THREE ESSAYS ON URBAN PUBLIC TRANSIT SYSTEMS IN THE U.S.

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The Supervisory Committee certifies that this ***disquisition*** complies with North Dakota State University's regulations and meets the accepted standards for the degree of

DOCTOR OF PHILOSOPHY

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ABSTRACT

Public transportation is a critical component of urban communities and plays an important role in facilitating mobility which is integral to economic development and the quality of life of urban residents. In recent years, urban transportation has evolved rapidly with the emergence of transportation network companies (TNCs) and e-commerce that drastically transformed urban living. The availability of TNCs has given consumers more transportation options. However, the implications of TNCs on public transit ridership are unknown. In addition, the rising online shopping trend has drastically reduced the businesses of brick-and-mortar retailers, but does the shift in consumer shopping behavior reduce the demand for public transit?

The objective of this dissertation is to address the following three research questions: (1) How is U.S. public transit ridership impacted by the rise of TNCs? (2) How have transit subcontracting (or purchased transportation) and TNC partnership affected transit productivity in recent years? (3) Has increased online shopping reduced the demand for public transit service?

The key findings of my study are: (1) transit effectiveness of both bus and rail transits declined over the study period; (2) TNC availability increased rail transit ridership in 2015; (3) transit effectiveness was highly significant for public transit, and when examining its effect year-by-year, rail transit effectiveness trumped TNC availability; (4) TNCs are neither a complement nor a substitute of bus transit; (5) for bus transit agencies, outsourcing or purchased transportation is associated with negative efficiency and productivity changes; (6) although purchased transportation has a positive effect on technological change for bus transit, the effect is not significant; (7) TNC partnerships also have a negative effect on efficiency and productivity changes in bus transit; (8) there is a positive significant relationship between shopping mall visits and public transit use; (9) however, the effect of mall visits on transit use is small relative to the

effects of car ownership; (10) taken together, the marginal effect of car ownership is 9 times larger than the effect of mall visits on transit use.

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DEDICATION

To my parents

Vijith and Champika Malalgoda

To my brother

Naveendra Malalgoda

To my wife

Maneka Malalgoda

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CHAPTER 1. INTRODUCTION AND OBJECTIVES

1.1. Overview

In this dissertation, I attempt to address the following three questions:

(1) What is the effect of the rise of transportation network companies on U.S. public transit ridership?

(2) What is the effect of transit subcontracting (or purchased transportation) and TNC partnership on transit productivity in recent years?

(3) What is the effect of online shopping on the demand for public transit service?

The introductory chapter provides an overview of the three essays.

1.2. Research Objectives

1.2.1. Essay 1: Do Transportation Network Companies Reduce Public Transit Use in the U.S.?

The rise of Uber and other transportation network companies (TNCs) in recent years has revolutionized urban transportation across the globe. Most noticeably, the increased popularity of Uber and other TNC services coincides with the declining trend of public transit ridership in the U.S. The impact of Uber on urban public transit needs to be carefully evaluated in light of the potential implications of any future policy changes in transit funding and planning. Using top 50 U.S. agency-level data from 2007 through 2017, this study examines the effect of Uber and transit effectiveness on public transit ridership in the U.S. The objective of this paper is to evaluate the impact of transit operational effectiveness and TNC availability on public transit ridership in major U.S. metropolitan areas. Specifically, I seek to answer the question of whether transit ridership trends in recent years were a result of transit providers' own performance, or if they were a result of TNCs' expanded presence. Simply put, was the driving factor of declined ridership internal or external, or could it be both?

The vast U.S. public transit systems are highly heterogeneous in operations and structures. This study focuses on the 50 largest transit agencies in the U.S. from 2007 to 2017. Out of the top 50 transit agencies, 32 agencies have functional rail services, while 45 transit agencies provide bus services. Using sequential data envelopment analysis (DEA), I first examine the operational performance or the effectiveness of rail and bus transit services over time. After that, I estimate a fixed effects regression model to determine the effects of operational performance and TNC availability on transit ridership. The results suggest that transit effectiveness is highly important for rail transit. The presence of TNC did not immediately lead to higher rail ridership, however, I observed some evidence of higher rail ridership in 2015 associated with TNCs in major U.S. metropolitan areas except New York City. Rail ridership increases were observed in 2016 and 2017, but this could be a result of the year-specific effects. Lastly, the influence of transit effectiveness on rail transit trumped that of TNCs. TNCs are neither a complement nor a substitute of bus transit.

