level of demand. Another reason for airlines to deviate from the single-hub solution in practice, as mentioned by Swan (2002), is airport congestion caused by the constantly increasing level of demand. Bypassing major hubs with nonstops is one of the ways the airline network reacts to congestion, diverting traffic and thus forming secondary hub(s) at major cities. In addition, by synchronizing flights to the same destination from both hubs, a multi-hub system can also be utilized to offer competitive complementary services in many connecting markets with the same origin and destination (O&D) at different times of the day (Geodeking 2010). Besides the reasons mentioned above, it has been argued that consolidation, strategic positioning and entry deterrence, better aircraft utilization, bilateral restrictions, and the influence of unions are incentives for airlines to adopt a multi-hub system rather than a single-hub system (Burghouwt 2013).

So far, theoretical settings with networks of arbitrary size and structure have found no support for the existence of multi-hub networks as a result of cost-minimizing behavior under symmetric cost functions (Hendricks et al. 1995, Wojahn 2001). As a result, there is little theoretical basis to evaluate the current literature's informal explanations of the existence of multi-hub networks. Looking beyond cost issues and economies of density, and including demand-related aspects to find a justification for multi-hub networks, Düdden (2006) used a simple theoretical model with exogenous price and demand. The model reasons that connecting certain spoke cities in the network can lead to a gain in high yield market share if competition is present, thus rendering a single-hub network inferior. Hence, the model gives justification for the rationality of multi-hub networks with one large and one small hub, yet cannot explain a strategy of equal-size hubs, suggesting the need for the present generalization.

To focus on the effect of network structure on profit, this chapter constructs a simple and general model based on the monopoly case, aiming to explicitly investigate the optimality of 2-hub (2H) networks versus 1-Hub (1H) networks and FC networks. The model shows that, using a functional specification that is quite common in the literature, and assuming symmetric markets and no connecting time cost and no fixed cost, a 2H network is always dominated by a 1H or an FC network, as is similarly shown in Pels (2000). However, this chapter sheds new light on the optimum choice of network structure by showing that such a conclusion no longer holds if asymmetric markets (where major cities become hubs, and smaller cities are spoke cities) and fixed cost are introduced into the model. Under such circumstances, the model shows that there exists a portion of the feasible parameter space where 2H network is preferred by a monopoly airline. In addition, the proportion of area in the feasible parameter space favoring the 2H network increases greatly when market asymmetry increases. However increasing the total number of cities or increasing the fixed cost of establishing a spoke would decrease of the proportion of feasible parameter space supporting the 2H network.

After establishing the above results, the chapter also analyzes an airline's choice of FC, 1H and 2H networks under Cournot duopoly, where a network airline is competing with a competitor who offers direct flights connecting the smaller cities.

Interestingly, the model reveals that the ongoing consolidation and reshaping of the hub landscape could be the result of network carriers responding to competition, since it is more profitable for the network carriers to switch to 2H when confronted with a competitor challenge. With a competitor connecting previously unconnected airports, part of the connecting market that once belonged to the monopolistic airline is "stolen". While an FC network is worthwhile when the demand is great between the smaller cities, this advantage is reduced when the competitor decreases revenue generated by the direct flights between the smaller cities, hence reducing the profitability of the FC networks.

This chapter is structured as follows: Section 2.2 presents the setup of the model, while Section 2.3 analyzes the monopoly airline's network choice between 1H and 2H. Section 2.4 extends the monopoly case to a scenario with LCC entry, and Section 2.5 offers conclusions.

2.2 Model Setup

2.2.1 Network Structure

The monopoly airline serves multiple symmetrically located cities, A, B, C and H. For simplicity, the model only distinguishes between two kinds of city size: a major city or a small city. Among the four node cities, two of them are major cities with greater population (B and H), and the other two are smaller cities with less population (A and C), as shown in Figure 2.1, where the size of the node presents the size of the city. In a 1H network, the airline operates flights connecting each spoke city (A, B and C) to the hub (H) which is also one of the major cities. Note that because of the symmetry, the two major cities H and B are identical, and whenever it is optimal to use a 1H network configuration with H as the hub, it is also optimal to use a 1H network with B as the hub.

In a 2H network, the other major city (B) becomes another hub, forming a symmetric network where all the spoke cities are connected to the two hubs, while the two hubs themselves are also connected by a direct flight. In an FC network, all the cities are connected to all other cities.

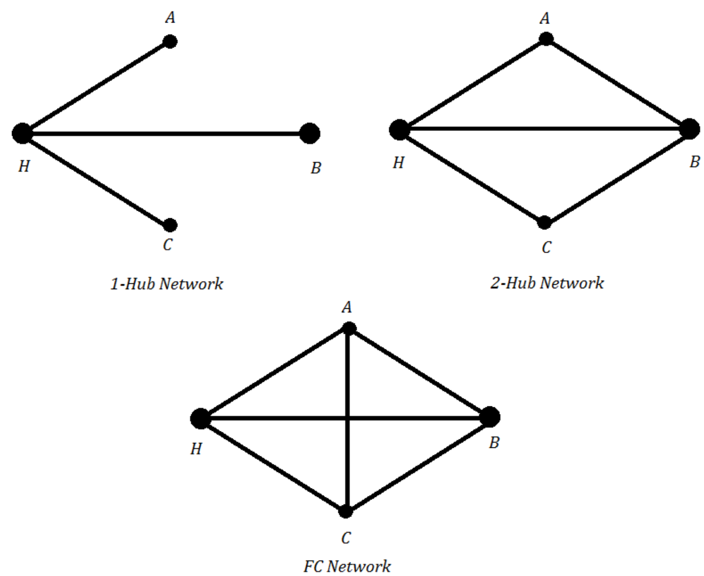


Figure 2.2 Network Types

In a 1H network, although passengers in markets from a spoke city to the hub city can enjoy nonstop service, passengers flying from one spoke city to another must make a connecting trip. In a 2H network, trips from spoke cities to either hub now have nonstop service, while passengers flying from one spoke city to another can choose connecting flights, changing planes at either hub. A direct route between the hubs (linking B and H) is also provided in the 2-hub case. In an FC network, passengers are able to fly to any other destination via nonstop service and connecting markets do not exist in such network.

Figure 2.1 only depicts the cases where the number of small cities is 2. By analogues, when there are more than 2 small cities, each small city and the non-hub major city are connected to the only hub in the 1H network. In the 2H network, when there are more than 2 small cities, each small city is connected to both hubs while there are no routes between the small cities. As for the FC network, each city is always connected to all other cities regardless of the total number of small cities.

2.2.2 Demand and Costs

Following the demand constructed by Brueckner (2005), consumer utility is defined as $u = C + B - G$, where C is consumption and B is travel benefit, which varies across consumers, and G is the time cost for nonstop travel between any pair of cities. For simplicity, frequency is also suppressed in the model, so that schedule delay is not included in consumer utility. To derive the demand function, let Y denote consumer income and p denote the airfare, so that a consumer will undertake travel if $Y - p + B - G \geq Y$, or if $B \geq p + G$. As an asymmetric city size model, it is reasonable to assume that more people tend to travel to and from major cities, so that the density of travel benefit B enlarges as the size of the end point cities increases. Suppose that B has a uniform distribution with support $[\underline{B}, \overline{B}]$ and density $\eta = \frac{\delta_i + \delta_j}{(\overline{B} - \underline{B})}$, where （$\delta_i + \delta_j$） denotes the magnitude of the benefit coming from the size of the city-pair market, which depends on the size of the two end node cities (δ_i and δ_j).

As mentioned in the previous section, the model only distinguishes between major cities and small cities, hence generating three distinct kinds of city-pair markets: small-small, small-major and major-major. Let the superscripts ss, sm and mm denote the three types of markets. Normalize the size of a small city to $\frac{1}{2}$, so that travel benefit B for a small-small market would have a uniform distribution with support$[\underline{B}, \overline{B}]$, and density $\eta^{ss} = \frac{1}{(\overline{B} - \underline{B})}$. Similarly, assuming that the size of a major city is δ times that of a small city ($\delta \geq 1$), then the benefit of a major-major city-pair travel would be have density $\eta^{mm} = \frac{\delta}{(\overline{B} - \underline{B})}$, and correspondingly, $\eta^{sm} = \frac{1+\delta}{2(\overline{B} - \underline{B})}$ for a small-major city-pair.

The number of consumers traveling between a major and a small city is then found by integrating the density of B over the interval $[p + G, \overline{B}]$. The demand function for a small-small market is thus given by $p^{ss} = \alpha - \beta\ q^{ss}$, where $\alpha = \overline{B} - G$, $\beta = \left(\overline{B} - \underline{B}\right)$ and q_{ss} is the number of consumers traveling. Similarly, the demand function for a major-major market is thus given by $p^{mm} = \alpha - \frac{1}{\delta}\beta q^{mm}$. By analogues, $p^{sm} = \alpha - \frac{2}{1+\delta}\beta q^{sm}$. When $\delta = 1$, all the cities are of the same size and the three demand functions are identical. However when δ is greater than 1, then the demand curve of a larger market <u>rotates</u> outward with its x-intercept fixed and becomes flatter (the slope of the demand curve is a function of δ, and the slope become less negative when δ increases) .

Connecting travel through the hub will incur extra time cost. Denoting the extra connecting cost by μ, the intercept of the demand curve for connecting flights would be $\alpha - \mu$ in a small-small market instead of α. Similarly, the intercept for the sm demand curves would decrease by μ, as would the intercept for the connecting markets.

The marginal cost function is assumed to be linear ($MC = 1 - 2\theta Q$), as in most of the airline network literature (see e.g. Brueckner 2001, Brueckner and Spiller 1991, Nero 1996, Zhang 1996, Zhang and Wei 1993 and Pels et al. 2000). Even though the HB route appears to be longer than other spokes according to Figure 1, the model assumes that this difference does not appear in the cost function for simplicity, so that distance is assumed not to matter.

Quantities and prices will be the same in markets of the same type (i.e. direct markets and connecting markets). Hence we distinguish between quantities (prices) in direct and connecting markets for three different market sizes (small-small, small-major and major-major), letting lower case letters (q^{ss}, q^{sm}, q^{mm} and p^{ss}, p^{sm}, p^{mm}) denote traffic and prices in direct markets and upper case letters (Q^{ss}, Q^{sm}, Q^{mm} and P^{ss}, P^{sm}, P^{mm}) pertain to connecting markets.

2.3 The Choice between 1H, 2H and FC networks

2.3.1 Basic Model

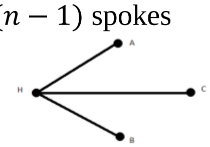
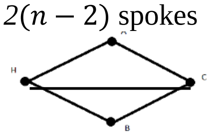
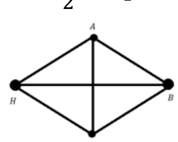
Consider a network with n nodes (including hubs) where $n \geq 3$ and the network structure follows Figure 1. The network structure, total traffic in direct and connecting markets and the traffic carried on each spoke for both 1H and 2H network are summarized in Table 2.1. Note that the subscripts h, $2h$ and fc denote the 1H, 2H and FC network respectively.

As described in Table 2.1, a 1H network (Panel A) consists of $n-1$ direct markets (there are 3 such direct markets when $n = 4$), $n-2$ among which are sm direct markets (HA and HB when $n = 4$) and only 1 mm market (HB when $n = 4$). There are also $\frac{(n-1)(n-2)}{2}$ connecting markets (when $n = 4$, there are 3 such markets), $\frac{(n-2)(n-3)}{2}$ among which are ss connecting markets and the rest $(n-2)$ are sm connecting markets. As for the cost side, each of the $n-1$ direct routes is used in $n-2$ connecting markets. Thus, for a given sm direct route, there are $n-3$ corresponding ss connecting markets and one sm connecting market that also make use of the same spoke, hence a total traffic of $q_h^{ss} + (n-3)Q_h^{ss} + Q_h^{sm}$ for each route (when $n = 4$, the HA or HB spoke needs to carry connecting traffic to the other small spoke city as well as the connecting traffic to the other major spoke city). As for the only mm route, besides its own direct traffic, it also needs to carry sm connecting traffic to all the other $(n-2)$ small cities, hence a total traffic of $q_h^{mm} + (n-2)Q_h^{sm}$. Profit in a 1-Hub network is then:

$$\pi_{1hub} = (n-2)q_h^{sm}\left[\alpha - \frac{2}{1+\delta}\beta q_h^{sm}\right] + q_h^{mm}\left[\alpha - \frac{1}{\delta}\beta q^{mm}\right] + \frac{(n-2)(n-3)}{2}Q_h^{ss}[\alpha - \beta Q_h^{ss} - \mu] + (n-2)Q_h^{sm}\left[\alpha - \frac{2}{1+\delta}\beta Q_h^{sm} - \mu\right] - (n-2)c(q_h^{sm} + (n-3)Q_h^{ss} + Q_h^{sm}) - c(q_h^{mm} + (n-2)Q_h^{sm}) \tag{2.1}$$

where $c(.)$ is the quadratic function $c(q) = q - \theta q^2 + \phi$, incorporating the returns- to-density parameter θ and the fixed cost per spoke parameter ϕ.

Table 2.1 Structure, Total Traffic and Spoke Traffic Compostition of Different Network Types

<table>
<tr><th>Structure</th><th colspan="3">Total Traffic in:</th><th>Spoke Traffic Composition</th></tr>
<tr><td colspan="5">Panel A. 1H Network</td></tr>
<tr><td rowspan="4">$(n-1)$ spokes
</td><td rowspan="2">Direct Markets</td><td>sm</td><td>$(n-2)q_h^{sm}$</td><td rowspan="4">• Each sm(mm) spoke carries direct traffic in the market: $q_h^{sm}(q_h^{mm})$
• Each sm spoke carries connecting traffic from $n-3$ ss connecting markets: $(n-3)Q_h^{ss}$
• Each sm spoke carries connecting traffic from one sm connecting markets: Q_h^{ss}
• The mm spoke carries connecting traffic from $n-2$sm connecting markets: Q_h^{sm}</td></tr>
<tr><td>mm</td><td>q_h^{mm}</td></tr>
<tr><td rowspan="2">Connecting Markets</td><td>ss</td><td>$\frac{(n-2)(n-3)}{2}Q_h^{ss}$</td></tr>
<tr><td>sm</td><td>$(n-2)Q_h^{sm}$</td></tr>
<tr><td colspan="5">Panel B. 2H Network</td></tr>
<tr><td rowspan="3">$2(n-2)$ spokes
</td><td>Direct Markets</td><td>sm</td><td>$2(n-2)q_{2h}^{sm}$</td><td rowspan="3">• Each sm(mm) spoke carries direct traffic in the market: q_{2h}^{sm} (q_{2h}^{mm})
• Each spoke also carries half of the connecting traffic from $n-3$ connecting markets involving non-hub cities: $\frac{n-3}{2}Q_{2h}^{ss}$</td></tr>
<tr><td rowspan="2">Connecting Markets</td><td>ss</td><td>$\frac{(n-2)(n-3)}{2}Q_{2h}^{ss}$</td></tr>
<tr><td>mm</td><td>q_{2h}^{mm}</td></tr>
<tr><td colspan="5">Panel C. FC Network</td></tr>
<tr><td rowspan="3">$\frac{n(n-1)}{2}$ spokes
</td><td rowspan="3">Direct Markets</td><td>ss</td><td>$\frac{(n-2)(n-3)}{2}q_{fc}^{ss}$</td><td rowspan="3">• Each spoke carries corresponding direct traffic in the market: q_{fc}^{ss}, q_{fc}^{sm} or q_{fc}^{mm}</td></tr>
<tr><td>sm</td><td>$2(n-2)q_{fc}^{sm}$</td></tr>
<tr><td>mm</td><td>q_{fc}^{mm}</td></tr>
</table>

There are two types of spokes in the 2-hub network (Panel B Column 3). First, along each spoke connecting a small city and a hub, in addition to the direct market, there are also traffic from $\frac{n-3}{2}$ ss connecting markets to other small spoke cities since passengers can fly from one spoke city to another via either hub, with the traffic for such markets split in half (if $n = 4$, then each spoke carries traffic in "one-half" a connecting market). Thus, on each spoke not connecting the hubs, the total traffic is $q_{2h}^{sm} + \frac{n-3}{2} Q_{2h}^{ss}$ (when $n = 4$, this is $q_{2h}^{sm} + Q_{2h}^{ss}$). In addition, the mm direct market carries traffic from its own direct market regardless of the total number of cities. Profit in a 2-Hub network is thus:

$$\pi_{2hub} = 2(n-2)q_{2h}^{sm}\left(\alpha - \frac{2}{1+\delta}\beta q_{2h}^{sm}\right) + \frac{(n-2)(n-3)}{2} Q_{2h}^{ss}[\alpha - \beta Q_{2h}^{ss} - \mu] + q_{2h}^{mm}\Big[\alpha - \frac{1}{\delta}\beta Q_{2h}^{mm}\Big] - 2(n-2)c\left(q_{2h}^{sm} + \frac{n-3}{2} Q_{2h}^{ss}\right) - c(q_{2h}^{mm}) \qquad (2.2)$$

For an FC network, the profit components are much simpler now that connecting markets are out of the picture. For a network with n nodes, and $\frac{n(n-1)}{2}$ spokes (when $n = 4$, there are 6 spokes), $\frac{(n-2)(n-3)}{2}$ of the spokes are ss direct markets (i.e. the AC market, when $n = 4$), while $2(n-2)$ of the spokes are sm direct markets (i.e. HA, HC, BA, BC markets, when $n = 4$) and the mm direct market again corresponds to one spoke (i.e. HB market, when $n = 4$). Hence, Profit in an FC-network is thus:

$$\pi_{fc} = 2(n-2)q_{fc}^{sm}\left(\alpha - \frac{2}{1+\delta}\beta q_{fc}^{sm}\right) + \frac{(n-2)(n-3)}{2} q_{fc}^{ss}\big[\alpha - \beta q_{fc}^{ss}\big] + q_{fc}^{mm}\left[\alpha - \frac{1}{\delta}\beta q_{fc}^{mm}\right] - 2(n-2)c\big(q_{fc}^{sm}\big) - \frac{(n-2)(n-3)}{2} c\big(q_{fc}^{ss}\big) - c\big(q_{fc}^{mm}\big) \qquad (2.3)$$

2.3.2 Solutions

Consider the simplest case where $n = 4$ (as depicted in Figure 2.1) $\mu = 0$ (the cases where μ does not equal to 0 will be discussed later), $\delta = 1$ so that all cities are of the same size, and where β is normalized to 1. Taking first order conditions and solving the equation system, the quantities that maximize (2.1) are:

$$q_h^{sm} = \frac{-1+\alpha+2\theta-4\alpha\theta+4\alpha\theta^2}{2-14\theta+20\theta^2} \qquad q_h^{mm} = \frac{-2+2\alpha+4\theta-8\alpha\theta+8\alpha\theta^2}{2(2-14\theta+20\theta^2)}$$

$$Q_h^{ss} = \frac{-4+2\alpha+8\theta-2\alpha\theta-4\alpha\theta^2}{2(2-14\theta+20\theta^2)} \qquad Q_h^{sm} = \frac{-4+2\alpha+8\theta-2\alpha\theta-4\alpha\theta^2}{2(2-14\theta+20\theta^2)} \tag{2.4}$$

Similarly, the quantities that maximize (2.2) are:

$$q_{2h}^{sm} = \frac{2-2\alpha+\alpha\theta}{2(-2+4\theta)} \qquad q_{2h}^{mm} = -\frac{-4+2\alpha+2\alpha\theta}{2(-2+4\theta)} \quad Q_{2h}^{ss} = -\frac{-1+\alpha}{2(-1+\theta)} \tag{2.5}$$

And the quantities that maximize (2.3) are

$$q_{fc}^{ss} = \frac{1-\alpha}{2(-1+\theta)} \qquad q_{fc}^{sm} = -\frac{(-1+\alpha)}{(-2+2\theta)} \qquad q_{fc}^{mm} = -\frac{(-1+\alpha)}{2(-1+\theta)} \tag{2.6}$$

The feasible parameter space is defined by the inequalities that result from the second order conditions for profit maximization ($\theta < \frac{1}{5}$) and the requirements of non-negative marginal costs and quantities in a 1H network: $\frac{2}{1+\theta} < \alpha < \frac{1}{3\theta}$ when $\theta < \frac{1}{5}$. The feasible region is shown in Figure 2, with the upper bound ($\alpha = \frac{1}{3\theta}$) and lower ($\alpha = \frac{1}{2+\theta}$) bound indicated.[17]

[17] It is shown in Appendix 3 that the feasible area in a 2H network fully encompasses the feasible area in a 1H network. Further details about how to deduce the feasible area are also shown in the Appendix 3.