1.2.2. Essay 2: Productivity Growth of Urban Transit Agencies in the U.S.

In recent years, TNCs have become a key transportation options in major metropolitan areas in the U.S. As new mobility service providers emerge, many public transit agencies in the U.S. have partnered, or are in the process of partnering, with them. The reasons for such partnerships can vary between increasing cost effectiveness, application of innovative ideas, avoiding large capital investments in park-and-ride facilities and providing more transportation options for existing and/or new transit customers. When these partnerships are formed and implemented in transit service provisions, they are reported to the Federal Transit Administration as purchased transportation for the specific transit agency. However, the implications of purchased transportation and TNC partnerships on transit productivity has not been previously examined. This essay assesses the productivity of U.S. urban public transit using data from the 45 largest bus agencies and 32 rail agencies in from years 2007 through 2017. I calculate the Malmquist productivity index of these agencies and decompose the index into technical efficiency change and technological change components. Following this, I conduct a regression analysis to determine the effects of purchased transportation and TNC partnerships on transit productivity growth and its two components.

I find that that both bus and rail transit agencies have experienced declining cumulative productivity growth during the study period. For bus transit agencies, outsourcing or purchased transportation is associated with negative efficiency change. Although purchased transportation has a positive effect on technological change for bus transit, the effect is not significant. The results suggest that transit agencies that seek to partner with shared-mobility service providers or to integrate shared-mobility with transit service must address challenges that hinder transit efficiency, and that transit technology has yet to keep up with technological progress in urban mobility.

1.2.3. Essay 3: Effect of Online Retailers on Transit Ridership in the U.S.

The rapid rise of online retailing especially in the last decade is having significant impacts on long established traditional business models as well as consumer behavior. The gradual shift towards online shopping has the potential to impact urban transportation but the implication is not well understood. According to Hortaçsu and Syverson (2015), online shopping may have reduced public transit use, as many consumers will prefer to shop from the comfort of their homes and have the products delivered to their doorsteps. Online shopping has not only impacted traditional retail stores but shopping malls which hosts many retailers at once. Many shopping malls in the U.S. and Europe has been impacted by lower foot traffic of customers which has lead mall closures (Ferreira and Paiva, 2017). Approximately 3,800 mall closures were reported around the world by 2005 (Garrefa, 2011), while Moccia (2012) found that nearly 7% of the malls in the U.S. were economically obsolete. In addition, due to advancements in e-commerce, consumers now have the opportunity search online for products of interest and learn about bargains as well as new retailers. In this context, e-commerce has the potential to result in more shopping trips because of the information on the internet, and to increase the length of trips due to the most appealing bargains being located in different regions (Choo and Mokhtarian 2004; Farag et al. 2006).

This essay attempts to determine how online shopping activities in general impact the use of public transit by consumers. Since nearly 21 percent of trips made using public transit is for shopping purposes, it is of interest to determine if online shopping activities may have led to an increase or a decrease in public transit ridership in the U.S. A bivariate probit model is used to determine the effect online shopping on mall visits and how mall visits affect transit use in 2012-2015 in the U.S.

1.3. Key Research Findings

The key findings are: (1) transit effectiveness of both bus and rail transits declined over the study period; (2) TNC availability increased rail transit ridership in 2015; (3) transit effectiveness was highly significant for public transit, and when examining its effect year-by-year, rail transit effectiveness trumped TNC availability; (4) TNCs are neither a complement nor a substitute of bus transit; (5) for bus transit agencies, outsourcing or purchased transportation is associated with negative efficiency and productivity changes; (6) although purchased transportation has a positive effect on technological change for bus transit, the effect is not significant; (7) TNC partnerships also have a negative effect on efficiency and productivity changes in bus transit; (8) there is a positive significant relationship between shopping mall visits and public transit use; (9) however, the effect of mall visits on transit use is small relative to the effects of consumer's car ownership; (10) taken together, the marginal effects of driver's license and auto insurance possessions contribute to a total of 32.9% lower probability of transit use among online shoppers; this effect is 9 times larger than the effect of mall visits on transit use.

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CHAPTER 2. DO TRANSPORTATION NETWORK COMPANIES REDUCE PUBLIC TRANSIT USE IN THE U.S.?[1]

2.1. Abstract

The rise of transportation network companies (TNCs) in recent years has revolutionized urban transportation across the globe. Most noticeably, the increased popularity of TNC services coincides with the declining trend of public transit ridership in the U.S. The impact of TNCs on urban public transit needs to be carefully evaluated in light of the potential implications of any future policy changes in transit funding and planning. Using top 50 U.S. agency-level data from 2007 through 2017, this study examines the effect of TNCs and transit effectiveness on public transit ridership in the U.S. We find that (1) transit effectiveness of both bus and rail transits declined over the study period; (2) TNC availability increased rail transit ridership in 2015; (3) transit effectiveness was highly significant for public transit, and when examining its effect year-by-year, rail transit effectiveness trumped TNC availability; (4) TNCs are neither a complement nor a substitute of bus transit.

2.2. Introduction

The rise of transportation network companies (TNCs)[2] in recent years has jolted and revolutionized urban transportation across the globe. More than doubling their services since 2012, TNCs transported more than 2.6 billion passengers in the U.S. in 2017 (Schaller, 2018). Most noticeably, the increased use of TNC services has resulted in a precipitous fall in the

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[1] The material presented in this chapter was co-authored by Malalgoda, N. and Lim, S. Malalgoda had primary responsibility for collecting data and performing the analysis. Malalgoda also drafted and revised all versions of this chapter. This chapter has been published in *Transportation Research Part A: Policy and Practice* (Malalgoda and Lim, 2019).

[2] Uber, Lyft and other ride-hailing companies are defined by the California Public Utilities Commission as transportation network companies (TNCs) in 2013 (Clewlow and Mishra, 2017). TNCs are also called ride-hail or rideshare companies (Schaller, 2018).

demand for taxicab services in major cities,[3] prompting protests by taxi cab owners/operators and even an outright or a partial ban by some governments or courts. Because TNCs do not fall under strict regulatory and licensing requirements that traditional taxi companies encounter, this has paved way for the former to gain a price advantage over the latter.[4]

The increased popularity of TNC services in the U.S. also coincides with the decline in public transit use, which because of government subsidies, has been traditionally a cheaper alternative to taxi despite their different service characteristics.[5] Rapid adoption of TNC services gives rise to more empirical and policy questions on the declining trend of public transit ridership in the U.S. Major cities like New York, Los Angeles, Chicago, Austin, and Washington, D.C., where public transit is the most common transportation mode, all underwent decreases in transit ridership despite heavy subsidization in the transit sectors. Decline in

[3] Cramer and Krueger (2016) found that Uber drivers achieve a substantially higher capacity utilization rate than taxi drivers. "Capacity utilization is measured either by the fraction of time that drivers have a fare-paying passenger in the car or by the fraction of miles that drivers log in which a passenger is in the car (Cramer and Krueger, 2016, page 177). Except in New York City, the capacity utilization rates between taxi drivers and Uber drivers are similar. The other 4 cities where observed disparities in capacity utilization are large are Los Angeles, San Francisco, Boston and Seattle.

[4] The taxicab industry is heavily regulated by local governments. In New York City, for example, taxi fares or metered rates are regulated by the Taxi and Limousine Commission. In contrast, price per TNC ride may vary depending on the timing of ride demand. For example, Uber adopts a price surge strategy, so when there are not enough drivers/vehicles to meet the rising demand for rides, the rates that passengers pay are higher than the standard rates. This rate flexibility allows TNCs to price according to changes in the supply and demand. Taxi fares, on the other hand, are set by local governments, and do not respond to changes in the market. Apart from regulations, TNCs also enjoy a cost advantage over taxicabs in part due to their dispatch platform technology. See Edelman and Geradin (2016) for a detailed discussion on how the technology enables TNCs to produce more efficiently than traditional taxicab operations. Lastly, the lower price of Uber's ride service is due to it being subsidized by the company (Bond, 2018) to increase sales and market share, and to drive out competitors.