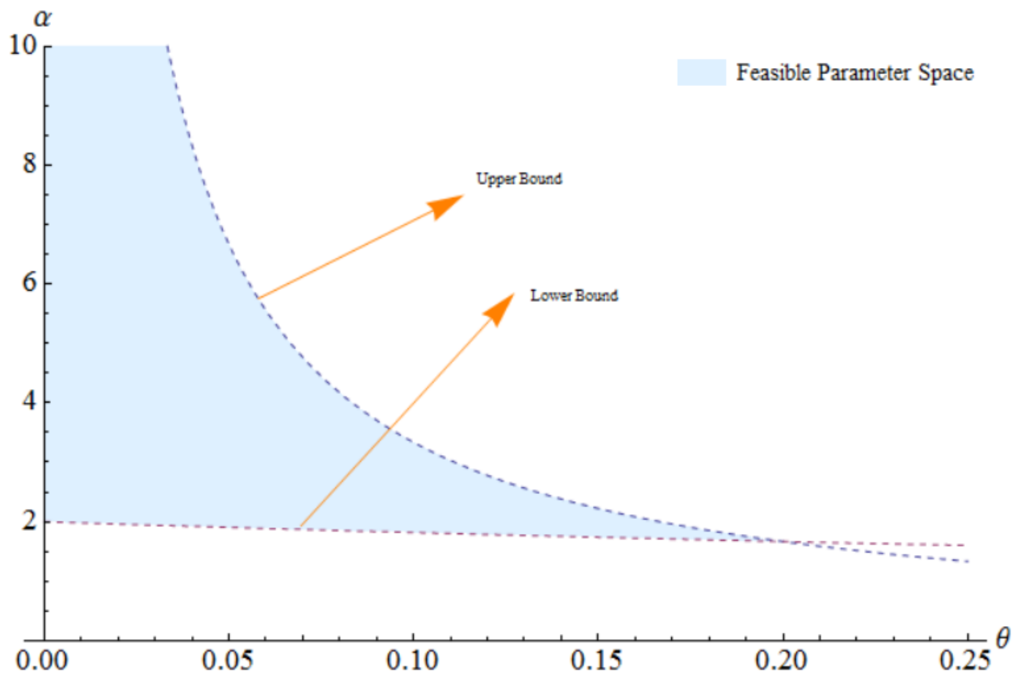


Figure 3.2 Feasible Parameter Space

$\boldsymbol{n = 4, \delta = 1, \phi = 0}$

2.3.3 Choice of network type

After solving the 1H, 2H and FC optimization problems, the airline must make a global choice of network type. To carry out the analysis, first determine parameter combinations (θ, α) that make the airline indifferent between the network types, with $\pi_{1hub} = \pi_{2hub}$, $\pi_{fc} = \pi_{2hub}$ and $\pi_{fc} = \pi_{1hub}$ holding. Let $2vs1, fvs2$ and $fvs1$ denote comparisons between 1H and 2H, FC and 2H, and FC and 1H. Solving $\Delta^{2vs1} = \pi^*_{2hub} - \pi^*_{1hub} = 0$, $\Delta^{fvs2} = \pi^*_{fc} - \pi^*_{2hub} = 0$ and $\Delta^{fvs1} = \pi^*_{fc} - \pi^*_{1hub} = 0$ (where profits are computed at the optimal prices and quantities), yields three profit indifference curves:

$$\alpha^*_{2vs1}(\theta) = \frac{-2-16\theta+22\theta^2 \pm \sqrt{2}\sqrt{2-19\theta+59\theta^2-79\theta^3+47\theta^4-10\theta^5}}{-17\theta+20\theta^2+\theta^3} \tag{2.7}$$

$$\alpha^*_{fvs2}(\theta) = \frac{1+4\theta \pm \sqrt{1-4\theta+5\theta^2-2\theta^3}}{4\theta+\theta^2} \tag{2.8}$$

$$\alpha^*_{fvs1}(\theta) = \frac{1+7\theta \pm \sqrt{1-7\theta+11\theta^2-5\theta^3}}{7\theta+\theta^2} \tag{2.9}$$

Checking the feasible parameter space confirms that $2-19\theta+59\theta^2-79\theta^3+47\theta^4-10\theta^5 \geq 0$, $1-4\theta+5\theta^2-2\theta^3 \geq 0$ and $1-7\theta+11\theta^2-5\theta^3 \geq 0$ hold, so that (2.7), (2.8) and (2.9) give real solutions inside the feasible parameter space.

As depicted in Figure 2.3, the expressions in (2.7), (2.8) and (2.9) constitute three backward bending indifference curves with vertexes at ($\bar{\alpha}_{2vs1} = \bar{\alpha}_{fvs1} = \frac{5}{3}, \overline{\theta}_{2vs1} = \overline{\theta}_{fvs1} = \frac{1}{5}$) and ($\bar{\alpha}_{fvs2} = \frac{1}{2}, \overline{\theta}_{fvs2} = \frac{4}{3}$). Conveniently, the vertex for indifference curves in equations (2.7) and (2.8) are at the intersection of the upper bounds and lower bounds of the feasible parameter space, where $\theta = \frac{1}{5}$. Figure 3 also shows that all three indifference curves' lower parts and the upper part of the $fvs2$ indifference curve are outside the feasible parameter space (shaded area), while a majority part of the upper $fvs2$ and $fvs1$ indifference curves ($\alpha^*_{2vs1}(\theta)^+$, when $0 < \theta < \frac{37-\sqrt{649}}{72}$ and $\alpha^*_{fvs1}(\theta)^+$ when $0 < \theta < \frac{1}{9}$)[18] are in between the upper and lower bounds of the feasible parameter space. A small portion of the two upper indifference curves ($\alpha^*_{2vs1}(\theta)^+$, for $\frac{(37-\sqrt{649})}{72} < \theta < \frac{1}{5}$ and and $\alpha^*_{fvs1}(\theta)^+$ when $\frac{1}{9} < \theta < \frac{1}{5}$) are above the upper bound but bend downward, connecting to the lower part of the indifference curves at the vertex of the feasible parameter space.

[18] Here the superscript "+" indicates the upper part of the indifference curve

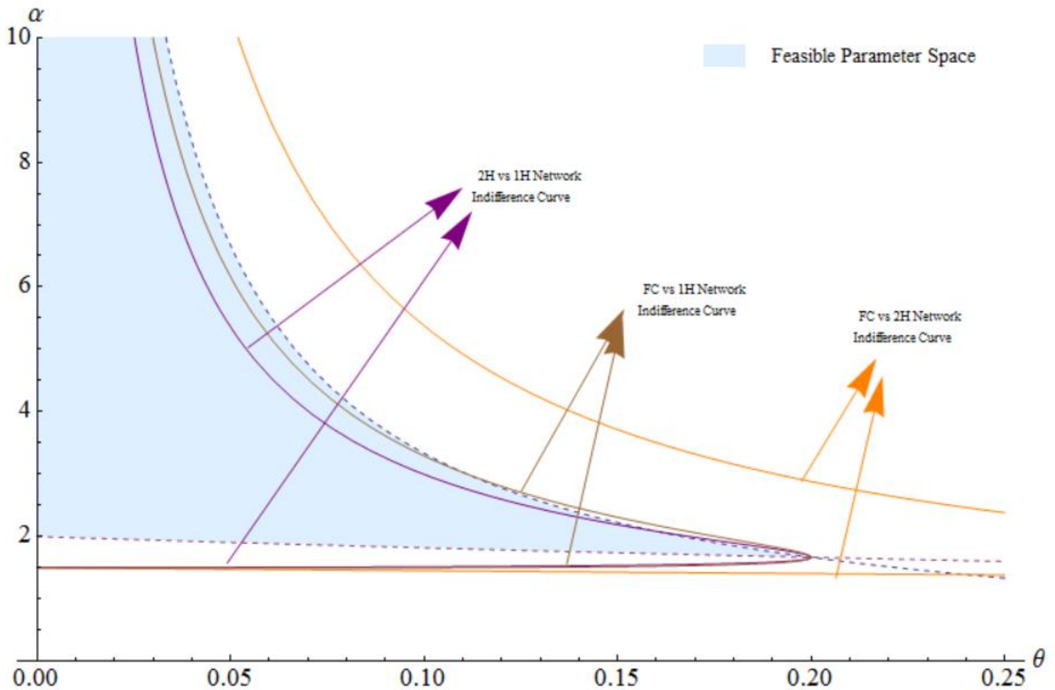


Figure 2.4 Profit Indifference Curves
$\boldsymbol{n = 4, \delta = 1, \phi = 0}$

Since the $fvs2$ profit indifference curve is outside the feasible parameter space, the feasible parameter space is split into three regions by the upper parts of the $2vs1$ and $fvs1$ profit indifference curves. As a result, Δ^{fvs2} is positive everywhere inside the parameter space, indicating that 2H is everywhere dominated by FC. The sign of Δ^{2vs1} and Δ^{fvs1} is negative (positive) above (below) the upper part of the indifference curves. Hence, given symmetric markets, linear marginal costs with 4 nodes, no connecting time cost and no fixed cost, a 2H network is always dominated by a 1H or an FC network. $\pi^*_{fc} > \pi^*_{1hub}$ if

$$\frac{2}{1+\theta} < \alpha < \frac{1+7\theta+\sqrt{1-7\theta+11\theta^2-5\theta^3}}{7\theta+\theta^2}, \theta < \frac{1}{9} \tag{2.13}$$

$$\text{Or } \frac{2}{1+\theta} < \alpha < \frac{1}{3\theta}, \quad \frac{1}{9} < \theta < \frac{1}{5} \tag{2.14}$$

And $\pi^*_{1hub} > \pi^*_{fc}$ if

$$\frac{1+7\theta+\sqrt{1-7\theta+11\theta^2-5\theta^3}}{7\theta+\theta^2} < \alpha < \frac{1}{3\theta}, \theta < \frac{1}{9} \tag{2.15}$$

As depicted in Figure 2.4, the dashed line depicts the upper and lower bound of the feasible parameter space. According to (2.13) (2.14) and (2.15), the feasible parameter space is divided into two regions, while in one of the regions (shaded by lighter gray in Figure 2.4), 1H network dominates the other two network types, and FC dominates in the other region (shaded by darker gray in Figure 2.4). Notice that the $fvs1$ indifference curve crosses the upper bound of the feasible parameter space at $\theta = \frac{1}{9}$, hence separating the region where 1H dominates into two parts: (1) when $\theta < \frac{1}{9}$, at any fixed value of θ, the FC network is more profitable than the 1H network if α is smaller than a certain threshold and (2) when $\frac{1}{9} < \theta < \frac{1}{5}$, the FC network is always more profitable than the 1H network regardless of the value of α. Similar to the results of Pels et al. (2000), an FC network is almost everywhere more profitable than an HS or an 2H network given zero fixed cost and symmetric market.

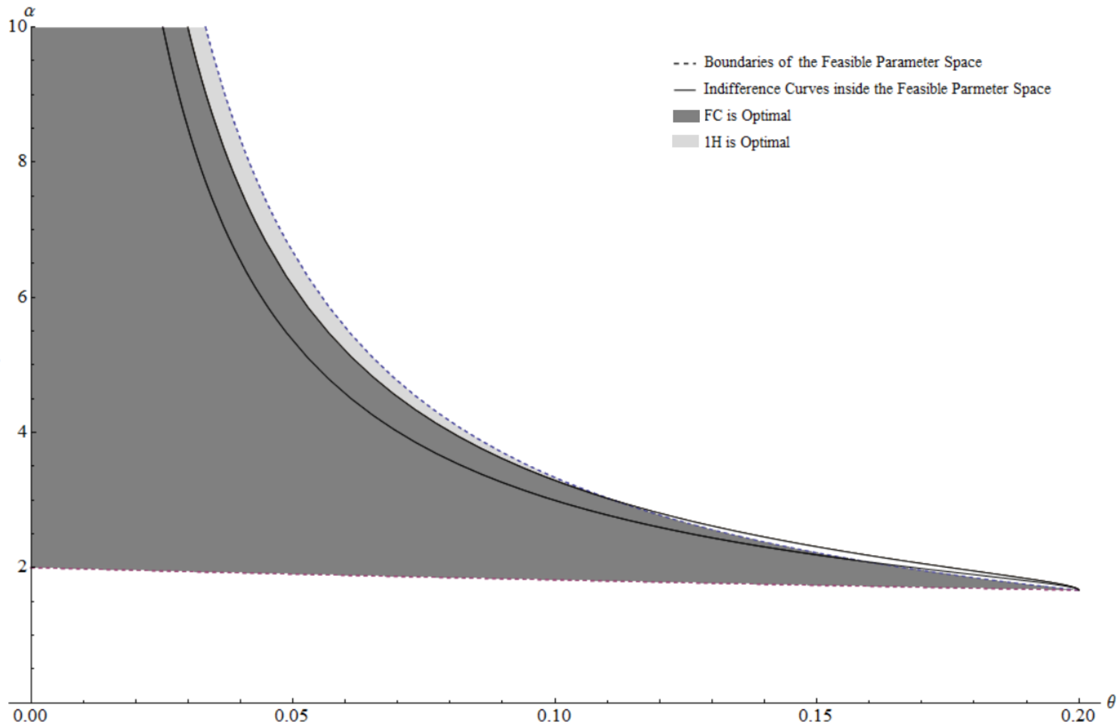


Figure 2.5 Parameter Spaces that Supports Each Network Type
n=4, $\boldsymbol{\delta = 1, \phi = 0}$

2.3.4 Adding Asymmetric Markets and Fixed Cost

In reality, hub cities (H and B) are usually larger than the spoke cities (A and C), and hence the size of markets with a hub or two hubs as endpoints is greater than the size of markets between the smaller spoke cities. In addition, establishing a new direct route between cities should incur a fixed cost for the airline. It follows that network structure might be made more realistic by accounting for asymmetric markets ($\delta > 1$) and a spoke fixed cost ($\phi \neq 0$). As is shown later in this section, adding only market asymmetry or only spoke fixed cost into the model does not explain the presence of the 2H network. Asymmetric markets and spoke fixed cost must both be present in order to make 2H a possible optimal network structure.

Figure 2.5 shows the case where asymmetric markets exists by assuming $\delta = 4$, so that the hub city is 4 times the size of a spoke city, and there is no fixed cost to establish a spoke ($\phi = 0$). Following the steps performed in the previous section, we can establish a new set of indifference curves. Similar to Figure 2.4, the feasible parameter space is divided into two regions, with the majority of it supporting the FC network (the dark grey area) and a small slice near the upper bound of the feasible parameter space supporting the 1H network (the light grey are). Therefore, if only market asymmetry is added to the model, the 2H network is still dominated by the other two network types.

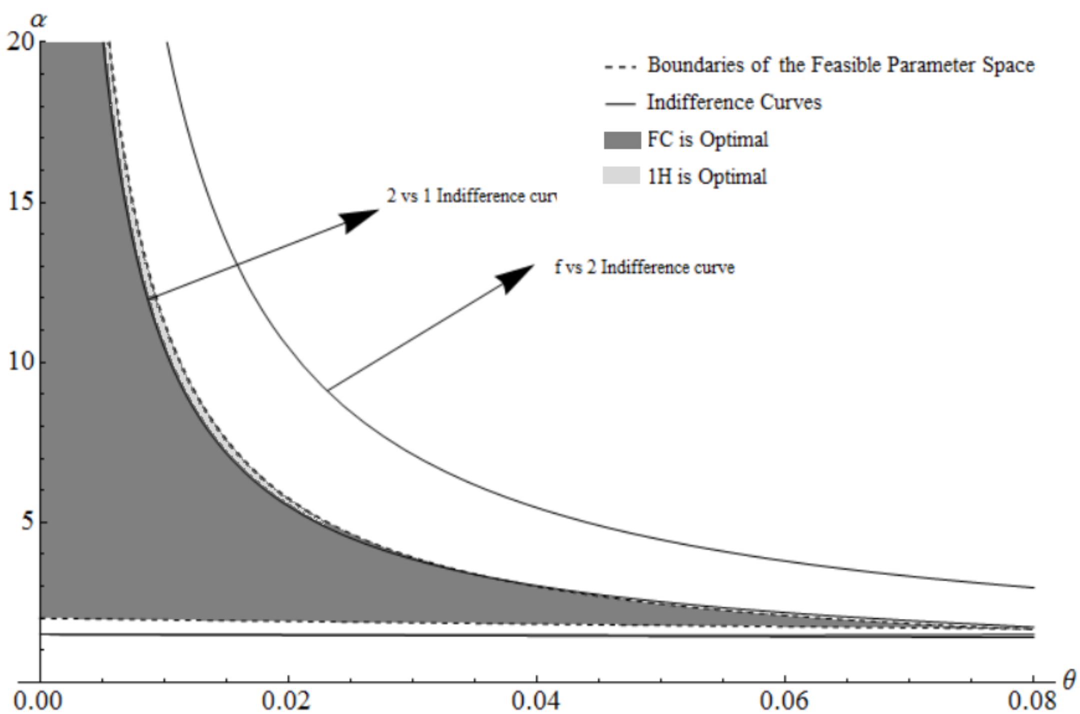


Figure 2.6 Parameter Space that Support Each Network Type
n=4, $\boldsymbol{\delta = 4}$, $\boldsymbol{\phi = 0}$

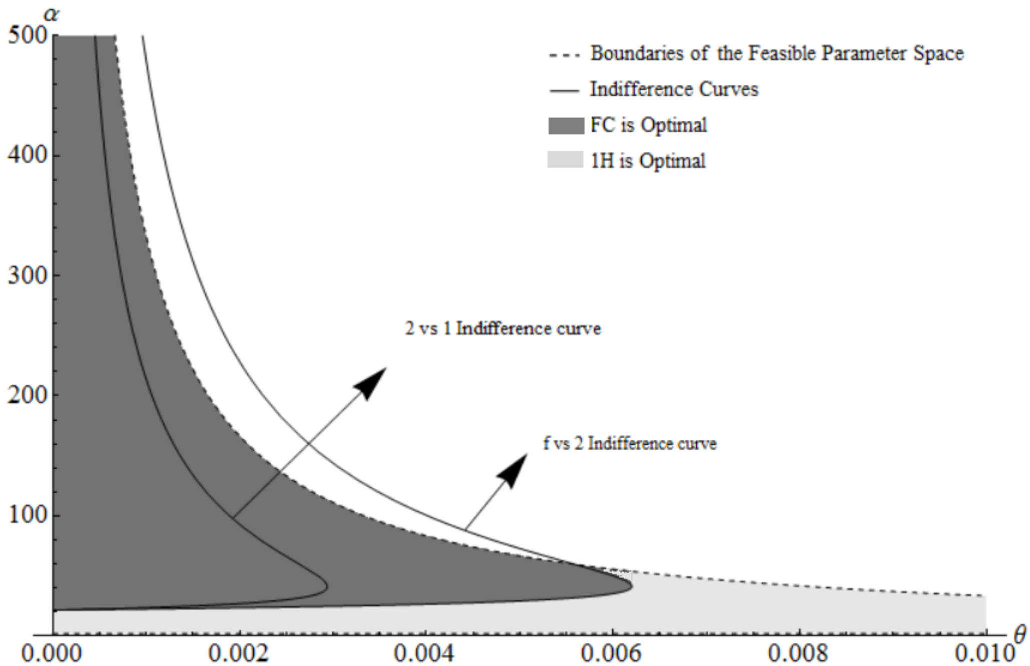


Figure 2.7 Parameter Space that Support Each Network Type
n=4, $\boldsymbol{\delta = 1, \phi = 10}$

Similarly, Figure 2.6 depicts the case where fixed cost ($\phi = 10$)[19] is added to the model but markets are considered symmetric. Again, the feasible parameter space is divided into two regions. When demands are high and economies of density is relatively low (the darker grey area), the FC network dominates the other two networks, and when demands are lower and economies of density is high (the lighter grey area), the 1H network dominates. As expected, the proportion of feasible parameter space supporting the FC network decreases compared to the cases without fixed cost as the FC network requires more spokes and hence is more costly when fixed cost is accounted for. Note that with only fixed

[19] The fixed cost $\phi = 10$ is picked randomly. However, by calculating the revenue given a parameter set in the feasible parameter space and compare the amount of fixed cost and revenue, it seems that $\phi = 10$ is reasonable. For example, assuming $\alpha = 10$, $\theta = 0.001$ (a point inside the feasible parameter space assuming $n = 4$, $\delta = 1$), the total revenue earned by each network type is about 140. Hence a FC network would spend around $\frac{3}{7}$ ($\frac{60}{140}$, where 60 is the amount of fixed cost spent on establishing the 6 routes in the FC network) of its revenue on setting up the spokes. Similarly, the ratio between total fixed cost and ratio for 1H and 2H networks are $\frac{5}{14}$ and $\frac{3}{14}$ respectively, which are reasonable proportions.

cost considered in the model, the 2H network is still dominated by the other two network types.

If both asymmetric markets and fixed cost are introduced into the model ($\delta = 4$ and $\phi = 10$),[20] the three profit indifference curves are illustrated in Figure 2.7. Unlike the cases in Figure 2.5 and Figure 2.6 where the indifference curves do not intersect each other inside the first quadrant, the three indifference curves in Figure 2.7 intersects at one point inside the feasible parameter space and divide the space (shaded area) into 6 regions, with each region representing a different ordering of the choice between the three network types. The choice between 1H, 2H and FC networks is summarized in Figure 2.8. The darkest shaded region of the feasible parameter space is where 2H network is optimal among the three network structures. The lightest shaded region of the feasible parameter space is where 1H network is favored and the rest of the feasible parameter space is where FC network is favored. As is shown in Figure 2.8, the regions favoring the FC and the 2H networks form a "wedge" in the feasible parameter space, such that when θ is greater than a certain threshold, the FC or the 2H network would be dominated by the 1H network. Moreover, the upper (lower) part of this "wedge" is where the FC (2H) network is dominant, indicating that in the markets with higher demands, the FC network is likely to be more profitable than the 2H network.

[20] Other parameter values will be considered in the following Sections.

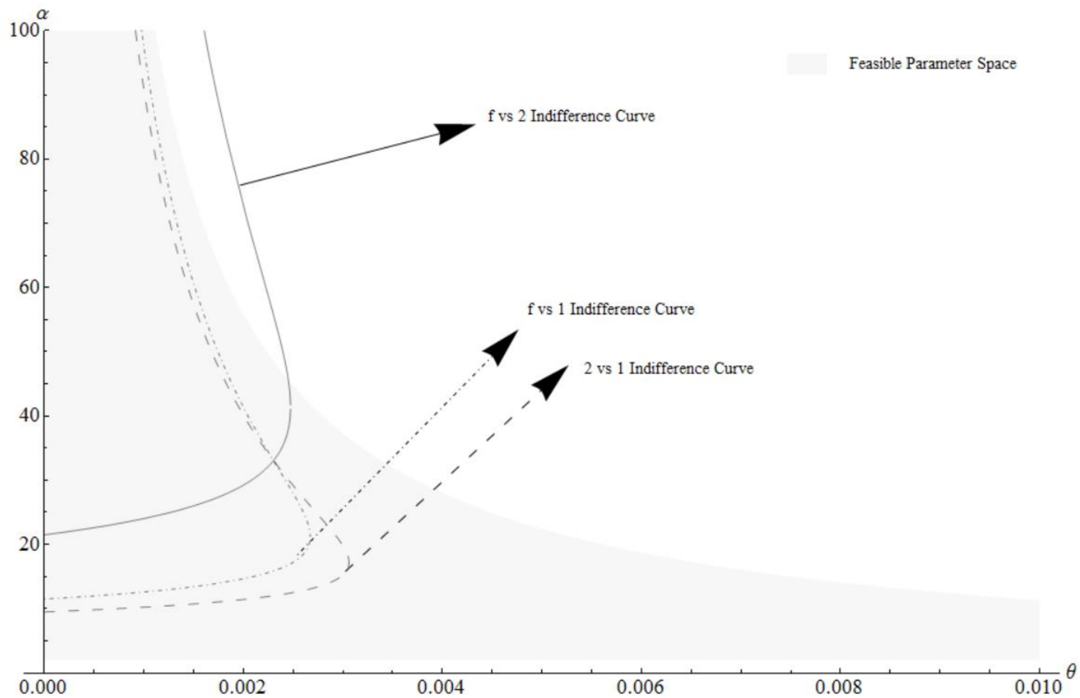


Figure 2.8 Indifference Curves
$\boldsymbol{n = 4, \delta = 4, \phi = 10}$

For example, when the value of θ is low (i.e. $\theta = 0.002$), the 2H network is more profitable than the 1H and FC network if α is between point C and D. The 1H network would be more profitable than 2H and FC network if α takes on a value between D and E or B and A. Similarly, the FC network would be optimal if α takes on a value between B and C. Yet when the value of θ is high (i.e. 0.008), then 1H network would be the optimal choice as long as α is in the feasible parameter space.

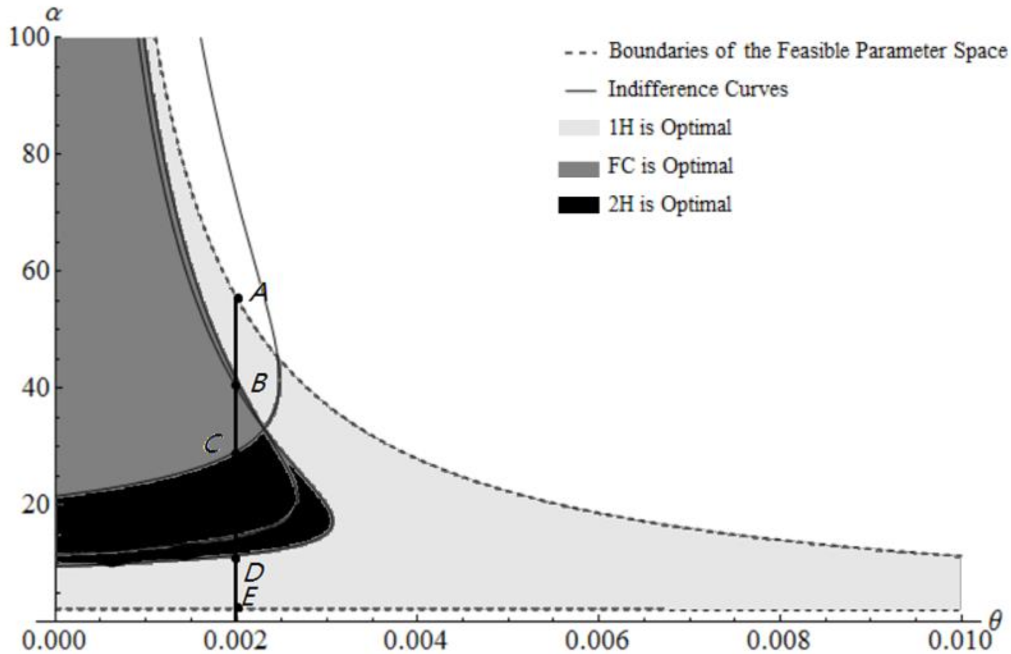


Figure 2.9 Parameter Spaces that Supports Each Network Type
$\boldsymbol{n = 4, \delta = 4, \phi = 10}$

It is clear from Figure 2.8 that $\Delta_\theta < 0$ holds along all three indifference curves, since moving to the left from a point on the curve raises the profit differences above zero. However, to get better insight, analysis is carried out to examine the relative profitability of the 1H, 2H and FC networks in the entire feasible parameter space.

The effect of a parameter on network choice is found by differentiating Δ^{2vs1}, $\Delta^{fvs1}$and Δ^{fvs2}, with respect to that parameter. If the derivative is positive, then a high value of the parameter favors the network with more spokes, with the opposite conclusion holding if the derivative is negative. Differentiation of the Δs with respect to θ using the envelope theorem yields the following equations:

$$\Delta_\theta^{2vs1} = (q_{2h}^{mm})^2 + 4\left(q_{2h}^{sm} + \frac{Q_{2h}^{ss}}{2}\right)^2 - [(q_h^{mm} + 2Q_h^{sm})^2 + 2(q_h^s + Q_h^{sm} + Q_h^{ss})^2] \tag{2.16}$$

$$\Delta_\theta^{fvs1} = q_{fc}^{mm\,2} + 4q_{fc}^{sm\,2} + q_{fc}^{ss\,2} - [(q_h^{mm} + 2Q_h^{sm})^2 + 2(q_h^s + Q_h^{sm} + Q_h^{ss})^2] \tag{2.17}$$

$$\Delta_\theta^{fvs2} = q_{fc}^{mm^2} + 4q_{fc}^{sm^2} + q_{fc}^{ss^2} - [(q_{2h}^{mm})^2 + 4\left(q_{2h}^{sm} + \frac{Q_{2h}^{ss}}{2}\right)^2] \quad (2.18)$$

It should be noted that since envelope theorem is used, quantities of traffic are all evaluated at their optimum values, so that assuming the signs of Δ_θ^{2vs1}, Δ_θ^{fvs1} and Δ_θ^{fvs2} is tantamount to assuming that a certain portion of the parameter space is relevant. Checking the feasible parameter space shows that $\Delta_\theta < 0$ holds in almost all of the feasible parameter space, except for a very small region near the bottom of the feasible region. Recall that $\Delta_\theta < 0$ always holds along the relevant indifference curve.

An intuitive explanation for this finding can be provided. Note that the sign of Δ_θ hinges on the relationships between $(q_{2h}^{mm})^2 + 4\left(q_{2h}^{sm} + \frac{Q_{2h}^{ss}}{2}\right)^2$, $(q_h^{mm} + 2Q_h^{sm})^2 + 2(q_h^s + Q_h^{sm} + Q_h^{ss})^2$and $q_{fc}^{mm^2} + 4q_{fc}^{sm^2} + q_{fc}^{ss^2}$, which in turn depend on the relationships between $(q_{2h}^{mm}) + 4\left(q_{2h}^{sm} + \frac{Q_{2h}^{ss}}{2}\right)$, $q_h^{mm} + 2Q_h^{sm} + 2(q_h^s + Q_h^{sm} + Q_h^{ss})$ and $q_{fc}^{mm} + 4q_{fc}^{sm} + q_{fc}^{ss}$. The three expressions give optimum total traffic carried by the spokes of the 2H, 1H and FC networks, respectively. Since the networks with fewer spokes are meant to save costs through economies of density, a natural expectation is that network structures with fewer spokes would transport more total passengers compared to the network structures with more spokes. Thus inequalities

$$(q_{2h}^{mm}) + 4\left(q_{2h}^{sm} + \frac{Q_{2h}^{ss}}{2}\right) < q_h^{mm} + 2Q_h^{sm} + 2(q_h^{sm} + Q_h^{sm} + Q_h^{ss}) \quad (2.19)$$

$$q_{fc}^{mm} + 4q_{fc}^{sm} + q_{fc}^{ss} < q_h^{mm} + 2Q_h^{sm} + 2(q_h^{sm} + Q_h^{sm} + Q_h^{ss}) \quad (2.20)$$

$$q_{fc}^{mm} + 4q_{fc}^{sm} + q_{fc}^{ss} < (q_{2h}^{mm}) + 4\left(q_{2h}^{sm} + \frac{Q_{2h}^{ss}}{2}\right) \quad (2.21)$$

should hold for most parameter values, implying the expressions in (2.16) (2.17) and (2.18) are likely to be negative[21]. Therefore, increasing θ tends to raise the advantage of the network that carries more total traffic on its spokes, in a two way comparison.[22]

2.4 Increasing Market Asymmetry

2.4.1 Increasing δ asymmetry

It would be of interest to see what happens to the choice of network structure after increasing market asymmetry in the model. A crude comparison can be made by increasing the asymmetry parameter δ from 4 in the basic model as described in the last section to 25[23], so that the size of the major cities increases from 4 times the size of small cities to 25 times their size. Figure 2.9 shows the shifts of two of the indifference curves (from the dotted line to the solid line). While the profit indifference curve between FC and 2H (the thinner curves) shifts leftward, the profit indifference curve between 2H and 1H (the thicker curves) shifts leftward and downward.

[21] Note that inequalities (2.19)-(2.21) do not guarantee that (2.16)-(2.18) are negative since $A + B < C + D$ does not guarantee that $A^2 + B^2 < C^2 + D^2$. However, $A + B < C + D$ is sufficient to prove $A^2 + B^2 < C^2 + D^2$ if additional conditions like $A < C$ and $B < D$ are given. In our context, for example, adding conditions: $\mathrm{q}_{2h}^{mm} < \mathrm{q}_{h}^{mm} + 2\mathrm{Q}_{h}^{sm}$ and $2\left(\mathrm{q}_{2h}^{sm} + \frac{\mathrm{Q}_{2h}^{ss}}{2}\right) < (\mathrm{q}_{h}^{sm} + \mathrm{Q}_{h}^{sm} + \mathrm{Q}_{h}^{ss})$ can guarantee the negativity of (16).

[22] Figures showing the sign of the Δ_αs in the feasible parameter space can be provided upon request.

[23] Outcome for more values of δ are also studied and summarized later in Table 2.2. For simplicity, Section 2.4.1 only gives details of the shifts in indifference curves for the case where δ increases from 4 to 25.

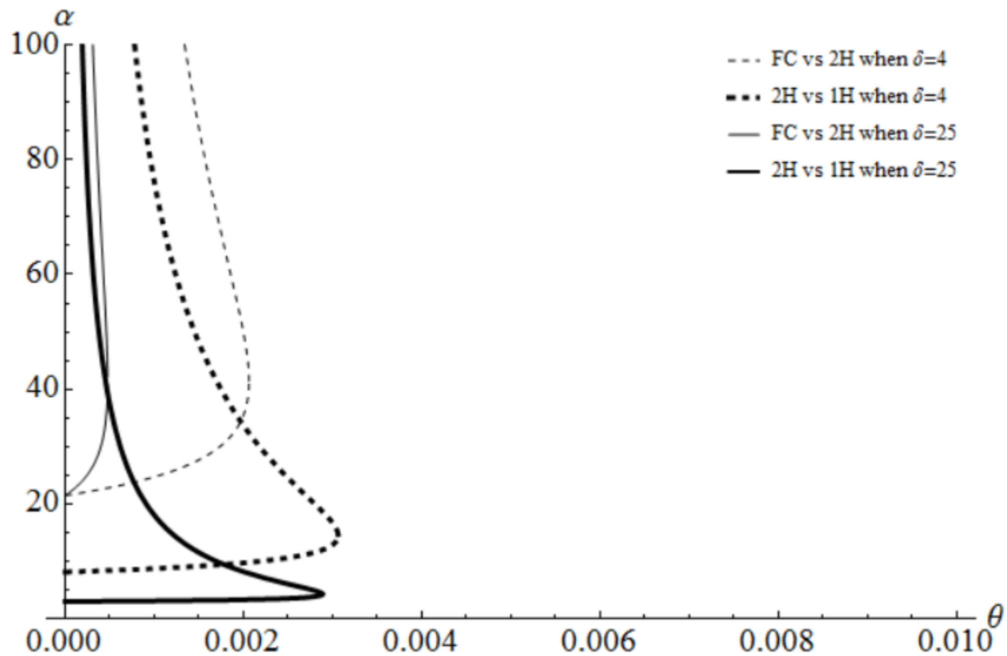


Figure 2.9 Shifts in the indifference curve when **δ** change from 4 to 25
$\boldsymbol{n = 4, \phi = 10}$

Figure 2.10 shows the change of the overall feasible parameter space, as well as the feasible parameter space favoring the 2H network, when δ increases from 4 to 25. Note that as the indifference curves shift, the feasible parameter space also shrinks. The "wedge" formed by the parameter space supporting the FC network (shaded by darker grey) and 2H network (shaded by light grey) takes up a higher proportion of the feasible parameter space, with the parameter space supporting the 1H network (the unshaded area inside the feasible parameter space) decreasing. Hence, even though the total area of the parameter space supporting the 2H network does not change much as δ increases, the percentage of the area in the overall feasible parameter space supporting the 2H network increases. By numerically integrating the areas in Figure 2.10,[24] the percentage of the feasible parameter space favoring the 2H network when δ takes on different values is reported in Table 2.2 Column 2. When δ increases from 2 to 25 as in Figure 2.10, the percentage of the feasible area favoring the 2H network increases from 1.5% to 43.1%. From the analysis above, it is safe to say that as asymmetry increases between the major cities and small cities, the network carrier becomes more likely to choose the 2H network.

Columns 3 and 4 of Table 2.2 report the percentage of the feasible parameter space favoring the 1H and FC network at different values of δ. As δ increases, the percentages of the feasible area supporting the 1H network and the FC network decrease (except for the case where δ increase from 2 to 4). The decrease in the percentage of the feasible parameter space is fast for the 1H network (it drops from 63% to 31% when δ increases from 2 to 25), while the percentage of the feasible parameter space supporting the FC network decreases much slower as δ increases. The percentage slightly increases from 35% to 38% when δ increases from 2 to 4, then decreases monotonically from 38% to 26% when δ increases from 4 to 25, which is small compared to the 32% drop of percentage of feasible parameter space supporting the 1H network. Hence, we can learn from Table 2.2 that, as market asymmetry increases, the possibility that 2H network is optimal increases mostly due to the decreasing possibility that 1H network is optimal.

[24] Since the areas are unbounded, the profit indifference curves and the upper bounds of the feasible parameter space are nonintegrable with respect to θ over its entire area. Noting that the α-axis is the asymptote for the two curves, approximating the areas by integrating them over a "truncated feasible parameter space", where the minimum θ equals 1×10^{-4} instead of 0, yields finite results. Note that the truncated parameter space captures nearly all of the actual region, and that the space extends up to an α value of 1.11×10^{4}.

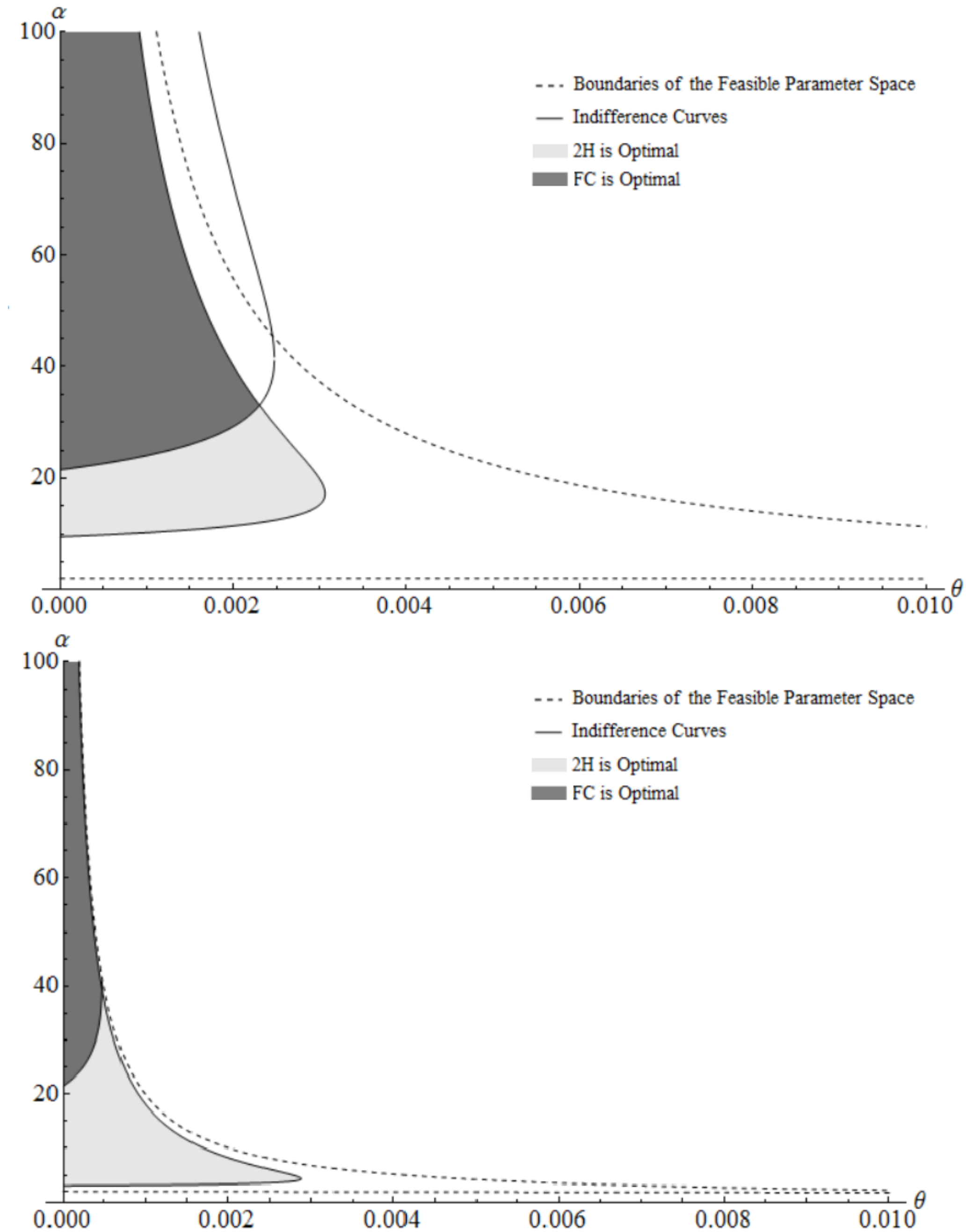


Figure 2.10 Feasible Parameter Space Supporting 2H network $\boldsymbol{n = 4}$, $\boldsymbol{\phi = 10}$, $\boldsymbol{\delta = 4}$ $(\boldsymbol{upper\ panel})$ $\boldsymbol{and}$ $\boldsymbol{\delta = 25}$ $(\boldsymbol{lower\ panel})$

Table 2.2 Percentage of Parameter Space Supporting 2H when $\boldsymbol{\delta}$ changes

$\mathbf{n = 4, \phi = 10}$

$\delta =$	Percentage of 2H	Percentage of FC	Percentage of 1H
2	0.0150	0.3590	0.6260
4	0.0687	0.3837	0.5476
5	0.0955	0.3830	0.5215
10	0.2086	0.3539	0.4375
15	0.2964	0.3192	0.3844
20	0.3687	0.2872	0.3441
25	0.4305	0.2582	0.3113

The above outcome is intuitively transparent. With growing market asymmetry, the carrier operating a 1H network would want to add direct flights to the potential hub city (city B) to capture its increasingly important direct market. However, there is less incentive to offer direct flights between smaller cities since these markets are thin and establishing direct routes is costly. Hence, relative attractiveness of the 2H network grows compared to the 1H and FC networks.