[5] Without government subsidies, the cost of public transit would be much higher for the general public (Button, 2010). For example, in 2017, passenger fares accounted for 32% of operating funds, while federal, state and local assistances accounted for 63.3% of the transit operating funding, and another 4.7% of funding came other non-fares revenue sources generated by transit operators (Federal Transit Administration, 2018). Hence, subsidies are crucial for maintaining the lower fares for passengers. Taxi companies, on the other hand, are privately owned and operated. The number of taxi licenses is restricted by city governments. Hence, taxicab licenses are very costly in some cities, which result in high costs of entry and operations for taxicab companies and for drivers who lease the taxicabs. Taxi fares, which follow a block-pricing method, are necessarily higher than transit fares for the taxicab drivers or operators to receive a profit. Unlike public transit, taxicab services do not have a fixed route or schedule, and they fill the service gap of public transit by offering point-to-point and flexible-route services.

ridership could further snowball because the decreasing number of passengers translates into a reduction in fare revenues, which in turn could lead to either fare increases and/or eliminations of low-performing routes. If fares are increased and services are reduced, ridership will continue to fall. According to Puentes (2017), all but seven of the country's largest urban areas lost riders in 2014 and 2016. The decrease in public transit use and the rise of TNC services have become a major challenge for governments and public transit agencies as they seek to device effective policies to reduce congestion and facilitate mobility in urban areas.

However, the effect of TNC services on public transit ridership is yet to be carefully examined (Puentes, 2017). Are TNC services the culprit of transit ridership decline, or is transit ridership decline independent of TNC services? In other words, do TNC services steer passengers away from city buses and rail? The answers to these questions have important implications for governments at all levels, both within and outside the U.S. Outside the U.S., TNCs have also penetrated urban markets in South and Central America, Europe, Africa, and Asia. Other similar companies such as, China’s Didi Chuxing and India’s Ola have recently expanded beyond their countries’ borders into Australia; a Singapore-based Grab is dominant in Southeast Asia. All these companies are rising key providers of transportation network services in major urban markets. Their presence and expansions in cities not only change the way people travel but also have implications on public transit systems.

Meanwhile, when attempting to study the declining ridership, one should not look at the effect of TNCs (an external factor) in isolation because the operational performance of transit services could be an important factor determining ridership. Ineffective transit service not only results in a waste of public resources but also signals transit mismanagement or inefficient operational practices that may lead to reduced ridership as consumers turn to more efficient means of transportation that are economical and convenient. Because public transit is an essential service that facilitates mobility and reduces congestion and pollution (Davis and Hale, 2007; Schrank et al., 2011; Federal Transit Administration, 2016), it is imperative that when we examine the impact of TNC services on public transit ridership, the operational performance of transit agencies is also carefully evaluated in light of the potential implications of any future policy on transit funding and planning.

The objective of this paper is to evaluate the impact of transit operational effectiveness and TNC availability on public transit ridership in major U.S. metropolitan areas. Specifically, we seek to answer the question of whether transit ridership trends in recent years were a result of transit providers' own performance, or if they were a result of TNCs' expanded presence. Simply put, was the driving factor of declined ridership internal or external, or could it be both?

The vast U.S. public transit systems are highly heterogeneous in operations and structures. This study focuses on the 50 largest transit agencies in the U.S. from 2007 to 2017. Out of the top 50 transit agencies, 32 agencies have functional rail services, while 45 transit agencies provide bus services. We first examine the operational performance or the effectiveness of rail and bus transit services over time. After that, we estimate a fixed effects regression model to determine the effects of operational performance and TNC availability on transit ridership. The results suggest that transit effectiveness is highly important for rail transit. The presence of TNC did not immediately lead to higher rail ridership, however, we observed some evidence of higher rail ridership in 2015 associated with TNCs in major U.S. metropolitan areas except New York City. Rail ridership increases were observed in 2016 and 2017, but this could be a result of the year-specific effects. Lastly, the influence of transit effectiveness on rail transit trumped that of TNCs. TNCs are neither a complement nor a substitute of bus transit.

2.2.1. Public Transit Ridership Decline and the Rise of Transportation Network Services

Public transit ridership has declined in many metropolitan areas in the U.S. (Mallett, 2018). Data from the National Transit Database (NTD) shows that between 2007 and 2017 bus transit agencies in the U.S. experienced a nearly 12% decline in the number of passenger miles traveled (APTA, 2007; APTA, 2017).[6] According to Mallett (2018), there is no comprehensive explanation for the overall decline, and the national trends may not necessarily reflect situations at the local level. In spite of that, transit ridership declines may be explained by two factors in general (Mallett, 2018).

The first factor is the availability of other transportation options. The cost of personal vehicle ownership is relatively low in the U.S. compared to other countries. Mallett (2018) found that, between 1969 and 2009, the share of households without a vehicle decreased from 21% to 9%. Puentes (2017) and Mallett (2018) both noted that low fuel prices may also be part of the reason that contributed to the switch from public transit to personal vehicle use.

The second factor, according to Mallett (2018), is the public transit service itself, and declines in ridership were particularly evident in places where service problems were observed. For example, operational deficiencies and safety issues in transit systems led to service disruptions and declined ridership in Washington, DC, and New York City in recent years.[7] In addition, access to transit such as distance to a transit stop, hours of service and service frequency also influence people's decision to take public transit. Carrel et al. (2013) found out through a survey that the most significant negative factors that drove the reduction in public transit use were delays perceived to be the fault of the transit agency, long waits at transfer

[6] From 21 billion passenger miles in 2007 down to 18.5 billion passenger miles in 2017.
[7] Recent events include a weeks-long shutdown of a portion of the Metrorail system in June 2016, and infrastructure-related problems and network congestions led to subway service disruptions in New York City.

points, and being prevented from boarding due to overcrowding. Throughout the years, inconveniences, uncertainty and opportunity costs of time associated with unreliable service have drawn many customers away from public transit. Transit reliability is crucial for these agencies to identify and evaluate internal inefficiencies, reduce operator costs, and improve transit revenue (Diab et al. 2015).

In recent years, the establishment and expanded presence of TNCs, such as Uber and Lyft, are among the top policy issues in major metropolitan areas. These two companies, which originated from San Francisco, have transformed urban transportation in hundreds of cities around the world. Although TNC ridership has grown rapidly in many metropolitan areas, Mallett (2018) reported that the effect of TNCs on transit ridership is unclear. TNC services could be a complement to public transit at times and locations where transit service is not available.

In a survey study conducted in San Francisco, Rayle et al. (2014) examine whether TNC services complement or substitute public transit and their potential impact on passenger miles traveled. Their results suggest that TNC services fill the gaps in point-to-point travel in urban areas. Most of the trips made by TNC customers would have taken longer time if public transit was taken. While the majority of the respondents reported that they used TNC services for leisure and social purposes, some respondents reported that they used TNC services to get to a transit stop. Also through survey studies, Shared-Use Mobility Center (SUMC, 2016 & 2018) find that TNC services are mostly used between 10 pm and 4 am and especially on weekends when public transit is either unavailable or infrequent. Thus, instead of competing for the same riders during the day, public transit and TNCs may be complementary since they serve different trip types. SUMC (2016) also find that using TNC services for commuting occurs only occasionally among those surveyed. The study also reports that people turn to TNC services after alcohol consumption. However, Brazil and Kirk (2016) found no evidence of causal relationship between Uber and traffic fatalities in top 100 metropolitan areas in 2009 and 2014.

A recent metropolitan-level study by Hall et al. (2017) find that TNCs are a complement for the average transit agency. They conclude that the entry of Uber has increased public transit use for the average transit agency. In addition, the effect of Uber is larger in bigger cities and for smaller transit agencies. However, Clewlow and Mishra (2017), through a survey targeting residents in seven major U.S. cities,[8] report findings that are contrary to those of Hall et al. (2017). Based on the results of their survey, they find that there is an approximately 6% net reduction in transit use after the initiation of TNC services. Hence, they argue that TNC services may not be a complement to public transit, however the demand for TNC services may vary depending on the type of transit service in question. Specifically, Clewlow and Mishra (2017) find that TNC services attract people away from bus services and light rail but increase their use of commuter rail. According to them, people in general substitute TNC services for public transit because transit services are too slow, or lack available stops. In addition, the survey respondents also report that transit services are not available during their travel times, and they also perceive transit services as unreliable. According to Schaller (2018), if TNC services were not available, about 60% of TNC customers in large metropolitan areas would have used public transit, walked, biked or refrained from making the trip. Limited parking and the lack of good and reliable public transportation are among the key factors that may have contributed towards the success of TNC services.

[8] Boston, Chicago, Los Angeles, New York, San Francisco/Bay Area, Seattle, and Washington, DC.

The TNC industry is becoming a challenge to traditional transportation systems like public transit and taxicab services (Clewlow and Mishra, 2017). Although the earlier years of TNC operations were less regulated, the nature of TNCs has prompted many states to establish policy to maintain the safety of riders and to assess its effect on other transportation modes. By the end of 2017, 48 states and Washington, D.C. had passed some sort of legislation regulating TNCs. Oregon and Vermont remain as the only states, where Uber-like companies have unlimited freedom in doing business (Texas A&M Transportation Institute, 2017). Mallett (2018) cautioned that the decisions of some transit agencies to work with TNCs to provide first-mile/last-mile services could be a concern in the future because TNCs appeared to have subsidized their services by charging a fare at only 60% of the trip cost. If they were to charge a price to breakeven, TNCs may no longer be an attractive alternative to public transit (Mallett, 2018).