2.4.2 Increasing ϕ asymmetry

By analogue to section 2.4.1, another exercise is to increase the fixed cost ϕ and analyze how the indifference curves and the parameter spaces supporting each network structure change. Assuming again a simpler network with only 4 nodes, and setting parameter $\delta = 25$ instead of the previous value of 4,[25] Figure 2.11 shows the change of overall feasible parameter space, as well as the feasible parameter space favoring the 2H network, when ϕ increases from 10 to 20.[26] Note that, in contrast to a changing δ, the overall feasible parameter space does not change while the two indifference curves move leftwards. By numerically integrating the areas in Figure 2.9, the percentage of the feasible parameter space favoring the 2H network decreases from 43% to 31%. The percentages of the feasible parameter space favoring the 2H network when ϕ takes on different values are computed and reported in Table 2.3 Column 1. It can be concluded from the table that, holding everything else constant, an increase in the fixed cost parameter ϕ decreases the proportion of the feasible parameter space favoring the 2H network.

Similar to the previous section, Columns 3, 4 and Columns 6, 7 of Table 2.3 report percentages of the feasible parameters space favoring the 1H and FC network at different value of ϕ given a high or low value of δ. As ϕ increases, the percentage of the feasible area supporting the FC network decreases along with that supporting the 2H network. The percentage drops from 38% to 12% when ϕ increases from 10 to 60 given $\delta = 4$, and it drops from 26% to 1% given $\delta = 25$. Hence, regardless of the extent of market asymmetry, increasing fixed cost would decrease the possibility that FC network is optimal. Oppositely, the percentage of the feasible parameter space supporting the 1H network increases significantly as ϕ increases. The percentage increases from 55% to 81% when ϕ increases from 10 to 60 when $\delta = 4$ and the percentage increases from 31% to 68% when $\delta = 25$.

[25] Here a greater value of δ is used so that the changes of indifference curves is significant enough to be observed visually in Figure 2.11 when ϕ increases. However, the change in parameter space supporting different networks given different value of ϕ when δ is small ($\delta = 4$) is also analyzed and reported in Table 2.3 Column 1. The same logic applies to Section 2.4.3.

[26] Outcome for more values of ϕ are also studied and summarized later in Table 2.3. For simplicity, Section 2.4.2 only gives details of the shifts in indifference curves for the case where δ increases from 10 to 20.

Hence, we can learn from Table 2.3 that, as fixed cost increases, the decrease in the percentage of the feasible parameter space supporting 2H mostly comes from the increase in possibility that 1H network is optimal.

Such an outcome can also be explained intuitively: since the FC network requires the carrier to establish more direct routes, which becomes costly as ϕ increases, it would be beneficial to the carrier to operate a network with fewer direct links. While the 2H network requires fewer direct spokes compared to the FC network, it almost doubles the required spokes needed by a 1H network ($2(n-2)$ spokes compared to $n-1$ spokes). Hence when ϕ increases, 1H becomes more favorable relative to the other two network types.

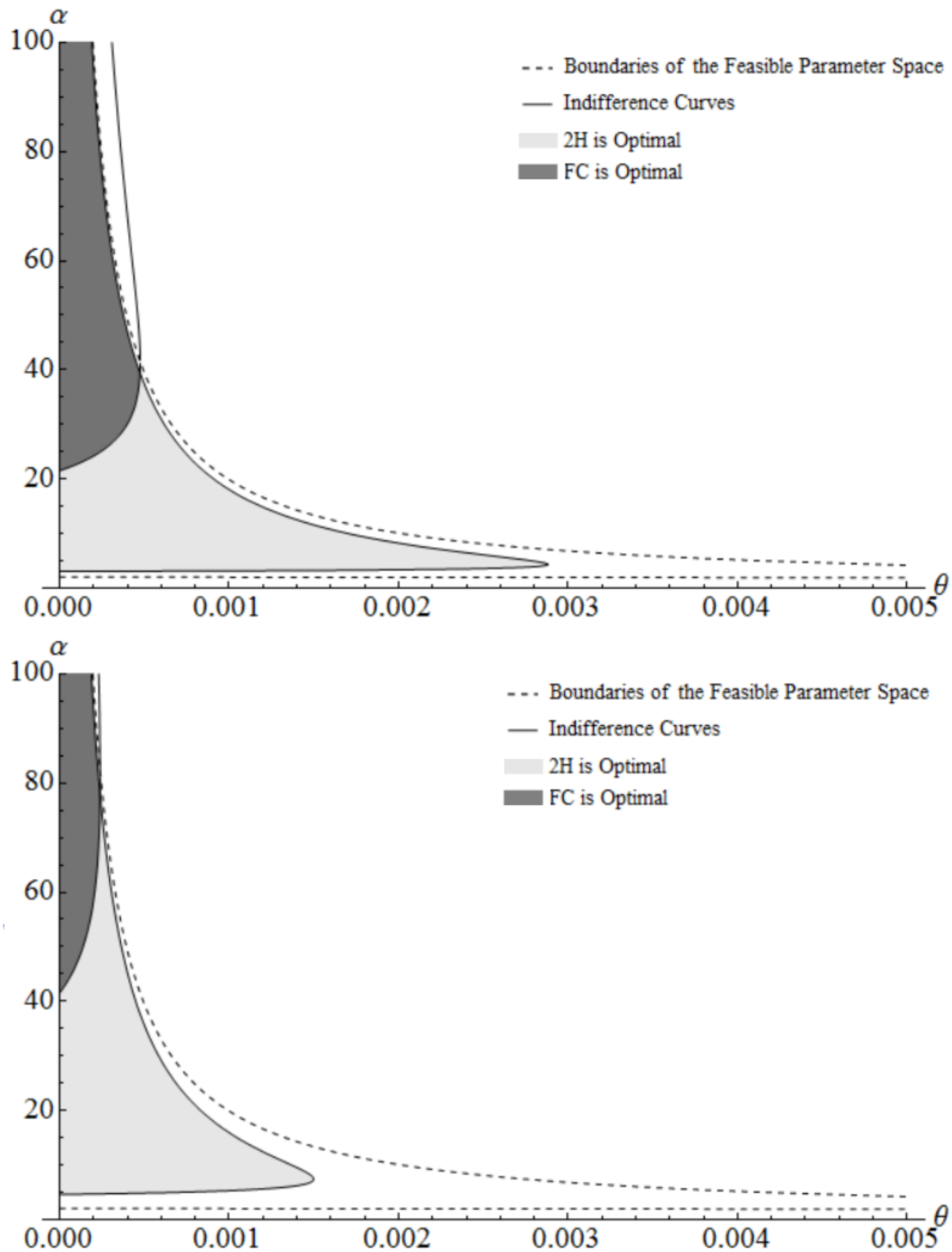


Figure 2.11 Feasible Parameter Space Supporting 2H network $\boldsymbol{n = 4, \delta = 25, \phi = 10 (upper\ panel)\ and\ \phi = 20 (lower\ panel)}$

Table 2.3 Percentage of Parameter Space Supporting 2H when $\boldsymbol{\phi}$ changes

$\mathbf{n = 4}$

	$\boldsymbol{\delta = 4}$			$\boldsymbol{\delta = 25}$		
$\boldsymbol{\phi} =$	% of 2H	% of FC	% of 1H	% of 2H	% of FC	% of 1H
10	0.0687	0.3837	0.5476	0.4305	0.2582	0.3113
20	0.0672	0.2784	0.6544	0.4195	0.1156	0.4649
40	0.0634	0.1770	0.7596	0.3655	0.0751	0.5594
60	0.0593	0.1215	0.8192	0.3114	0.0128	0.6758

2.4.3 Increasing Number of Cities

Another exercise is to increase the number of cities served by the airline. Fixing the asymmetry parameter ($\delta = 25$) and the fixed cost parameter ($\phi = 10$), Figure 2.12 compares the cases where $n = 4$ and $n = 10$[27]. Again, the lightly shaded areas again show the feasible parameter space favoring 2H and the darkly shaded areas show the feasible parameter space favoring FC, while the rest of the feasible parameter space favors 1H. Numerically integrating the areas, the percentage of the feasible parameter space favoring 2H network decreases from 43% to 25%. Further analysis shows that further increasing the number of cities would decrease the percentage, so that it can be concluded that, as the total number of cities increases, the 2H network becomes relatively less profitable.

Again, Columns 3 and 4 in Table 2.4 show the change in the percentage of the parameter space for the 1H and FC networks. Similar to the case where ϕ increases, an increase in n also decreases the percentage of the parameter space supporting FC while increasing the parameter space supporting 1H.

[27] Outcomes for more values of n are also studied and summarized later in Table 2.4. For simplicity, section 2.4.3 only gives details of the shifts in indifference curves for the case where n increases from 4 to 10.

The above observation seems counterintuitive, as one would naturally think increasing the number of cities in the network would result in a need for more hubs. However, as the number of cities increases, the 1H network can make more use of economies of density now that there are more connecting passengers traveling out of any given spoke city. While the 2H network also utilizes economies of density, connecting passengers are split between the two hubs and thus each hub has a much lower utilization of economies of density as compared to the 1H network. Hence, the 2H and FC network become less profitable compared to the 1H network, decreasing the percentage of the feasible parameter space supporting the network structures with more spokes.

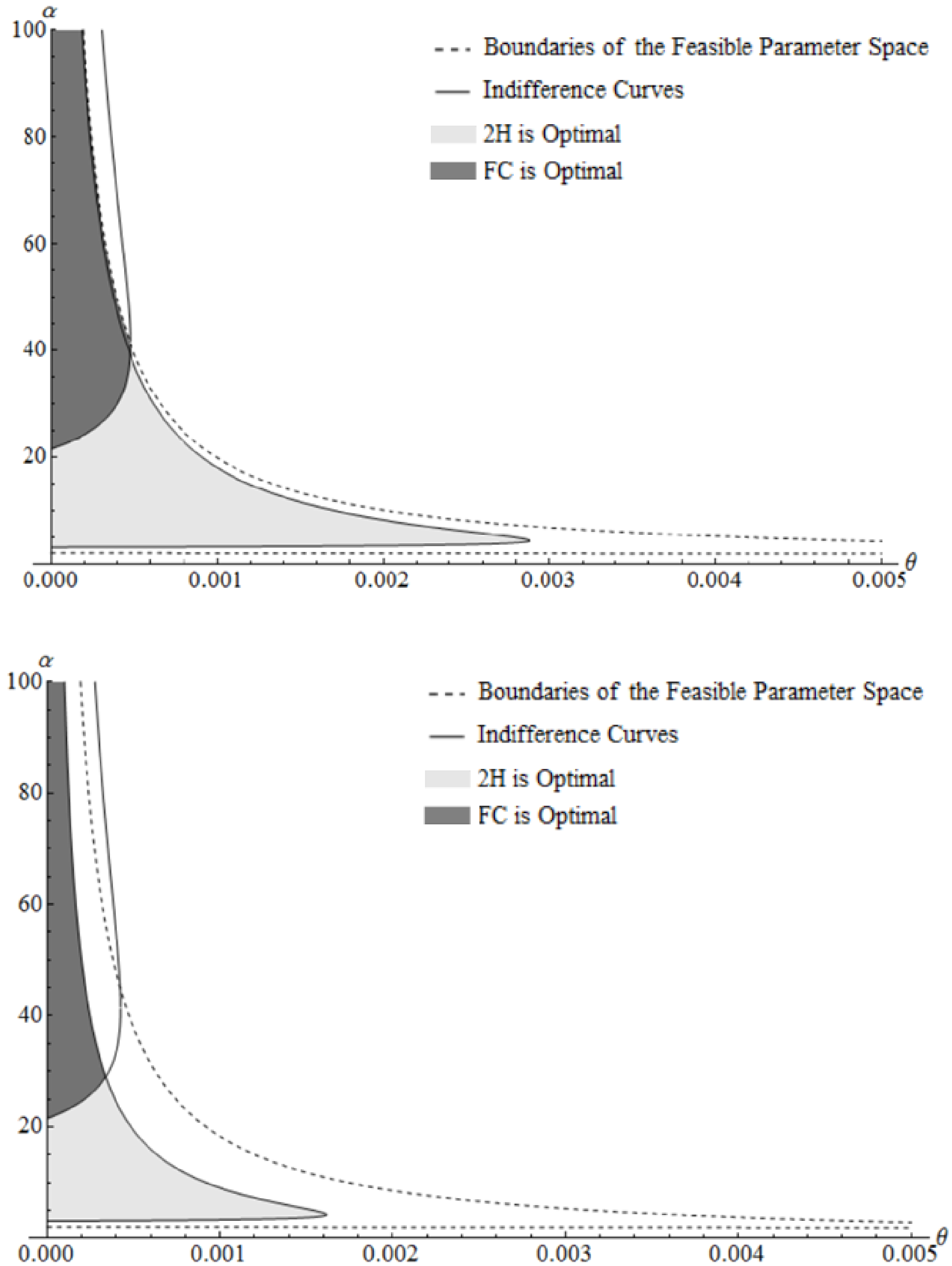


Figure 2.12 Feasible Parameter Space Supporting 2H network

$\boldsymbol{\delta = 25, \phi = 10, n = 4(upper\ panel)\ and\ n = 10(lower\ panel)}$

Table 2.4 Percentage of Parameter Space Supporting 2H when $\boldsymbol{\delta}$ changes

$\boldsymbol{\delta = 25, \phi = 10}$

$\boldsymbol{n} =$	Percentage of 2H	Percentage of FC	Percentage of 1H
4	0.4305	0.3837	0.1858
8	0.2892	0.3830	0.3278
10	0.2502	0.1001	0.6497
16	0.1653	0.0600	0.7747
20	0.1312	0.0473	0.8215

2.5 The choice between 1H and 2H network after competitor entry

Now consider the effect of the entry of a competitor on network choice. Similar to the monopoly airline case described in section 2.2, the network carrier (NC) serves multiple symmetrically located cities with asymmetric city sizes: two major cities (H and B) and two small cities (A and C). Different from the monopoly model, a competitor enters the market by connecting the two small cities A and C, as depicted by Figure 2.13 for the case of four cities. For simplicity and to focus only on the effect of network structure on network choice, assume that the competitor and network carrier share the same cost function, with the same value of θ.

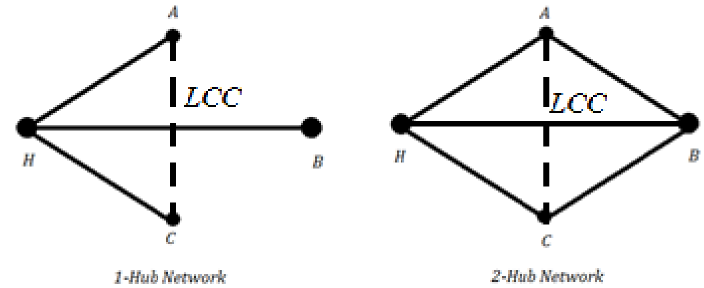


Figure 2.13 Network Types with Competitor

Additionally use superscript N(C) to denote the type of carrier: Network Carrier (Competitor). Note that the presence of the competitor creates competition in the AC market, so that the demand functions in the AC market for 1H, 2H and FC network become:

$$p_h^{ss^N} = \alpha - \beta(q_h^{ss^C} + Q_h^{ss^N}) - \mu \qquad p_h^{ss^C} = \alpha - \beta(q_h^{ss^C} + Q_h^{ss^N})$$

$$p_{2h}^{ss^N} = \alpha - \beta(q_{2h}^{ss^C} + Q_{2h}^{ss^N}) - \mu \qquad p_{2h}^{ss^C} = \alpha - \beta(q_{2h}^{ss^C} + Q_{2h}^{ss^N})$$

$$p_{fc}^{ss^N} = p_{fc}^{ss^C} = \alpha - \beta(q_{fc}^{ss^C} + q_{fc}^{ss^N})$$

Other than the changes in the demand functions, the network carrier's profit functions for the three network types remain unchanged. The competitor's profit is:

$$\max\ \pi^{ss^C} = q^{ss^C} p^{ss^C} - c\left(q^{ss^C}\right) \tag{2.27}$$

Again, consider the simplest case where $n = 4$ and where β is normalized to 1. Solving for the optimal quantities, prices and the feasible parameter space,[28] the new profit indifference curves can be compared with the ones before the competitor entry. In the case where $\phi = 10, \delta = 4$, Figure 2.14 shows that within the feasible parameter space, the profit indifference curve comparing 2H and 1H (the thick black curve) does not visibly change as a competitor enters the market, while the profit indifference curve comparing the FC network and 2H network (the thin black curve) shifts up after the competitor's entry. Thus,

[28] Since the analytical solution in this case is extremely complex, the process is not repeated here.

the area of feasible parameter space supporting the 2H network increases (from the black area to the summation of black and gray areas) when Cournot competition is introduced. Numerically integrating the areas in Figure 2.14 and the corresponding feasible parameter spaces shows that the percentage of the feasible parameter space favoring the 2H network increases from 6.9% with monopoly to 9.3% after introducing competition.

To sum up, given asymmetric markets, linear marginal costs with 4 nodes and fixed cost per spoke, competitor entry connecting one pair of the spoke cities shrinks area of the feasible parameter space and increases the percentage of the feasible space favoring the 2H network. Hence, the network carrier is more likely to choose the 2H network after the entry of a competitor.

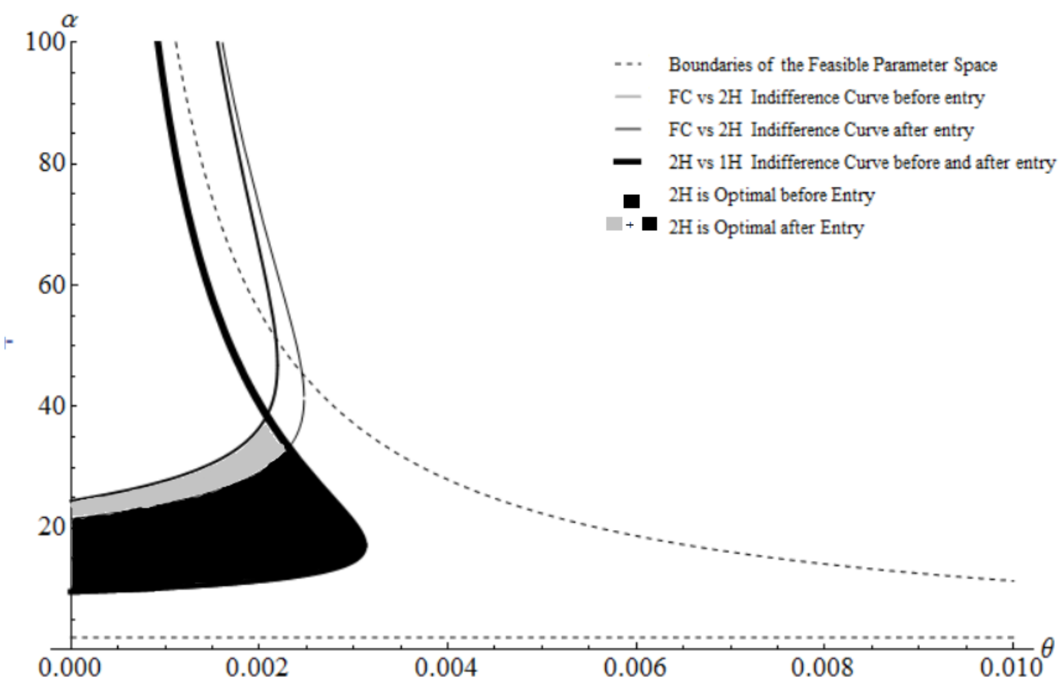


Figure 2.14 Shifts in the Indifference Curve before and after Competitor Entry
$\boldsymbol{n = 4, \delta = 4, \phi = 10}$

2.6 Conclusion

This chapter has provided a simple justification for the existence of the multi-hub networks adopted by many large network carriers around the world. It shows analytically that, for a monopolist airline using a cost function specification that is quite common in the literature, economies of density do not guarantee optimality of the 1H or FC network if fixed cost and asymmetric markets are introduced into the model. A two-hub network may be favored in a large portion of the feasible parameter space as long as there is a large asymmetry between the sizes of major cities and small cities. Moreover, with increasing asymmetry in market sizes, the monopoly airline has a higher likelihood of adopting the 2H network. Increases in fixed cost or number of cities would slightly decrease this likelihood.

After incorporating competition from another carrier offering a non-hub direct route from one small spoke city to another, the model reveals that such competition makes the network carrier more prone to adopt a multi-hub network. For future work, a useful extension would add flight frequency and aircraft-size to the model, so that the effect of these factors on network structure choice could also be evaluated. Another extension would be welfare analysis comparing the network choices of the monopolist and social planner.