2.2.2. Transit Effectiveness

Past studies that examined the operational performance of public transit have attempted to differentiate transit effectiveness from transit efficiency (Chu et al., 1992; De Borger et al., 2002; Karlaftis, 2004) because of the various definitions or measures of transit output. According to De Borger et al. (2002), transit outputs have in the past been measured by either supply indicators, such as vehicle-miles or seat-miles, or by demand indicators like passenger miles or number of passengers. There were arguments for or against the two measures, and no consensus was reached.

Hatry (1980) argued that the distinction between transit effectiveness and efficiency matters when it comes to assessing local government's performance and accountability to the public. According to Hatry (1980, page 312), "the term 'efficiency' refers to the relation of the amount of input required to the amount of output produced. ‘Effectiveness’ refers to the impacts and quality of the service delivery, whether the service achieves its purpose, and how responsive it is to community needs.” Chu et al. (1992), for example, attempted to develop an efficiency index and an effectiveness index for transit agencies. Using a supply indicator as the output measure, the efficiency index that Chu et al. (1992) estimated sought to answer questions concerning the productive or technical efficiency of transit service or whether resources are used efficiently. In addition, using a demand indicator as the output measure, the effectiveness measure developed by Chu et al. (1992) provided a sense of “how effective a transit agency is in having its transit service consumed (page 225).”

While there appears to be no consensus on which measure should be preferred, De Borger et al. (2002) argued that demand factors should be more relevant because it takes the objectives and economic motives of transit agencies into account, and if demand is ignored, then the most “efficient” firms may be the ones that provide services that nobody wants. In other words, overlooking transit effectiveness when studying ridership could erroneously suggest that the most efficient operators could be those whose buses are vacant (Croissant et al. 2013).

In the context of our study, transit effectiveness is paramount, because transit users typically are not concerned about whether transit input use is minimized at a given level of vehicle-miles supplied, or whether the number of vehicle-miles is stretched to the maximum at a given level of input use. They are, however, concerned about whether transit agencies are delivering services that they want. Thus, we focus on transit effectiveness, as opposed to transit efficiency, as a potential factor of ridership, especially given that the use of demand-related indicators more closely reflects the level of service actually used.

The transit effectiveness index can be estimated via data envelopment analysis (DEA) (Chu et al. 1992, Karlaftis, 2004; Karlaftis and Tsamboulas, 2012). DEA is a non-parametric method that is based on input and output data.[9] We apply a sequential DEA method to obtain the effectiveness index. The advantage of using sequential DEA, as opposed to a traditional contemporaneous DEA[10], is that sequential DEA enables us to construct the current period transit technology using data represented in all past periods and up to the current period. This means that the transit technologies that were used in the past periods are still in or available for use at present (Tulkens and Vanden Eeckaut 1995). In other words, the benchmarking exercise using sequential DEA allows an agency to not only compare its own performance with the performance of its counterparts but also its own performance in the past. Additionally, the use of sequential DEA index also addresses the issue of potential contemporaneous (causality) relationship between ridership and the effectiveness index since the index is derived from reference sets of past and current data, while ridership is measured only by current-year data.

In our sequential DEA model, there are t time periods. In time period s, we have J_s transit agencies, $s = 1, \dots, t$. We assume that transit agencies use $n = 1, \dots, N$ inputs to produce $m = 1, \dots, M$ outputs. Now, let $\mathbf{X}_{\theta t}$ and $\mathbf{Q}_{\theta t}$ be, respectively, the $N \times 1$ input quantity vector and the $M \times 1$ output quantity vector of agency θ in period t. Additionally, we denote $\mathbf{X}_{\theta s}$ as the sequential $N \times s$ matrix of N inputs used and $\mathbf{Q}_{\theta s}$ as the sequential $M \times s$ matrix of M transit outputs produced by transit agencies in each of the periods $s = 1, \dots, t$. Let $\mathbf{X}_s = \{\mathbf{X}_{1s}, \dots, \mathbf{X}_{\theta s}, \dots, \mathbf{X}_{J s}\}$ be an $N \times \sum_{s=1}^{t} J_s$ matrix of N inputs used by J_s agencies in each of the

[9] The advantage of using DEA is that, unlike its parametric counterpart -- the stochastic frontier analysis (SFA) method, DEA does not require any a priori assumptions about the distribution of the efficiency (effectiveness) term in the model.