Appendix 2

Derivation of the Parameter Space: Matrix of the second order derivatives for the 1H network maximization problem is:

$$\text{(a1)} \quad \begin{bmatrix} -4+4\theta & 0 & 4\theta & 4\theta \\ 0 & -2+2\theta & 0 & 4\theta \\ 4\theta & 0 & -2+4\theta & 4\theta \\ 4\theta & 4\theta & 4\theta & -4+12\theta \end{bmatrix}$$

For (a1) to be negative definite, the following conditions must be satisfied:

(a1) $-4+4\theta<0$

(a2) $1-2\theta+\theta^2>0$

(a3) $(1-3\theta)(-1+\theta)<0$

(a4) $1-7\theta+10\theta^2>0$

Combining the above conditions, $\theta<\frac{1}{5}$ must hold for the Hessian matrix to be negative definite. When $\mu=0$, the non-negativity constraints (when $\theta<\frac{1}{5}$) for q_h^{ss}, q_h^{mm}, Q_h^{ss}, Q_h^{sm}, p_h^{ss}, p_h^{mm}, P_h^{ss}, P_h^{sm}, and the corresponding marginal cost(MC) are listed below:

(a5) $\frac{1}{1-2\theta}<\alpha$ when $\theta<\frac{1}{5}$

(a6) $\frac{2}{1+\theta}<\alpha$ when $\theta<\frac{1}{5}$

(a7) $\frac{1}{-1+8\theta}<\alpha$ when $\frac{1}{8}<\theta<\frac{1}{5}$, $0<\alpha$ when $\theta<\frac{1}{8}$

(a8) $\frac{2}{-1+11\theta}<\alpha$ when $\frac{1}{11}<\theta<\frac{1}{5}$, $0<\alpha$ when $\theta<\frac{1}{11}$

(a9) $\alpha<\frac{1}{3\theta}$ when $\theta<\frac{1}{5}$

When $\theta\neq\frac{1}{8}$ *and* $\theta\neq\frac{1}{11}$, it is easy to simplify the above conditions to:

(a10) $\frac{2}{1+\theta}<\alpha<\frac{1}{3\theta}$ when $\theta<\frac{1}{5}$

Thus, equation (a10) describes the feasible parameter space in the optimization problem for HS network.

Similarly, matrix of the second order derivatives for the 2H network maximization problem is:

(a11) $$\begin{bmatrix} -8+8\theta & 4\theta & 0 \\ 4\theta & -2+2\theta & 0 \\ 0 & 0 & -2+2\theta \end{bmatrix}$$

For (a11) to be negative definite, the following condition must be satisfied:

(a12) $-8+8\theta<0$

(a13) $16-32\theta>0$

(a14) $(16-32\theta)(-2+2\theta)<0$

Hence $\theta<\frac{1}{2}$ must hold for the Hessian matrix to be negative definite. When $\mu=0$, the non-negativity constraints (when $\theta<\frac{1}{2}$) for q_{2h}^{sm}, Q_{2h}^{ss}, Q_{2h}^{mm}, p_{2h}^{sm}, P_{2h}^{ss}, P_{2h}^{mm}, and the corresponding marginal cost(MC) are listed below:

(a15) $\frac{2}{\theta-2}<\alpha$,

(a16) $1<\alpha$

(a17) $\frac{2}{1+\theta}<\alpha$

(a18) $0<\alpha$, when $0<\theta\leq\frac{2}{7}$, $0<\alpha<\frac{2}{-2+7\theta}$, when $\frac{2}{7}<\theta\leq\frac{1}{2}$

(a19) $0<\alpha$, when $0<\theta\leq\frac{1}{5}$, $0<\alpha<\frac{2}{-1+5\theta}$, when $\frac{1}{5}<\theta<\frac{1}{2}$

(a20) $0<\alpha<\frac{2-3\theta}{3\theta-5\theta^2+\theta^3}$, when $0<\theta\leq\frac{1}{2}$

(a21) $0<\alpha<\frac{1}{\theta+\theta^2}$, when $0<\theta\leq\frac{1}{2}$,

When $\theta\neq\frac{2}{7}$ and $\neq\frac{1}{5}$, it is easy to simplify the conditions (a12) ~ (a15) to:

(a22) $\frac{2}{1+\theta} < \alpha < \frac{1}{\theta+\theta^2}$ when $\theta < \frac{1}{2}$

Similarly, the matrix of the second order derivatives for the FC network maximization problem is:

(a23) $$\begin{bmatrix} -2+2\theta & 0 & 0 \\ 0 & -8+8\theta & 0 \\ 0 & 0 & -2+2\theta \end{bmatrix}$$

For (a22) to be negative definite, the following conditions must be satisfied:

(a24) $-2+2\theta < 0$

(a25) $16(-1+\theta)^2 > 0$

(a26) $32(-1+\theta)^3 < 0$

Hence $\theta < 1$ must hold for the Hessian matrix to be negative definite. When $\mu = 0$, the non-negativity constraints (when $\theta < \frac{1}{2}$) for $q_{fc}^{sm}, q_{fc}^{ss}, q_{fc}^{mm}, p_{fc}^{sm}, p_{fc}^{ss}, p_{fc}^{mm}$, and the corresponding marginal cost(MC) are listed below:

(a27) $1 < \alpha$

(a28) $0 < \alpha$ when $0 < \theta \leq \frac{1}{2}, 0 < \alpha < \frac{1}{-1+2\theta}$ when $\frac{1}{2} < \theta < 1$

(a29) $0 < \alpha < \frac{1}{\theta}$

it is easy to simplify the conditions (a24) ~ (a29) to:

(a30) $1 < \alpha < \frac{1}{\theta}$ *when* $\theta < 1$

Comparing (a10), (a22) and (a30), it is easy to see that the feasible areas in a 2H and an FC network fully encompass the feasible area in a 1H network. Figure a1 below demonstrates the relationship between the three feasible areas. The shaded area is the feasible area that we adopt for the analysis.

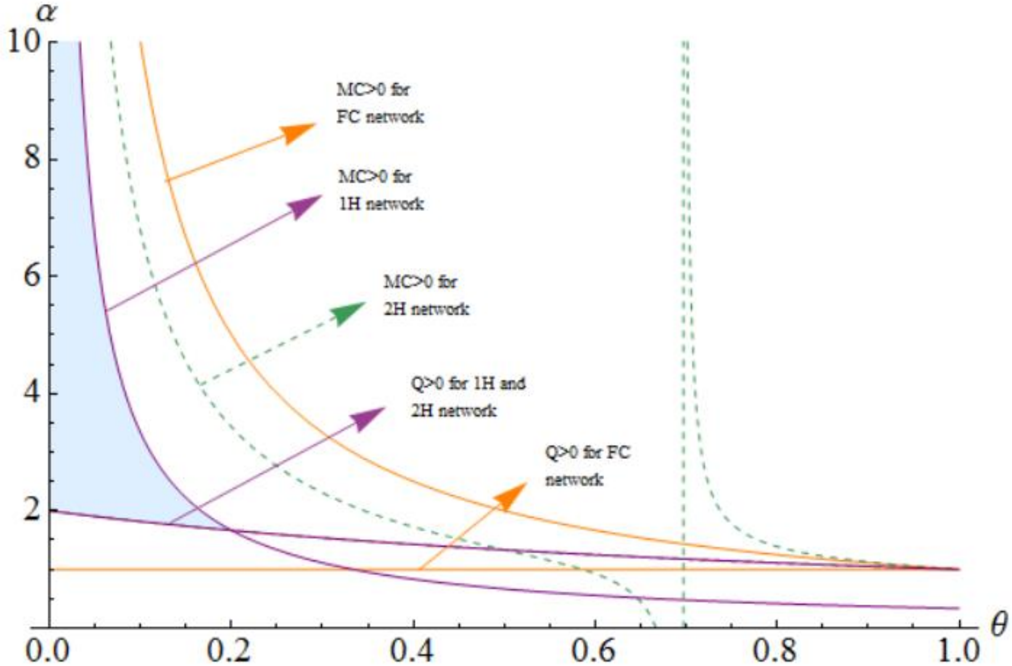


Figure 2.A1 Profit Indifference Curve and Feasible Parameter Space

Chapter 3

Service Competition in the Airline Industry: Schedule Robustness and Market Structure

3.1 Introduction

Starting from as early as 1987, air traffic delays and their impact on consumers have become a significant issue in the airline industry. Over the past 20 years, on-time arrival performance (percentage of flights arriving at the destination gate within 15 min of scheduled arrival) has fluctuated between 65% and 90% on a seasonal basis.[29] The successful implementation of solutions to flight delays depends on understanding the airline's scheduling decisions, given the impact of these decisions on delays. While a large literature studies the factors that affect airlines' scheduling decisions, little attention has

[29] The terrorist attack of 9-11 and the subsequent crisis of SARS alleviated the flight delay concerns for a short period after 2001, but the issue returned in 2005.

been paid to the relationship between market structure and airlines' schedule robustness (how well can a schedule cope with a delay to a particular aircraft). To remedy this issue, the present study attempts to answer the question of how airline decisions on schedule robustness are affected by market structure. The contribution of this study is to measure a flight's “ground buffer”, which equals the excess turnaround time over the minimum possible time, and to relate it to measures of competition. The results show how competition affects the “tightness” of airline scheduling, and thus the schedule's robustness to disruptions. More generally, this study provides evidence on product-quality competition in the airline industry, asking whether carriers improve the robustness of their schedules when markets become more competitive.

High costs arise from delays for airlines and passengers. For airlines, delays increase the costs of staffing, fuel, maintenance and potential rebooking (Peterson et al. 2013). Besides these direct costs, delays also have an impact on airlines’ revenue, as inferior on-time performance may lead passengers to switch to airlines with better on-time performance (Cook, Tanner, and Lawes 2012). For passengers, delays cause unanticipated additional travel time, hence creating opportunity costs both for leisure and business activities (Baumgarten et al., 2014). In addition, delays also induce a welfare loss incurred by passengers who avoid air travel. Using econometric and simulation models, Ball et al. (2010) estimate the costs of delays borne by airlines in 2007 due to above factors to be $8.3 billion, and the total costs of delay borne by passengers to be $18.9 billion. Moreover, travel delays are also estimated to reduce gross domestic product (GDP) by a further $4 billion.

To identify the cause of delays, airlines are required by DOT to report the causes of flight delays using the following five tracking codes: 1) carrier delays: airline-specific factors including mechanical failures, limited labor resources, gate/ramp congestion, etc. 2) extreme weather 3) National Airspace System (NAS): delays and cancellations attributable to the national aviation system arising from a broad set of conditions, such as non-extreme weather conditions, airport operations, heavy traffic volume, and air traffic control 4) security: delays caused by bomb threats, weapon issues and excessive lines at security screening area, etc. 5) late arriving aircraft. It should be noted that airport congestion caused by limited airport capacity is one of the major contributors to NAS delays (i.e. aircraft queuing for runways).

Figure 3.1 summarizes the total number of delay minutes associated with each cause in the period Aug 2004 - May 2005. It shows that carrier-related delays cause 28% of overall flight delays, and NAS related delays are responsible for around 31% of delays. It should be noted that the most important source of delays is aircraft late arrivals, which account for 34% of total delays. Moreover, as Figure 3.2 shows, this percentage has been increasing over the years. Since the year 2004, late arriving aircraft delays have become the #1 cause of delays. Taking a closer look at the cause of delays through a single day, Figure 3.3 shows that late aircraft delays snowball through the day as the follow-on impact of carrier, weather and airspace delays is felt on future flight departures using the impacted aircraft (Jenkins et al. 2012).

Airport congestion is a major cause of NAS delays and may be the original cause of late arriving aircraft delays (i.e. aircraft encountered runway congestion during their previous flight segment), and a large literature focuses on mitigating such congestion, mainly through investigating the relationships between on-time performance, airlines' bank structure, airport hubbing, and airports' competitive structure (Mazzeo and Michael, 2003; Rupp et al. 2006). Among these studies, the existence of internalization of airport congestion has been shown to have important public policy implications for the magnitude of airport congestion tolls. Internalization by airlines (where carriers take account of self-imposed congestion) implies that flight operations in airports where one airline operates most of the flights will be organized to generate less congestion on the runways and gates than in airports where multiple airlines operate and each airline operates a small share of the flights, limiting the extent of internalization (Brueckner, 2002; Brueckner and Pels, 2005; Pels and Verhoef, 2004; Zhang and Zhang, 2006; Basso and Zhang, 2007; Brueckner, 2009).

Figure 3.1 Minutes of Flight Delays and Percentage of Total Delays for Different Causes of Delay. Aug 2004-May 2005

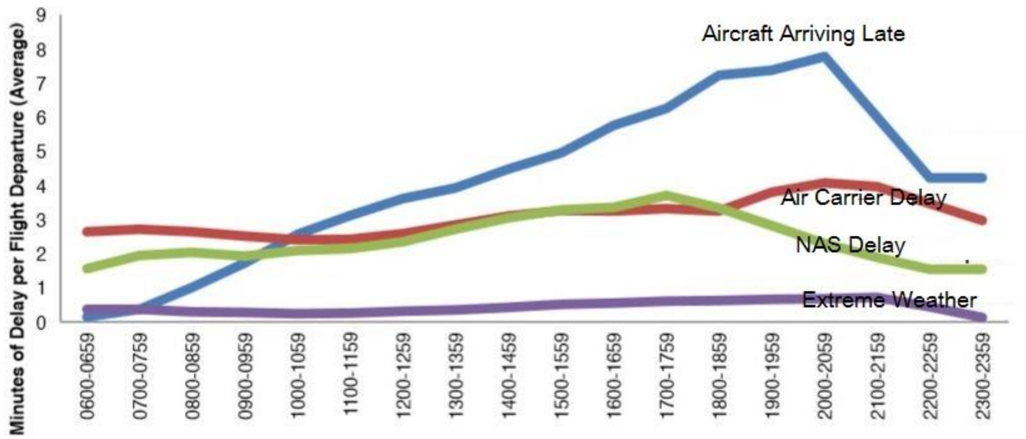


Figure 3.2: Percentage of Total Delay Minutes by Cause, from 2003 to 2014.
SOURCE: Bureau of Transportation Statistics

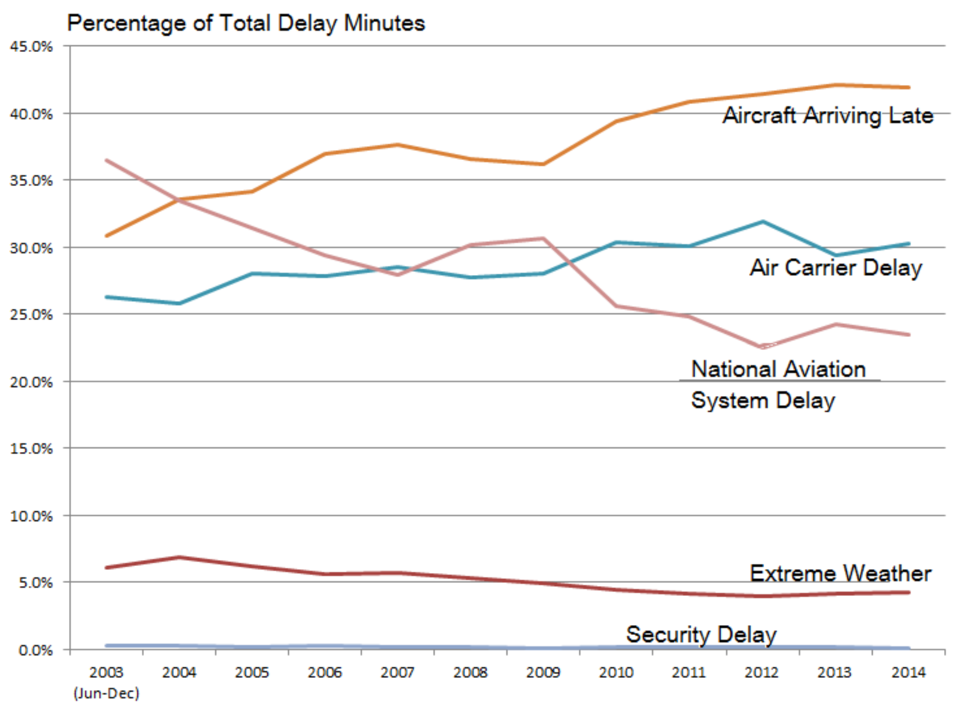


Figure 3.3: Average Delay per Scheduled Flight, by Cause and Hour of Day.
SOURCE: "The State of US Aviation: Comprehensive Analysis of Airline Schedules and Airport Delays" by Jenkins et al. 2012, *American Aviation Institute*.

However, one should also realize that, besides reducing airport congestion and increasing airport capacity, on-time performance can also be improved through mitigating the “snowball effect” of late aircraft delays by loosening aircraft rotation schedules, allowing more “buffer” time between flights. Therefore, it is crucial to understand how such scheduling decisions are made and how they depend on the competitive structure of the market.

Combining elements of previous approaches, this chapter explores this issue, offering an innovative addition to the theoretical and empirical literature on the cause of delays and the effect of market structure on delays. While empirical literature on the subject mainly focuses on the relationship between market structure and airport congestion-related delays (Daniel (1995) and Ater (2012)), this chapter explores how market structure affects airlines’ scheduling-related delays. In particular, this chapter hypothesizes airlines would respond to competition by adjusting the operational robustness of their schedules, which is captured by the buffer time built into an aircraft’s turnaround time. This buffer time equals the extra time beyond the minimum time required for loading and unloading that is incorporated in the turnaround interval. The connection is explored by relating the length of buffer time (in minutes) to the extent of route competition (measured by the number of carriers serving the same route) and airport concentration (measured by the Herfindahl-Hirschman index (HHI), which is computed from airline flight shares at the airport).

Theoretically, buffer time should be added until the resulting marginal cost equals the marginal benefit from fewer flight delays caused by foreseeable factors. However, such marginal costs and marginal benefits are also subject to change under a different competitive environment. Following this intuition and to motivate the empirical analysis, section 3.2 provides a simple theoretical model with price and service-level competition (each firm simultaneously chooses a service level and a price level). Such “attraction models" (Bernstein and Fedegruen (2004)) are commonly used in the marketing and operations research literature. For example, Calton (1989) and Calton and Perloff (1999) argue that demand functions should be specified as a function of prices and customer service levels, which they quantify by the customer's waiting time. Banker et al. (1998) and Tsay and Agrawal (2000) characterize the equilibrium behavior of oligopolies with a fixed number of firms competing simultaneously with their price and a "quality" or service instrument. Similar models are also used to explain flight frequency in the airline industry (Brueckner and Flores-Fillol (2006), Brueckner and Zhang (2010), Brueckner (2010), and Brueckner and Luo (2012)).

The model points out that airlines face a trade-off between benefits arising from increased operational robustness through adding buffers into flight schedules and the costs due to a decrease in fleet utilization. Moreover, the model yields a unique Nash equilibrium and provide comparative-static properties of the equilibrium. A large empirical literature studies such a choice of product quality using structural models (Berry (1994), Berry, Levinsohn and Pakes (1995)), yielding estimates of taste and cost parameters, which are then used to simulate the effects of mergers on product quality or variety. By contrast, the goal of this study is to measure the direction and strength of market-structure effects on airline scheduling decisions instead of identifying the underlying parameters of the utility and production parameters.

Guided by the theoretical model in section 3.2, the first step of the empirical analysis is to use a Tobit model to verify that an increase in the length of the ground buffer indeed reduces departure and arrival delays (the negative empirical relationship is shown in Figure 3.4 after controlling for other factors that may contribute to delays (including schedule-related factors like airport congestion and non-schedule related factors like weather). The measure of ground buffer is derived using flight schedules, following a detailed procedure described in section 3.3.2. The estimation reveals that around 0.35 minutes of departure delay can be eliminated by 1 extra minute of buffer, while the effect of buffers on arrival delays is around 0.23 minutes.

The second step of the empirical analysis examines how buffer length is affected by market structure, which is quantified at the route and airport level using the airport concentration level and route competition. While route competition is used to account for the direct effects of competition driven by the non-stop passengers on the route, it should be noted that airlines operating hub-and-spoke networks will inevitably compete on one-stop routes that originate at the airport, flying passengers to the same destinations via different hubs. Hence effects of competition at such a level is captured by the airport concentration at the origin airport, as the concentration levels reflect the choice sets of airlines for the originating passengers.

Controlling for route-specific effects, the baseline estimations reveal a significant positive effect of competition on buffer time, so that decreasing the market concentration at the origin airport, or increasing the number of competitors serving a route, increases the operational robustness of flight schedules, improving on-time performance. As an extension of the baseline estimations, the study also explores whether this positive relationship between competition and buffer time is heterogeneous across routes playing different roles in a hub-and-spoke network. In such a network, a longer buffer time at hub airports not only improves the operational robustness of the schedule, but it also serves as a tool to synchronize the arrival and departure banks (waves of flights departing or arriving at the hubs). Moreover, longer buffer time at the hubs also prolongs the layover time for connecting passengers. With this additional trade-off between achieving economies of density and lower demand (due to the longer layovers), the effect of market structure on buffer decisions for hub originating flights is expected to differ from non-hub originating flights. Interacting the market structure measures with an indicator of an airline-hub originating flight, extended estimation in section 3.4 reveals that the effect of competition on operational robustness is weaker for the hub originating flights.