[10] The frontier of contemporaneous DEA envelops the observations under study in the current period only (Shestalova, 2003).

periods, $s = 1, \ldots, t$. Next, let $\mathbf{Q}_s = \{\mathbf{Q}_{1s}, \ldots, \mathbf{Q}_{\theta s}, \ldots, \mathbf{Q}_{Js}\}$ be an $M \times \sum_{s=1}^{t} J_s$ matrix of M outputs produced by all J_s agencies in each of periods, $s = 1, \ldots, t$. Thus, the matrices $\mathbf{X}_s$ and $\mathbf{Q}_s$ are sequential because they include data for all agencies in periods 1 through t. We can compute the sequential input-oriented transit effectiveness of agency θ by solving the following linear programming problem:

$$
\begin{gathered}
[D_t(\mathbf{Q}_{\theta t}, \mathbf{X}_{\theta t})]^{-1} = \min_{\pi, \lambda_s} \pi \\
\text{subject to } \pi \mathbf{X}_{\theta t} \geq \lambda_s \mathbf{X}_s, \\
\lambda_s \mathbf{Q}_s \geq \mathbf{Q}_{\theta t}, \\
\lambda_s \geq 0, \\
\textstyle\sum_i \lambda_{is} = 1, \quad i = 1, \ldots, \sum_{s=1}^{t} J_s. \qquad (2.1)
\end{gathered}
$$

The value of π is between 0 and 1. An agency that is fully operationally effective relative to its peers and itself in the past would have $\pi = 1$. If π is less than 1, then the agency is less than fully effective. For example, if $\pi = 0.75$, that means the agency could use 25% less input without reducing transit consumption. Alternatively, we can also compute the sequential output-oriented transit effectiveness of agency θ by solving the following linear programming problem:

$$
\begin{gathered}
[D_t(\mathbf{Q}_{\theta t}, \mathbf{X}_{\theta t})]^{-1} = \max_{\eta, \lambda_s} \eta \\
\text{subject to } \mathbf{X}_{\theta t} \geq \lambda_s \mathbf{X}_s, \\
\lambda_s \mathbf{Q}_s \geq \eta \mathbf{Q}_{\theta t}, \\
\lambda_s \geq 0, \\
\textstyle\sum_i \lambda_{is} = 1, \quad i = 1, \ldots, \sum_{s=1}^{t} J_s. \qquad (2.2)
\end{gathered}
$$

The value of η is also between 0 and 1. If η = 1, the agency is considered operationally effective. If, for example, η = 0.87, then the agency could achieve 13% more transit consumption without additional input.

In models (1) and (2), agencies use 3 inputs (number of employees, total vehicle operating hours and fuel) to produce transit service measured by total passenger miles, which is the cumulative total of distances traveled by each passenger on transit vehicles (APTA 1994). Both full time and part time employees as well as permanent and temporary employees are included in the number of employee counts. Vehicle operating hours, commonly known as platform time, represents the actual hours that a vehicle travels from the time it pulls out from its garage to go into revenue service, to the time it pulls in from revenue service. Fuel represents the total fuel consumption of the transit agency. All gallons of fuel, including diesel, biodiesel and kWh of electricity, were converted into BTUs. Since the effectiveness indices from (1) and (2) were derived using sequential data, agency θ's index in year *t* reflects how effective it operates relative to its peers and including itself in all preceding time periods.

2.3. Conceptual Framework and Model

Demsetz (1973) and Peltzman (1977) theorize that more efficient firms tend to grow more, because they are able to better-serve customers, or they have a better way to produce a good or service. The same notion can be extended to understanding the relationship between transit service effectiveness and ridership. Specifically, changes in ridership may be a reflection of how well the city’s transportation needs are met by public transit given the transportation options within the market. Agencies that have chronic ineffectiveness may see declines in transit ridership especially when an alternative to public transit becomes available.