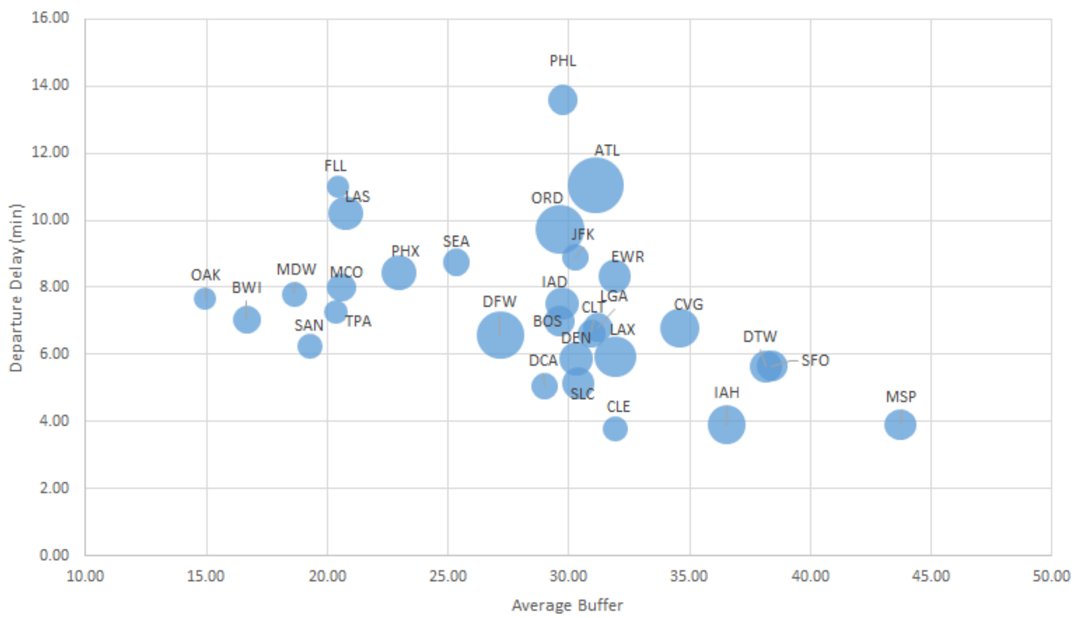


Figure 3.4: The relationship between ground buffer time and departure delay for airports with at least 1 percent of flights, calculated from flights departed during Aug 2004 - May 2005. This figure displays a negative empirical relationship between ground buffer length and departure delay experience by flights. The bubble size denotes the percentage of total flights handled by the airports.

The remainder of the chapter is organized as follows. Section 3.2 describes the theoretical model that guides the empirical estimation. Section 3.3 presents the sources of data and the construction of variables used in the estimation. Section 3.4 discusses the empirical model and presents the estimation results. Section 3.5 concludes the chapter.

3.2 Theoretical Framework

3.2.1 Turnaround time and buffer

Before the theoretical model is presented, it is important to clarify the concepts of turnaround time and buffer, as well as the relationships between them and delay. Before an airplane can make another trip, it must remain at the gate to allow passengers to disembark, have cargo and baggage unloaded, have the airplane serviced, have cargo and baggage loaded, and to allow passengers to board for the next trip. According to Geodeking (2010), the time span from touching the gate ("on blocks") until pushing back from the gate again ("off blocks") is called turnaround time, or TAT, of an aircraft.

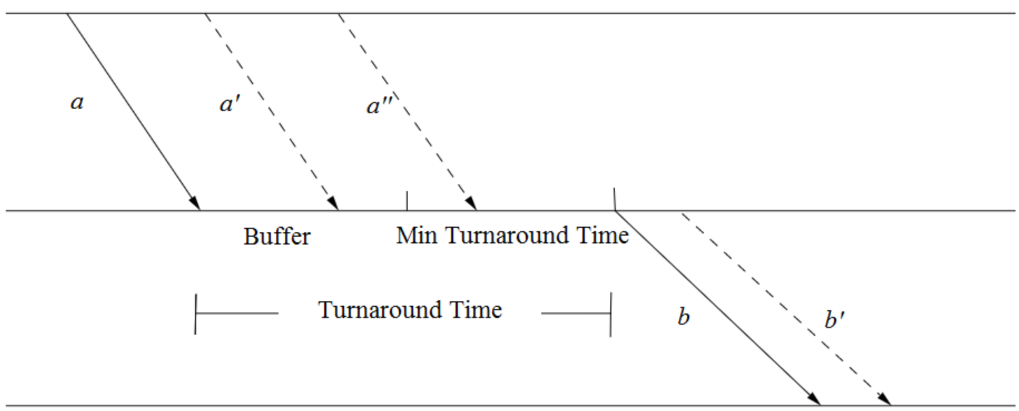


Figure 3.5: The relationships between turnaround time, buffer and departure delay. The solid arrows represent the scheduled arrival time and the scheduled departure times of flights $\boldsymbol{\alpha}$ and $\boldsymbol{b}$. The dotted arrows represent the actual departure and arrival times of flights $\boldsymbol{\alpha}$ and $\boldsymbol{b}$. The scheduled turnaround time (TAT) is the time in between flight $\boldsymbol{\alpha}$'s scheduled arrival and flight $\boldsymbol{b}$'s scheduled departure. The TAT must be larger than the minimum turnaround time (minTAT) required for turning the aircraft, and the additional time in TAT in excess of minTAT is the (ground) buffer.

Because each aircraft routing is a sequence of flight segments flown by a single aircraft, and arrival delay will result in a departure delay if not enough TAT is scheduled between the two consecutive flight segments in that routing. This "delay propagation" often results in delays for downstream flight segments. Building buffers into ground times[30] helps reduce departure delays, as shown in Figure 3.5. The solid arrows in Figure 3.5 represent the original schedule for two flight segments α and b, performed by one aircraft. The dotted arrows represent the actual departures and arrivals of these flight segments. As illustrated in the figure, the scheduled TAT consists of two components: the minimum turnaround time (minTAT) which is the minimum time required to turn the plane around, and the buffer built into the TAT to reduce the vulnerability of the schedule structure to delays. Hence, buffer is the additional time in TAT in excess of minTAT:

$$\text{Buffer}_{ab} = \text{TAT}_{\text{ab}} - \; min\text{TAT} \tag{3.1}$$

If the arrival delay of flight α is shorter than the buffer built into the turnaround time (i.e., the actual departure and arrival time follows α'), then the arrival delay can be absorbed by the buffer and the aircraft can depart on time for its next flight segment b. However, if the actual arrival delay of flight α is longer than the buffer built into the turnaround time between flight α and b (i.e., the actual departure and arrival time follows α''), then some portion of the arrival delay cannot be absorbed and is propagated to flight b, causing the actual departure and arrival time at b to be postponed to b'.

3.2.1 Theoretical model

Consider a travel market connecting two cities. Passengers in the market have mass M, and the market is served by n identical competing airlines. First consider the demand side of the model, where consumers value consumption and travel, and travel valuation depends on the airline used to make the trip. Assume a random utility model in which

[30] Adding buffers to "airtime" was found ineffective in reducing delays by the airlines, as these buffers were reabsorbed probably due to down-prioritization when approaching a congested airport and to less favorable taxiing routes or gate allocation (Geodeking, 2012, p.69).

consumers make a discrete choice among the n airlines in the market, selecting the alternative yielding the greatest utility (Ben-Akiva and Lerman, 1985; McFadden, 1974). In the model, indirect utility for consumer i traveling by airline j is given by $y - p_j + travel\ benefit - flight\ delay\ cost_j + \epsilon_{ij}$, where y is income, and p_j is airline j's fare, so that $y - p_j$ is consumption of other goods if the price of the other goods is normalized to 1. The term ϵ_{ij} represents an individual-specific component of utility that is uncorrelated with price, p_j.

Flight delay measures the difference between the scheduled departure and the actual departure times. As was previously discussed, shorter turnaround time for a flight means a higher expected departure delay, implying a negative correlation between turnaround time T_j and expected departure delay. For determinate results, assume that the expression for expected departure delay takes the following specific form: $D + \frac{\omega}{T_j}$, where $\omega > 0$ indicates the magnitude of reduction in departure delay from adding turnaround time (or adding buffer time, since turnaround time T_j equals the minimum turnaround time plus buffer time). When the turnaround time is set to a value that is sufficiently large (so that $\frac{\omega}{T_j}$ is sufficiently small), departure delay can still happen due to other factors such as weather; hence the expected departure delay given enough turnaround time is denoted by D. Flight delay cost is given by a disutility parameter $\psi > 0$ times the above expression, thus equaling $\psi\left(D + \frac{\omega}{T_j}\right) \equiv F + \frac{\phi}{T_j}$ for $j = 1,2 \ldots n$ where $F = \phi D$ and $\phi = \psi\omega$.

Given the expression for the flight delay cost, the indirect utility function for consumer i flying on airline j is $y - p_j + b - F - \frac{\phi}{T_j} + \epsilon_{ij}$, where b denotes the travel benefit, assumed to be constant for all airlines and consumers. Hence, the only quality difference among different airlines is on-time performance. Let $B = b - F$, so the indirect utility function can be simplified to $y - p_j + B - \frac{\phi}{T_j} + \epsilon_{ij}$.

If the ϵ_{ij}'s are independently and identically distributed according to the Type I extreme value distribution, the choice probability, or the aggregate market share of airline j, has the familiar multinomial logit form:

$$\Pi_j = \frac{exp(y - p_j + B - \frac{\phi}{T_j})}{\sum_{k-1}^{n} exp(y - p_k + B - \frac{\phi}{T_k})} \tag{3.2}$$

Recalling that the total consumer population is M, the quantity of passengers for airline j is simply

$$q_j = M\Pi_j \tag{3.3}$$

On the cost side, following Brueckner (2004), but changing the specification of cost per flight to cost per hour, the cost of operating a flight per hour is given by $\theta + \tau s$, where s equals the number of seats on the flight. Each operation hour thus entails a fixed cost θ and also a marginal cost per seat τ. Under such a specification, cost per seat (given by $\frac{\theta}{s} + \tau$ realistically falls with the total number of seat flown per hour. Multiplying the expression by total air time e gives the total air-time cost $e\theta + \tau s$.

In addition to the cost incurred while an aircraft is in the air, the fixed cost per hour (θ) is also incurred when an aircraft is not generating passenger miles (when the aircraft is on the ground). Recalling that the turnaround time (TAT) scheduled for a flight before take-off is T, the total cost of operating a flight is $c(T) = e(\theta + \tau s) + \theta T$, or $c(T) = e\tau s + (e + T)\theta$, where the first term denotes the variable cost per flight, and the second term is the fixed cost per flight. Under this specification, total cost per flight rises with the number of seats on an aircraft and rises if more operation time is required by a flight (if $e + T$ increases).

To account for aircraft utilization in the model, let H denote the total number of hours that an aircraft is "available" in a given period (i.e. a year)[31]. Hence, dividing aircraft availability H by the operation time of a flight ($e + T$) gives the maximum number of flights an aircraft can complete in a given period. Moreover, the total number of flights provided by an airline is the product of the number of aircraft it operates and the maximum number of flights that can be provided by each aircraft, or $fh/(e + T)$, where f represents the number of aircraft operated by the airline. Using this information, the airline's total cost is assumed to be given by

$$c(T) = (e\tau s + (e + T)\theta)\left(\frac{fH}{e + T}\right)^{\alpha} \tag{3.4}$$

where α is the economies of scale parameter. For example, when $\alpha = 1$, the average cost per flight does not rise with the total number of flights operated (the total cost is linear in $fH/(e + T)$. However, when $\alpha > (<)1$, the average cost per flight increases (decreases) when the total number of flights operated increases.

A final assumption in the model is that all aircraft seats are filled, with the load factor equal to 100 percent. Under this assumption, total seats provided by the airline must be sufficient to accommodate its passenger volume, requiring

$$\frac{sfH}{e + T} = q \tag{3.5}$$

Combing the above elements, airline j's profit-maximization problem can be stated. Given that an airline can adjust its flight schedule fairly easily, it may be reasonable to

[31] In the airline industry, H is usually called the aircraft availability (Mirza, 2008).

assume that in maximizing profit to the constraint in (3.5), the airline chooses the fare and the length of turnaround time simultaneously, taking the choices of its competitors as given in Nash fashion. Thus, the problem is

$$\max_{\{p_j,T_j\}} \pi_j = p_j q_j - \big(e\tau s + (e+T_j)\theta\big)\left(\frac{fH}{e+T_j}\right)^{\alpha} \tag{3.6}$$

$$= p_j q_j - \big(e\tau s + (e+T_j)\theta\big)\left(\frac{q_j}{s}\right)^{\alpha} \tag{3.7}$$

$$= p_j M\Pi_j - \big(e\tau s + (e+T_j)\theta\big)\left(\frac{M\Pi_j}{s}\right)^{\alpha} \tag{3.8}$$

where the second equality is derived using (3.5) and the third equality is derived using (3.3).

With the model specification now clear, the first-order conditions are

$$\frac{\partial \pi_j}{\partial p_j} = M\Pi_{\mathrm{j}} + Mp_j\frac{\partial \Pi_j}{\partial p_j} - \left(\frac{1}{s}\right)^{\alpha}\big(e\tau s + (e+T_j)\theta\big)\alpha M\big(M\Pi_j\big)^{\alpha-1}\frac{\partial \Pi_j}{\partial p_j} = 0 \tag{3.9}$$

$$\frac{\partial \pi_j}{\partial T_j} = p_j M\frac{\partial \Pi_j}{\partial T_j} - \left(\frac{1}{s}\right)^{\alpha}\left[\theta\big(M\Pi_j\big)^{\alpha} + \big(e\tau s + (e+T_j)\theta\big)\alpha M\big(M\Pi_j\big)^{\alpha-1}\frac{\partial \Pi_j}{\partial T_j}\right] = 0 \tag{3.10}$$

The second-order conditions $\partial^2\pi_j/\partial p_j^2, \partial^2\pi_j/\partial T_j^2$ are satisfied if $\alpha > 1$ and the remaining positivity condition on the Hessian determinant is assumed to hold. Consider the choice of $T_j$holding p fixed. The first-order condition for T says that the increase in revenue after increasing turnaround time should equal the increase in costs, which consist of the increase in cost per flight and the increase in the total number of flights operated to accommodate the increased number of passengers. While the optimality rule embodied in (3.10) is unsurprising, its usefulness lies in formalizing the trade-off between better on-time performance and higher operation costs.

It is easily verified that, the price sensitivity of each firm's market share with respect to its own price is given by $\frac{\partial \Pi_j}{\partial p_j} = -\Pi_j(1 - \Pi_j)$. Similarly, it can be proven that $\frac{\partial \Pi_j}{\partial T_j} = \frac{\phi}{T_j^2}\Pi_j\left(1 - \Pi_\mathrm{j}\right)$. Moreover, with firm symmetry, the symmetric equilibrium is the natural focus. This equilibrium can be found by setting $p_j = p_k, T_j = T_k, \forall j \neq k$ and $\Pi_j = \frac{1}{n}, \forall j$ in (3.9) and (3.10) and solving for these values. Substituting (3.8) into (3.9), the T_j and p_j solution satisfies

$$p_j = \left(\frac{1}{s}\right)^{\alpha} (e\tau s + \left(e + T_j\right)\theta\alpha \left(\frac{M}{n}\right)^{\alpha - 1} + \frac{n}{n-1} \tag{3.11}$$

$$T_j = \sqrt{\frac{s^{\alpha}\phi n^{\alpha-1}}{\theta M^{\alpha-1}}} \tag{3.12}$$

The optimal T is increasing in the number of seats (s) and the efficiency of turnaround time ϕ, while decreasing in the amount of fixed cost (θ). These results also capture the trade-off between improving service quality (higher T) and the increased cost from the increased cost per flights (longer $(e + T)$) and the requirement of a larger fleet (higher f).

Moreover, the effect of the number of competitors on turnaround time depends on the parameter α. When the cost function exhibits diseconomies of scale $(\alpha - 1 > 0)$, an increase in the number of competitors (n) increases turnaround time (T). However, there has been an ongoing debate over the existence of economies of scale in the airline industry. Caves et al. (1984) show that there is little evidence of economies of scale in the airline industry. However, that paper and others focus on evaluating the economies of scale on the network level instead of the route level. Hence, given the current empirical literature, the magnitude of α and thus the effect of market competition on T is hard to infer. Given this lack of generality, the current analysis should be viewed as only providing an example of how optimal turnaround time can be derived in a full theoretical model, a demonstration that helps to motivate the ensuing empirical work.

A final point is that, the model only considers the decision on the turnaround time at the route level, and the role of network structures and banking behaviors in the choice of buffer time is overlooked. For instance, prolonging buffers for aircraft at a hub airport allows the hub originating flights to “collect" connecting passengers from more arrival flights, which lowers the average cost per seat for the airlines by increasing load factors of the airline-hub originating flights. However, prolonging the buffer time of such flights also induces longer layovers for connecting passengers, hence presenting a new trade-off for the airlines on their decisions on buffer length at hubs. Such issues are explored further in the empirical models.

3.3 Data and variable construction

3.3.1 Dataset

The most important data source for this study is the On-Time Performance Database from Bureau of Transportation Statistics (BTS), which includes data on all non-stop domestic flights operated by airlines carrying more than 1% of US domestic passengers. The 19 reporting carriers during the sample period, Aug 2004-May 2005 were American, Alaska, JetBlue, Continental, Independence, Delta, ExpressJet, Frontier, AirTran, Hawaiian, America West, Envoy, Northwest, Comair, Skywest, ATA, United, US Airways and Southwest. For each flight, the dataset provides the scheduled and actual departure and arrival times, the departure and arrival delays, flight origin and destination, distance, and tail number of the aircraft that flew the flight. A majority of the variables used in the empirical estimation are constructed from the original dataset of 5 million flights during the sample period. For example, the tail numbers are used to reproduce historical aircraft rotations (routes and schedules of a specific aircraft), which is then used to derive the scheduled and actual Turnaround Time (TAT) before each flight, as well as the scheduled buffer time before each flight in the dataset. Due to computational constraints presented by such a large dataset, a 10% sample from the original dataset is randomly selected after all the variables are constructed, reducing the sample size to around 0.5 million.

The On-Time Performance Database has limits that prevent this study from fully reproducing the historical schedule. First, international flights are not included. This is an issue because some airports analyzed in the study are also important international hubs. Thus, the study is missing a proportion of the airlines' scheduled operations as international departures and arrivals at not accounted for. Hence, in this study, buffer time and on-time performance for international flights cannot be observed and no formal conclusion on how international flights are handled in airline scheduling can be drawn. The second limitation of the On-Time database is that it does not include all flights flown domestically, as many small affiliate airlines are not required to report their on-time statistics. Without these affiliate airline flights, market structures including route competition and airport concentration, operation rates and flight frequencies at the origin and destination airports cannot be accurately calculated.

Using the aircraft tail number, the characteristics of the aircraft are known including type of the aircraft and seat capacity.[32] The number of runways of each airport in the dataset is tabulated using the FAA's airport data (from the National Flight Data Center (NFDC)).[33] Finally, daily weather data at both origination and destination airports are collected from the U.S. National Oceanic & Atmospheric Administration (NOAA). [34]

3.3.2 Measuring Turnaround Time and Buffer

The BTS on-time performance data includes reported scheduled gate departure and arrival times, the actual gate departure and arrival times, and the tail number of each flight as a unique identifier for the aircraft. This information is used to construct each aircraft's daily itinerary and to derive the scheduled and actual turnaround times by calculating the elapsed time between the arrival and departure of consecutive flight segments. The same method is employed by Robingson et al. (2011) using Airline Service Quality Performance (ASPQ) data. For example, Table 3.1 shows the BTS flight records from October 28, 2004 for Delta Airlines (DL) tail number N326DL. This aircraft was scheduled to arrive at ORD at 7:48am and to depart ORD to return to ATL at 9:05am, leaving 77 minutes to "turn" the aircraft. Using a similar method, the scheduled and actual TATs are calculated for all flights in the sample period. If the scheduled TAT is greater than 200 minutes,[35] then it is most likely that the previous flight segment of the aircraft happened on the previous day, or that the aircraft was on a flight with international endpoint and hence the record is incomplete,

[32] Since some of the tail numbers in the On-Time dataset are actually fleet numbers (or registration numbers), two websites (rzjet and avitop) are used to recreate the tail numbers of the aircraft (available at http://rzjets.net/aircraft and http://www.avitop.com). Then, the "Landings" database (available at http://www.landings.com) and the FAA aircraft registration database (available at http://registry.faa.gov/aircraftinquiry) are used to find the type of aircraft for each tail number.
[33] Available at http://nfdc.faa.gov/xwiki/bin/view/BFDC/Airport+Data.
[34] Available at http://www.ncdc.noaa.gov/cdo-web.
[35] The maximum turnaround time for a large aircraft type such as the Boeing 747, DC-8 or MD-11 is 180 minutes according to Schaefer and Tene (2003). Allowing for some slack, 200 minutes is used as the cutoff point.

resulting in large TATs. Such TATs were considered invalid and the observations were deleted.

Table 3.1 October 28, 2004 Aircraft Rotation for Delta Airline Tail Number N326DL

Origin	Destination	Scheduled			Actual		
		Depart Time	Arrive Time	Turn Time	Depart Time	Arrive Time	Turn Time
ATL	ORD	6:50	7:48	N/A	6:59	7:50	N/A
ORD	ATL	9:05	12:06	77	9:31	12:18	99
ATL	MKE	12:49	13:49	43	12:55	14:03	36
MKE	ATL	14:55	17:57	66	14:56	18:21	53
ATL	RIC	18:47	20:23	50	19:39	21:15	78

Figure 3.6 shows the distribution of all turnaround times under 200 minutes. The distribution is skewed to the right, with the mean TAT equal to 53.9 minutes and 99% of flights having a TAT greater than 16 min (the 1st percentile of the distribution is thus 16 minutes).

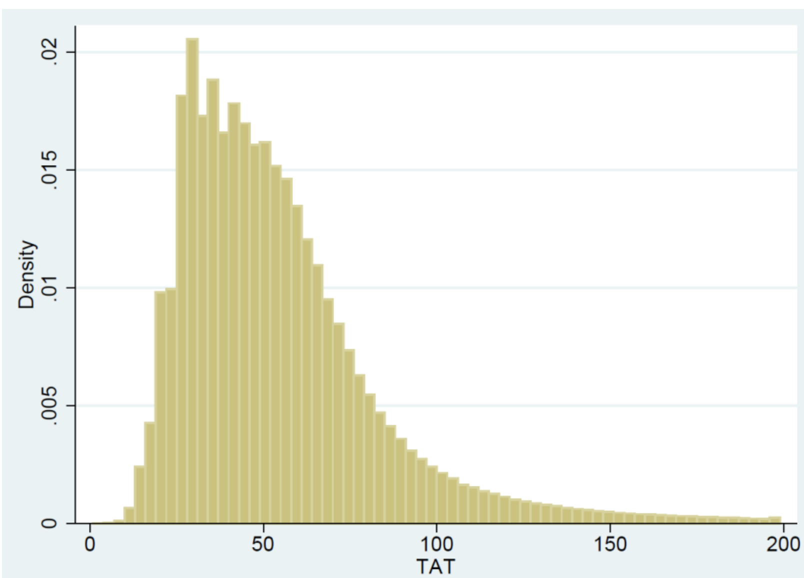


Figure 3.6 Distribution of turnaround times that are less than 200 min

Note that the TAT of a flight depends upon the aircraft type, the airline operating the aircraft and the airport at which the turn occurs. The same logic applies to the minimum TAT. Without official data on airport, airline and aircraft specific-minimum TATs, the BTS dataset is exploited to measure the minimum TAT for each airport-airline-aircraft configuration. The minimum TAT is set equal to the 1st percentile[36] of all the valid actual TATs in a specific airport-airline-aircraft configuration. For example, among all Delta operated Boeing 757-232s (with a passenger capacity of 240) that departed from Atlanta (ATL), 1% of them departed with an TAT of less than or equal to 42 minutes. Thus the minimum TAT for the configuration ATL-DL-Boeing 757-232 is 42 min. Similarly, for a smaller aircraft like the Boeing 737-2H4 (with a passenger capacity of 130) operated by Southwest departing from Houston (IAH), the minimum TAT is 10 minutes. Finally, applying equation (1) the scheduled ground buffer time of a flight was then calculated by subtracting the minimum TAT from the scheduled TAT.

3.3.3 Airport concentration and route competition

To examine the effect of competition on schedule robustness, airport concentration (the HHI based on the share of flights by the various airlines that serve the airport each day) and route competition (the number of airport-pair competitors) are constructed. The role of affiliate airlines in the airline scheduling process is also considered when constructing the two measures since affiliate airlines can make up a large portion of total operations at hub airports.

Affiliate airlines developed in response to the creation of the hub-and-spoke network (Gillen 2005). Since major airlines do not have enough aircraft to serve all the endpoints in their hub-and-spoke networks, they seek arrangements with smaller airlines operating regional aircraft, with these “feeder” airlines “feeding” passengers from smaller

[36] Buffers can also be derived using the a minimum TAT set equal to the 5th percentile. However, the estimation results are qualitatively unchanged. These results are available upon request.

origins/destinations to/from the hubs. To identify partnerships, the regional carrier assignment information provided by Pai (2007) and the annual 10K reports filed each year with the Securities and Exchange Commission for all the carriers are analyzed, and the carriers are regrouped using the assignments in Table 3.2.

Table 3.2 Affiliated Airlines Assignment, Aug 2004 ~ May 2005

Major Carrier	Feeder Airline
United(UA)	Skywest[a]
	Independence Air
American(AA)	Envoy*
Delta(DL)	Independence Air
	Skywest[b]
	Comair*
Continental(CO)	ExpressJet
	Skywest[c]
Southwest(WN)	ATA*

Note : Flights of Independence Air are assigned based on hub identities. Asterisks indicate that the feeder airline is owned by the major carrier.
[a] Including routes involving Portland, OR (PDX), Seatle/Tacomo, WA (SEA), Los Angeles, CA (LAX), Denver, CO (DEN), Chicago, IL (ORD).
[b] Only routes involving Dallas, TX (DFW) for flights in 2004, and routes involving Salt Lake City, UT (SLC) for flights in 2005.
[c] Only routes involving Houston, TX(IAH).

In all, the sample includes 4475 routes and 486 airports. Route competition and airport concentration variables are then constructed using the adjusted carrier identifications. Slightly more than 50% of flights serve monopoly routes, and one third of the flights are on duopoly routes while the rest of the flights are serving routes with more than two carriers. Table 3.3 identifies the major carriers and reports airport concentration, average buffer time and average departure delay for all airports with at least 1 percent of the total flights during the sample period.

Table 3.3 Buffer and Concentration for Airports with at least 1 percent of Flights during Aug 2004 ~ May 2005

Airports	% of Total Flights	Average Buffer (min)	Airport Concentration[a] (flights')	Dominant Carrier	Departure Delay (min)
Atlanta(ATL)	5.95	31.11	0.37	Delta	11.04
Chicago O'Hare (ORD)	4.8	29.62	0.37	American+[b]United	9.73
Dallas-Fort Worth (DFW)	4.51	27.15	0.58	American	6.59
Los Angeles (LAX)	3.26	31.92	0.21	United+Delta	5.94
Houston (IAH)	2.91	36.54	0.52	Continental	3.91
Cincinnati (CVG)	2.9	34.59	0.55	Delta	6.79
Phoenix (PHX)	2.39	22.95	0.26	Southwest	8.45
Las Vegas (LAS)	2.28	20.76	0.22	Southwest	10.21
Denver (DEN)	2.19	30.29	0.38	United	5.88
Newark (EWR)	2.16	31.90	0.44	Continental	8.34
Salt Lake City (SLC)	2.08	30.38	0.26	Skywest	5.13
Washington Dulles (IAD)	2.06	29.72	0.48	United	7.53
Detroit (DTW)	1.99	38.14	0.40	Northwest	5.65
Minneapolis-St.Paul (MSP)	1.97	43.71	0.42	Northwest	3.91
Philadelphia(PHL)	1.83	29.75	0.26	US Airways	13.60
Boston (BOS)	1.83	29.59	0.13	American+Delta	7.01
San Fransisco (SFO)	1.77	38.40	0.29	United	5.65
LaGuadia (LGA)	1.74	31.18	0.16	American+Delta	6.82
Orlando(MCO)	1.61	20.59	0.10	Southwest	7.99
Charlotte (CLT)	1.59	30.92	0.36	US Airways	6.63
Baltimore (BWI)	1.49	16.67	0.22	Southwest	7.05
Seattle (SEA)	1.47	25.35	0.16	Alaska	8.75
Washinton National(DCA)	1.39	29.01	0.21	US Airways	5.04
New York International (JFK)	1.37	30.29	0.11	JetBlue+ExpressJet	3.80
Chicago Mideway (MDW)	1.25	18.63	0.45	Southwest	7.81
San Diego (SAN)	1.22	19.27	0.13	Southwest	6.23
Tempa (TPA)	1.09	20.37	0.08	Southwest	7.27
Oakland (OAK)	0.99	14.95	0.21	Southwest	7.67
Fort Lauderdale (FLL)	0.98	20.42	0.14	Southwest	11.00

[a] Note: The measurement of market concentration is affiliation adjusted so that feeder carriers and its major carrier are considered the same carrier and their total operation at one airport is used to calculate the market share and the market concentration.

[b] Note: "+" here denotes that the airlines have similar shares of total operation at the airport.

Note that the two competition measures capture the effects of competition on service quality from different sources. Route competition captures the direct effect under which non-stop passengers on this route may switch to another airline if their flight is frequently delayed. However, in current hub-and-spoke networks, a large proportion of the passengers are transported from the origin to the destination through connecting flights at the airline's hub. Hence, airlines can compete in the same origin and destination market without operating the same route. As such, competition cannot be captured by the route-competition measure alone, being partially measured by airport concentration.

Airport concentration at the origin affects the available airline choices for all originating passengers. For example, if an airport is served by only one airline (having an airport concentration of 1), then all the passengers in the catchment area of this airport can only travel on this particular airline, regardless of their destination. With other airlines present, passengers unhappy with the on-time performance of a given flight could switch to a connecting (rather than nonstop) flight to their destination. In this way, lower airport concentration can raise competition on a route even while route-level competition itself remains fixed. Another source of competition captured by origin-airport concentration is competition for frequent fliers in the catchment area (Bilotkach & Lakew, 2014), as airlines at less concentrated airports are expected to compete more aggressively for frequent fliers residing in the airport's catchment area.

3.3.4 Other control variables

To isolate the effect of market structure on schedule robustness, it is necessary to control for factors that also affect the choice of buffers. One such variable is a bank departure indicator, which equals one if the flight departs during a bank period. As was mentioned in section 3.2, operational stability and hubbing activities are also interdependent, and flights that depart in a bank at the airline's hub airport may have longer buffers to synchronize the arrival banks and the departure banks. Because of the irregularity in the spacing and length of banks, heuristic procedures for identifying bank flights are developed for this study. The appendix contains a detailed description of the bank identification procedure. In all, around 30% of the flights in the sample were identified as departing their airline’s hub (from which the airline serves more than 26 destinations) during a bank. Among all the flights that depart from their airline's hub, more than 70% depart during a bank period.

Congestion at the origin and sometimes the destination airport is also included as a control variable. Congestion is measured by the operation rate per hour, which divides the airport's daily operations (takes-offs at the origin airport and landings at the destination airport) by the number of runways at the airport. As runway congestion reduces the efficiency of the buffer (with on-time departures becoming less efficient in reducing arrival delays), shorter buffers may be assigned to flights departing or landing during peak hours. In addition, a longer buffer can be crucial for an aircraft departing later in a day as these aircraft are more likely to experience an arrival delay on their previous flight segment. Moreover, for an aircraft flying a longer route (i.e., from the East coast to the West coast), a longer buffer may be required as it takes a longer time to prepare these flights for take-off. For aircraft scheduled to fly “ping-pong" schedules (a daily routing with multiple short-haul flight segments between the hub and non-hub airports), shorter buffers are natural because of the need to operate many segments per day. Hence, the departure hour (measured on a 24-hour clock), flight distance, and flight segments per day (to capture the “ping-pong" effect) are also included as control variables.

3.4 Empirical estimation

3.4.1 Delays and buffer

Before exploring the relationship between market structure and scheduled robustness, it is important to confirm that improving schedule robustness through adding buffers into the schedule can actually reduce delays. Departure and arrival delays happen when the time a flight is ready to take off or land is later than the scheduled time of departure or arrival. In most cases, a flight would choose to depart or arrive on time even if it is ready to depart or arrive before schedule, so that the dependent variables of departure and arrival delays are truncated at zero. Hence, a Tobit model is used to estimate the impact of buffers on delays, aiming at establishing a link between ground buffers and better on-time performance. The empirical Tobit model for the estimation of the impact of buffers on departure or arrival delays of flight i flying from airport j to airport k at time t is:

$$\begin{aligned} delay_{ijkt} = \beta_0 + \beta_1 Buffer_{ijkt} + \beta_2 Prev\_delay_{ijkt} \\ +\beta_3 Orig\_hub_{jt} + \beta_4 Dest\_hub_{kt} \\ +\beta_5 Operation\_rate_{jt} + \beta_6 Operation\_rate_{kt} \\ +\beta_7 SeatCapacity + \beta_8 Distance_i + \beta_9 Dep\_Time_i \\ +\sum_w \omega_w Weather_t + \sum_l \delta_l Carrier_l + \sum_w \gamma_w Day\_of\_week_w \\ +\sum_m \gamma_m Month_m + \sum_n \gamma_n Quarter_n + \epsilon_{ijkt} \end{aligned} \quad (3.13)$$

The control variables include $Prev\_delay_{ijkt}$, which is the arrival delay of the previous flight segment. In addition, delays may also depend on whether an airport is a hub, since hub airports may experience greater delays due to the banking activities by the hub airline (i.e., waiting for connecting passengers). Mayer and Sinai's (2003a) definition for hub airport is used, with airports that serve more than 26 destinations considered hubs. In addition to these control variables, the two congestion measures mentioned above are also included in the regressions. A high operation rate at the origin may produce departure delays, and a high operation rate at the destination may have the same effect, with aircraft subject to origin "ground holds" when the destination is congested.

Important logistical factors such as seat capacity of the aircraft, distance of the flight and departure time are also included as control variables. The control variable $Weather$ is a vector covering the daily weather conditions at both origin and destination airports, including daily precipitation, minimum and maximum temperature, average wind speed and snow depth. To address carrier-specific characteristics and weekly and seasonal demand fluctuations, all estimations include $Carrier_l$, Day_of_week, $Month_m$ and $quarter_n$, which are carrier, day of week, month and quarter fixed effects, respectively. Dummy variables for each origin and destination airport are included in some of the regressions to control for unobserved airport-specific effects that may affect delays, such as runway layout, equipment and maintenance facilities. Note that the hub indicators for the origin and destination airports are dropped in such regressions, as there is not enough variation in hub status over time to identify the airport hub effects. Descriptive statistics for the variables are presented in Table 3.5.

The Tobit results are shown in Table 3.4.[37] The first two columns of the table give the effect of buffers on departure delays, and columns 3 and 4 give the effect of buffers on arrival delays. Origin and destination airport fixed effects are included in the even columns. All the regressions reveal that a longer ground buffer before the scheduled departure time

[37] Estimations for the subset of non-slot constrained airports are also conducted and the results are provided in the Appendix, Table A.1. The four airports during the sample period that operated under the FAA's High Density Traffic Airports Rule (HDR) established in 1969 are ORD (Chicago O'Hare), LGA (Laguadia New York), JFK (New York), and DCA (Washington Reagan), this rule requires that each carrier obtain a "slot" for each take-off and landing during a specific 60 minute period, which may affect the delays experience by flights related to such airport. The results show that excluding the slot controlled airports slightly increases the effect of buffers in reducing departure and arrival delays.}

of a flight reduces departure and arrival delays. In all the regressions, the buffer coefficients are negative with an absolute value smaller than 1 minute, implying that departure or arrival delays decrease by less than 1 minute with a 1 minute increase in the buffer. More specifically, according to the Tobit estimations, a buffer increase of 1 minute is associated with a 0.35 minute reduction in departure delay. The effect of buffers on arrival delay is slightly smaller, implying that, although buffering ground time is useful when preventing the propagated delay from spreading to an aircraft's other flight segments, on-time departure alone does not guarantee on-time arrival of a flight, as other factors like weather and airport congestion occurring after take-off also contribute to arrival delay.

Table 3.4 Tobit Estimation of the Effect of Ground Buffers on Departure and Arrival Delay, 10% sample of U.S. Domestic Flights, Aug 2004 ~ May 2005

Dependent Variable: Minutes of:	Departure Delay				Arrival Delay			
	(1)		(2)		(3)		(4)	
	Coef	Std Error	Coef	Std Error	Coef	Std Error	Coef	Std Error
Ground buffer (min)	-0.35***	(0.01)	-0.35***	(0.01)	-0.24***	(0.01)	-0.23***	(0.01)
Previous delay (min)	0.99***	(0.01)	0.98***	(0.01)	0.90***	(0.01)	0.89***	(0.01)
Hub airport at origination	3.27***	(0.34)			2.43***	(0.41)		
Hub airport at destination	0.00	(0.98)			1.11***	(0.29)		
Operation rate at origination	0.23***	(0.04)	0.33***	(0.04)	0.21***	(0.03)	0.53***	(0.05)
Operation rate at destination	0.06***	(0.01)	0.04**	(0.02)	-0.15	(0.18)	0.06***	(0.02)
Distance (100 miles)	0.29***	(2.58)	0.25***	(2.58)	0.24***	(0.03)	0.32***	(0.03)
Seat Capacity	0.01***	(0.00)	0.01***	(0.00)	0.01***	(0.00)	0.01***	(0.00)
Scheduled departure time	0.57***	(0.03)	0.58***	(0.03)	0.32***	(0.03)	0.40***	(0.03)
Weather	Yes		Yes		Yes		Yes	
Carrier FE	Yes		Yes		Yes		Yes	
Month FE	Yes		Yes		Yes		Yes	
Quarter FE	Yes		Yes		Yes		Yes	
Airport FE	No		Yes		No		Yes	
R square	0.12		0.13		0.08		0.09	
Observations	432,918		432,918		432,918		432,918	

Note: Standard errors are clustered by carrier, month and year (i.e Delta August 2004). Hubs are defined as airports that serve more than 26 markets. Operation rate is calculated by dividing the total number of flights per day by the number of runways at the orgin or destination airport. Scheduled departure time are measured by a 24 hour clock. Airport fixed effects are included in even columns, and hub airport indicators are dropped in even columns as there is little variation through out time for these variables.
* Significant at the 10% level
** Idem. 5% level
*** Idem. 1% level

The coefficients on the arrival delay from the previous flight segment are positive and significant, as expected. Increasing the arrival delay of the previous flight segment by 1 minute increases the departure delay of the next flight operated by the same aircraft by as much as 0.9 minutes, which indicates that delay propagation is a major factor in departure delays. Hubbing at the origin airports also contributes to departure and arrival delays, as flights with a hub-airport origin experience 3 more minutes of departure delay. The coefficients for the operation rate at the origin airport is positive and significant: adding one flight per runway can increase the departure delay and arrival delay of flights by around 0.2-0.5 minutes, while the effect of runway congestion at the destination is much smaller. Such results imply that runway congestion, especially runway congestion at the origin airport, has a strong impact on the length of delays. The coefficients for distance are positive, so that longer flights are more likely to be delayed (increasing the distance of a flight by 100 miles increases the departure delay by 0.3 minutes). The coefficients on the scheduled departure hour are positive, implying that both departure delays and arrival delays increase as a day progresses onward, so that flights departing later during a day experience more delays than flights departing early in the morning.

Table 3.5 Descriptive Statistics

Variables	Description	Mean	Std
Dep_delay	Difference between the actual departure time and the scheduled departure time	9.274	27.386
Arr_delay	Difference between the actual arrival time and the scheduled arrival time	10.892	28.612
Buffer	The excess turnaround time over the minium possible time	26.097	22.978
Prev_delay	Arrival delay of the previous flight in an aircraft rotation (not applicable to the first flight in an aircraft rotation)	9.524	24.873
Bank_flight	Dummy variables=1 if the flight depart from a bank of its airline's hub	0.315	0.463
Airp_conc_orig	Airport concentration (HHI) at the origin airport of flight	0.337	0.177
Route_competition	Number of competitors on the route of flight	1.696	0.842
Orig_hub	Dummy variable=1 if the origin airport is a hub	0.744	0.493
Dest_hub	Dummy variable=1 if the destination airport is a hub	0.744	0.493
Operation_rate_orig	The origin airport's hourly operations divided by the number of runways at the scheduled departure time of flight	5.925	4.233
Operation_rate_dest	The destination airport's hourly operations divided by the number of runways at the scheduled arrival time of flight	8.271	9.956
Distance	Length of flight in miles	7.144	5.687
Dep_time	Scheduled time of departure of the flight	13.130	4.647
Segment	Total number of flight segments scheduled in the day for the aircraft used by flight	5.568	2.159
Orig	Dummy variables indicating the origin airport of flight	NA	NA
Dest	Dummy variables indicating the destination airport of flight	NA	NA
Carrier	Dummy variables indicating the airline that flew flight (adjusted for affiliated airline)	NA	NA
Month	Month of flight	NA	NA
Day_of_week	Dummy variables indicating the day of the week of flight	NA	NA
Quarter	Dummy variables indicating the quarter of flight	NA	NA
Prcp_orig	Precipitation level at the origin airport on the day of flight	25.170	81.878
Snow_orig	Snow level at the origin airport on the day of flight (tenths of mm)	1.820	13.128
Tmax_orig	Maximum temperature at the origin airport on the day of flight	149.016	616.17(
Tmin_orig	Minimum temperature at the origin airport on the day of flight	84.557	90.494
Awnd_orig	Average wind speed at the origin airport on the day of flight(tenths of meters per second)	36.968	16.564
Prcp_dest	Precipitation level at the destination airport on the day of flight	25.263	82.430
Snow_dest	Snow level at the destination airport on the day of flight (tenths	1.794	12.907
Tmax_dest	Maximum temperature at the destination airport on the day of flight	185.488	96.584
Tmin_dest	Minimum temperature at the destination airport on the day of flight	84.478	90.611
Awnd_dest	Average wind speed at the origin airport on the day of flight (tenths of meters per second)	36.977	16.605

3.4.2 Delays and buffer

With the results in the previous section confirming that schedule robustness can effectively improve on-time performance, this section explores the main focus of this study: the effect of airport concentration and route competition on schedule robustness, as measured by buffers. The central question then is: all else equal, will competition increase or decrease the length of buffers and thus schedule robustness? An underlying assumption is that airlines, operating flights on a daily basis, can learn firsthand how many flights other airlines operate and when. Using information on the amount of traffic, market structure at the origination and destination airports, competition at route level, departure time, day of the flight, and the type of aircraft, the hub carrier can adjust the length of the buffer of each flight.

3.4.2.1 Empirical model

a.. Baseline estimation

To estimate how the length of buffers of flight i departing from airport j to airport k at time t varies with the market structure, variations of the following baseline equation are estimated:

$$\begin{aligned} Buffer_{ijkt} = \beta_0 + \beta_1 Airp\_Conc_{jt} + \beta_2 Route\_Compet_{jkt} \\ + \beta_3 Bank\_flight_{jt} + \beta_4 Operation\_rate_{jt} \\ + \beta_5 Aircraft_{char} + \beta_6 Route_{char} + \sum\nolimits_c \sigma_c Carrier_c \\ + \sum\nolimits_w \gamma_w Day\_of\_week_w + \sum\nolimits_m \gamma_m Month_m + \sum\nolimits_n \gamma_n Quarter_n \\ + \gamma_y Yeat2005 + \sum_j \phi_j Origin_j + \sum_k \phi_k Dest_k + \epsilon_{ijkt} \qquad (3.14) \end{aligned}$$

As described in section 3.3, in addition to market structure measures, variables that could affect carriers' decisions on buffer times are included. These factors include the bank-departing flight indicator, the operation rates at the origin airport, as well as aircraft characteristics variables (seat capacity and the type of engine) and route characteristics, including scheduled departure time, flight distance, and the total number flight segments each day scheduled for the aircraft used by flight i. Again, all estimations include carrier, day-of-week, month and quarter fixed effects. As buffer choices are likely to be clustered due to unobserved influences like carrier experience or previous weather conditions, standard errors are clustered into the following groups: carrier × month × year (i.e., Delta August 2004). Basic descriptive statistics of all the variables are also presented in Table 3.5.

In this set of regressions, airport fixed effects are also added to control for unobserved airport-specific effects that may affect buffer choices, such as equipment, airport facility and the airport's position in the carrier's network. Since these variables eliminate any time-invariant airport specific effects, identification of the coefficients is driven by the variation in variables within, not across, airports and routes. For instance, the coefficient on airport concentration reveals how buffers respond to changes in concentration at the endpoint airports of a route over time, not how buffers respond to differences across airports. Note that as the market structure measures are constructed daily and the panel is sufficiently long, within-route variation in the key market structure measures is enough for identification of market-structure effects.

b. Hub vs. non-hub originating flights

According to Mirza (2008), buffer (and turnaround time) for flights departing a hub may be longer to allow for synchronization between the feeder network and trunk routes. However, longer turnaround times at the hub airport usually mean a longer connecting time for passengers (Geodeking 2010) as aircraft will have to wait longer on the ground, shifting the departure bank away from the previous arrival bank and prolonging bank length. This relationship between buffers for hub departure flights and bank length (reflecting average layover times of the passengers) at hubs is depicted empirically in figure 3.7, where bank length is calculated heuristically using the method described in the appendix. As these longer layovers may generate disutility for the passengers, buffer decisions for flights leaving a hub also take into consideration the trade-off between bank synchronization (lower cost through economies of density) and longer layovers (less demand). With such considerations, the sources of service competition is different for flights flying different routes: while passengers on a flight originating from the airline's hub airport care about both layover time and on-time performance, passengers on a flight originating from a non-hub airport are mostly local passengers who only care about on-time performance. Consequentially, the market-structure/schedule-robustness relationship may be different between flights originating from the airline's hub airport and flights originating from a non-hub airport.

In order to test the above prediction and better understand the effect of market structure on buffers at the network level, the main sample is supplemented by a sub-sample including flights destined for non-hub airports. As passengers on such flights are terminating, not connecting at the destination, possible hubbing activities are not considered by airlines when making the buffer choice for these flights. Moreover, in regressions using the sub-sample, interaction terms between an airline-hub-originating indicator variable (equal to 1 if the flight originates from the airline's hub) and the market-structure variables are added to the baseline estimation, so that the difference in market structure's effect on schedule robustness between airline-hub originating flights and non-hub originating flights can be captured.

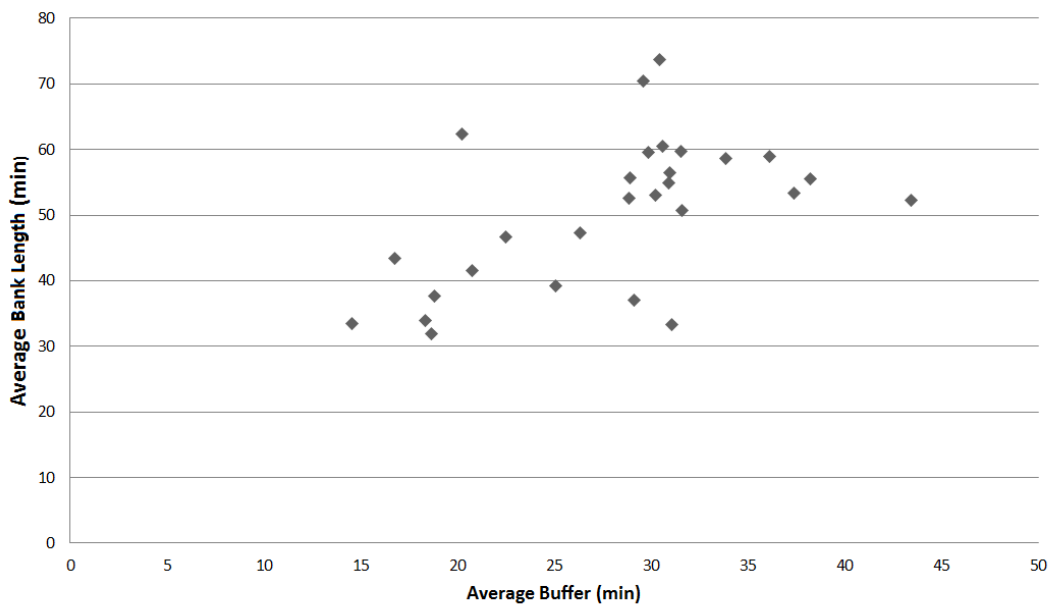


Figure 3.7 The Relationship between Airport Average Buffer Time and Average Bank Length for the 30 Biggest Airports in the US. This figure displays a strong positive relationship between the buffer times of flights departing these airports and bank length. Bank length is derived using a peak and trough identification algorithm described in the appendix A.3.1

3.4.2.2 Results

a. Baseline estimation

Results for the baseline estimations are shown in Table 3.6.[38] While column 1 and 2 only include one of the two market-structure measures, column 3 includes both measures in the estimation. The most noteworthy finding from Table 3.6 is that, when market structure becomes more competitive (airport concentration decreases or route competition increases), longer buffers are chosen. Numerically, when market concentration at the origin airport decreases by 0.1, buffer time increases by around 1.3 minutes. Moreover, an increase of one competitor on a route would cause the carriers to increase the buffer of the flights on this route by around 0.4 minutes. The results thus show evidence of service competition in the airline industry, as competition drives the carriers to improve the robustness of their schedules and thus on-time performance. Moreover, recall that, in the theoretical model presented in section 3.2, buffer increases with the number of competitors on a route when $\alpha > 1$ is satisfied. Therefore, the empirical positive effect of competition on the buffer is consistent with decreasing returns of scale in the number of flights on a route.

There are no surprises present in the coefficients for control variables. The regression reveals that flights departing in a bank period at the airline's hub experience around 2.7 minutes of additional buffer time, confirming the argument that flights are waiting longer at the hub airport to synchronize the arrival and departure banks, "collecting" passengers and thus increasing load factors. Increasing the operation rate at the origin airport shortens buffers, as congestion on the origin runways reduces the efficiency of buffers in limiting departure delays. Aircraft configurations also affect the choice of buffer length. Larger aircraft are given less buffer time, probably because the long minimum turnaround

[38] Estimations for the subset of non-slot constrained airports are also conducted. However, the results are qualitatively unchanged. These results are available upon request.

time assigned for these larger aircraft makes buffers less important. Turboprops are scheduled longer buffers probably because such aircraft are sometimes not assigned a gate after they land, so that longer buffers are needed to control for such an uncertainty. Other control variables all show the expected signs. Flights that depart later in a day, or flights flying a longer distance are given longer buffers, and aircraft flying more segments per day are given shorter buffers, probably due to their demanding schedules. Although not shown in the tables, the signs of the carrier fixed effects also show expected signs and magnitudes, with the hub-and-spoke carriers like United, American, Delta, Continental and Northwest scheduling longer buffers, and low cost carriers like Southwest and JetBlue scheduling shorter buffers.

Table 3.6 The Effect of Market Structure on Ground Buffer, 10% sample of U.S. Domestic Flights, Aug 2004 ~ May 2005

	Dependent Variable: Minutes of Ground Buffer					
	(1)		(2)		(3)	
	Coef	Std Error	Coef	Std Error	Coef	Std Error
Market Structure						
Airport concentration at origin	-13.67***	(2.54)			-13.11***	(2.54)
Route competition			0.48***	(0.13)	0.40***	(0.12)
Banking and Congestion						
Depart in a bank	2.70***	(0.30)	2.79***	(0.31)	2.77***	(0.30)
Operation rate at origin	-0.15***	(0.06)	-0.15**	(0.06)	-0.15***	(0.06)
Aircraft Charateristics						
Seat capacity	-0.01***	(0.00)	-0.01***	(0.00)	-0.01***	(0.00)
Turboprop	6.90***	(0.72)	7.06***	(0.72)	7.00***	(0.71)
Route Characteristics						
Scheduled departure hour	0.45***	(0.03)	0.45***	(0.03)	0.45***	(0.03)
Distance	0.18***	(0.02)	0.19***	(0.02)	0.19***	(0.02)
Segment	-1.95***	(0.13)	-1.97***	(0.13)	-1.95***	(0.13)
Fixed Effect						
Carrier FE	Yes		Yes		Yes	
Day of Week FE	Yes		Yes		Yes	
Month FE	Yes		Yes		Yes	
Quarter FE	Yes		Yes		Yes	
Year FE	Yes		Yes		Yes	
Airport FE	Yes		Yes		Yes	
Observations	432,918		432,918		432,918	
R-squared	0.18		0.18		0.18	

Note:Standard errors are clustered by carrier, month and year (i.e Delta August 2004). Operation rate is calculated by dividing the total number of flights per hour by the number of runways at the orgin or destination airport. Segment is the total number of flight segment served by an aircraft per day.

* Significant at the 10% level

** Idem. 5% level

*** Idem. 1% level

b. Hub vs. non-hub estimations

Taking into consideration the network effect on schedule decisions, Table 3.7 gives the results after sub-sampling flights heading toward a non-hub airport and including interaction terms between the origin airline-hub indicator and the market structure variables from the baseline model. Several stylized facts appear from the tables. First, similar to the results obtained in the baseline model; lower market concentration and higher route competition are associated with longer buffers for flights destined for non-hub airports. Numerically, a flight between two non-hub airports experience an additional 2.3-2.6 minutes additional buffer, when the origin airport market concentration falls by 0.1. Moreover, a flight between two non-hub airports with one more competitor serving the same route is given around 0.8-1 minutes more buffer. Note that the market structure effects in this sub-sample almost double the effect estimated in the baseline model. Therefore, it appears that the results for the full sample estimation are mainly driven by flights with passengers terminating at the destination.[39] While passengers care most about the on-time arrival performance at their final destination (arriving late at a hub for connecting trips may not generate disutilities for the passengers, as long as the delays do not lead to missed connections), it is expected that service competition is the fiercest on routes where most of the passengers are terminating at the destination.

Second, as predicted in section 3.4.2.1, the association between buffers and competition is slightly weakened for flights departing from an airline's hub airport, as the signs of the coefficients on the interaction terms are the opposite of those on the market structure variables, reducing the effects. According to column 3 in Table 3.7, hub originating flights

[39] Regressions using flights destined for the airline-hub airport shows that origin airport concentration has little effect on buffer choices. These results are available upon request.

are scheduled around 2.2 more minutes[40] of additional buffer time when the origin airport market concentration falls by 0.1. Similarly, the effect of an extra route competitor reduces to around 0.4 minutes for hub originating flights. Although the individual coefficients on the interaction terms in column 1 and column 2 are insignificant, an F-test also finds joint significance of sum the market structure coefficient (airport concentration or route competition) and the interaction term coefficient for each regression. The above results provide some evidence that airlines are less motivated to compete via on-time performance on routes originating from the airline's hub, since longer buffers for such flights improve on-time performance, at the expense of prolonging layover time, which reduces the utility of connecting passengers.

[40] The effect of market concentration on buffer for flights originating from the airline-hub airport is calculated as follows: $(-26.09 + 5.85) * 0.1 = 2.24$ minutes.

Table 3.7 Sub-sample Estimation of the Effect of Market Structure on Buffer with Interaction Terms

	Dependent Variable: Minutes of Ground Buffer					
	(1)		(2)		(3)	
	Coef	Std Error	Coef	Std Error	Coef	Std Error
Market Structure and Interaction Terms						
Airport concentration at origin	-23.45***	(3.68)			-26.09***	(3.85)
Route competition			0.81***	(0.21)	0.99***	(0.25)
Airport concentration at origin * airline hub at origin	2.00	(1.72)			5.85***	(2.03)
Route competition * airline hub at origin			-0.06	(0.26)	-0.55*	(0.31)
Congestion						
Depart in a bank	1.77***	(0.38)	2.02***	(0.38)	1.86***	(0.38)
Operation rate at origin	0.00	(0.06)	0.01	(0.06)	0.00	(0.06)
Aircraft Charateristics						
Seat capacity	-0.03***	(0.00)	-0.03***	(0.00)	-0.03***	(0.00)
Turboprop	10.81***	(0.91)	11.10***	(0.91)	11.02***	(0.91)
Route Characteristics						
Scheduled departure hour	0.44***	(0.03)	0.44***	(0.03)	0.44***	(0.03)
Distance	0.13***	(0.03)	0.14***	(0.03)	0.14***	(0.03)
Segment	-2.38***	(0.18)	-2.41***	(0.18)	-2.37***	(0.18)
Fixed Effect						
Carrier FE	Yes		Yes		Yes	
Day of Week FE	Yes		Yes		Yes	
Month FE	Yes		Yes		Yes	
Quarter FE	Yes		Yes		Yes	
Year FE	Yes		Yes		Yes	
Airport FE	Yes		Yes		Yes	
Observations	328,364		328,364		328,364	
R-squared	0.13		0.13		0.13	

Note:Standard errors are clustered by carrier, month and year (i.e Delta August 2004). Airline hubs is defined as dummy variable that equal to one if the carrier serves more than 26 destinations at the airport. Operation rate is calculated by dividing the total number of flights per hour by the number of runways at the airport. Segment is the total number of flight segment served by an aircraft per day.
* Significant at the 10% level
** Idem. 5% level
*** Idem. 1% level

3.4 Conclusion

This chapter differs from most studies examining on-time performance in the airline industry in one important way. Instead of looking at how market structure directly affects on-time performance at the route level, this study asks how carriers adjust their schedule robustness when market structure changes, recognizing that schedule robustness is an important factor affecting the flight on-time performance.

To answer this question, the chapter first recreates each flight's ground buffer time from historical flight schedules, using it as a measure of schedule robustness. Examining the relationship between on-time performance and buffers of flights confirms that lack of schedule robustness is a major culprit in producing delays.

Further examining the relationship between buffers and market structure shows that there exists service-quality competition in the airline market, with carriers adopting more robust flight schedules when competition heats up. Furthermore, examining the association between competition and schedule robustness using interaction terms shows that market structure's effect on buffer choices is slightly attenuated for hub-originating flights.

Such results shed new light on the debate in the internalization literature, where some empirical evidence fails to support the basic prediction that more-concentrated airports should have better on-time performance. While congestion externalities can be internalized when an airport is dominated by one carrier, this study shows that airport domination may also induce worse on-time performance as the dominant carriers reduce their schedule robustness, hence offsetting the probable improved on-time performance brought about by internalization.

Appendix 3:

Because of the irregularity in the spacing and length of banks, heuristic procedures for identifying bank characteristics are developed for this study.

For each hub airport, and each major carrier in the hub airport, the total number of departure and arrival flights for each 5 minutes is derived using the BTS dataset. Then, as depicted by Figure A.3.1, a 1-hour moving average (MA) is calculated to smooth out the flight frequency time series. The smoother MA is then compared with the daily mean of flight frequency per 5 minutes. A peak occurs when the MA is higher than the daily mean of the departure frequency (the constant threshold) while trough occurs when the MA is lower than the daily mean. The algorithm then locates the point with the minimum MA level for each trough period, and these minimum points are identified as the “cutoff points” between banks, and the length of time between the cutoff points is derived and considered the length of a bank. However, without further constraint, it is possible that two cutoff points are extremely close to each other if the MA process exhibits a volatile fluctuation, as in the cases illustrated by the black circles in the upper panel of Figure A.3.1. Hence, to eliminate such cases, the second cutoff point is deleted if the time gap between two points is within 1 hour.

In all, around 30% of the flights in the sample were identified to be departing their airline's hub (an airport serving more than 26 destinations for the airline) during a bank. The average departure bank length is around 110 minutes (less than 2 hours), so that on average, a hub would operate around 10 banks per day (assuming it operates from 6am to 11pm).

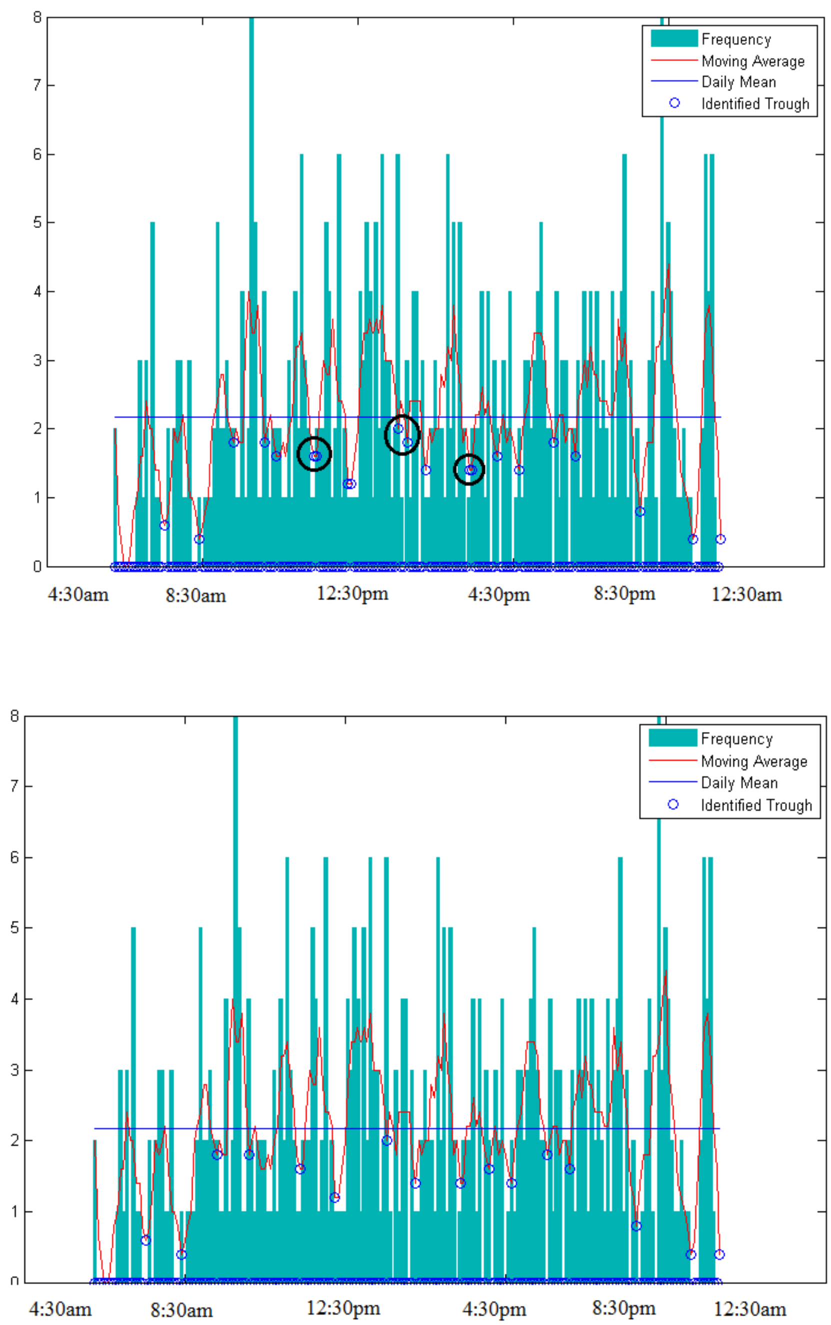


Figure A.3.1: Departure Bank of AA at DFW on 08/01/2004. The figure illustrates the algorithm used to identify banks in DFW, where AA operates as a hub-carrier. The smooth line depicts the 1 hour moving average based on the hub-carrier number of departing flights.

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