Microeconomic demand theory provides a solid conceptual framework to transit demand analysis. Besides TNC's, socio-economic, urban and transit characteristics jointly determine the demand for public transit, and the relative effects of these factors are usually determined by a transit demand function (Berechman, 1993). There are a variety of transit demand models and demand modeling techniques due to the types of transit data. In general, transportation demand may be developed based on either an aggregate (market) modeling approach or a disaggregate (individual) modeling approach (Kanafani, 1983; Winston, 1985; Oum, 1989; Berechman, 1993). The former requires data that are more easily attainable, but are insensitive to the transit mode. The latter, on the other hand, requires detailed data on travel choices of individuals in addition to other individual-specific, mode-specific, and/or even travel- or route-specific data which may not be attainable (Winston, 1985; Oum, 1989; Berechman, 1993).[11] If the purpose of a study is to predict aggregate changes in volumes, then the natural and more preferred choice is to use aggregate data (Oum, 1989), and the demand functions can be specified independent of supply factors, or as equilibrium functions based on equilibrium analysis of supply and demand (Berechman, 1993).

A direct approach to modeling transit demand is relating the number of passenger trips to a set of demand and supply factors (Kraft and Wohl, 1967) using either individual or market level data (Kanafani, 1983). In addition, given the objective of this study, it is also necessary to consider "demand cross-relations" among competing or complementary services (Kraft and Wohl, 1967). Since the data for this study are available at the agency-level, we conduct a market-

[11] Domencich and McFadden (1975) provide a detailed discussion on urban travel demand models and urban transportation planning models; note that they are different from transit demand models.

level analysis. Based on consumer theory, the general structure of transit demand function with cross-relations between transit and TNC services is given by

$$R = f(V, Eff, F, Z_1, \dots, Z_K), \tag{2.3}$$

where R is measured by total unlinked passenger trips, V is the availability of TNC, Eff is a transit performance indicator, F is the average transit fare, and $Z_1, \dots, Z_K$ are other control variables including transit, passenger and urban characteristics (Berechman, 1993).

If transit agencies are effective in producing transit service, then Eff is expected to have a positive effect on R. According to demand theory, if TNC was a competing service, then V would have a negative effect on the number of transit passenger trips, since the availability of TNC reduces the volume of transit demand. If TNC was complementary to public transit service, the effect of TNC would be positive.[12]

To explicate the relationships between TNC and transit ridership, the general form of demand function (3) can be expressed in various functional forms. The most common forms of transit demand functions are of linear, multiplicative and exponential specifications, as well as demand models that incorporate any of the three functional forms (Kraft and Wohl, 1967; Domencich et al., 1968; Kanafani, 1983). Each of these forms yields its own behavioral interpretation, and the choice of model therefore must be based on a ratiocinative predication of the causal relationships between the variables in the model (Kanafani, 1983). For example, the linear demand function assumes that the determinants of transportation demand have independent additive effects, the multiplicative demand function implies that the effects of the determinants on demand are not independent, and the exponential demand function combines the

[12] Ideally, a more appropriate measure of V is the price of TNC service. But the data on the TNC quantity (ridership) and TNC charges per trip for each of the metropolitan areas are not accessible to us, the TNC price variable is thus proxied by the availability of TNC service.

features of the two previous functional forms. The factors in demand equations, such as (3), are usually not mutually independent (Kanafani, 1983), as such a linear demand functional form would not be realistic since the parameters associated with the explanatory variables in a linear equation do not depend on each other.[13]

Based on the conceptual framework developed by Quandt and Baumol (1966) and Quandt and Young (1969) for passenger travel demand, the multiplicative and exponential forms of equation (3) are given respectively by

$$R = \alpha \cdot V^{\beta_1} \cdot Eff^{\beta_2} \cdot F^{\beta_3} \cdot Z_1^{\gamma_1} \dots Z_K^{\gamma_K},$$

and

$$R = \alpha \cdot \exp(\beta_1 V + \beta_2 Eff + \beta_3 F + \gamma_1 Z_1 + \cdots + \gamma_K Z_K),$$

where the parameters can be obtained by log-transforming the equations and estimating them respectively as

$$\ln(R) = \ln\alpha + \beta_1 \ln V + \beta_2 \ln Eff + \beta_3 \ln F + \gamma_1 \ln Z_1 + \cdots + \gamma_k \ln Z_k, \qquad (2.4)$$

and

$$\ln(R) = \ln\alpha + \beta_1 V + \beta_2 Eff + \beta_3 F + \gamma_1 Z_1 + \cdots + \gamma_k Z_k. \qquad (2.5)$$

The parameters in equation (4’) yield elasticity measures which are useful for result interpretation, while the parameters in equation (5’) yield semi-elasticity measures.[14] However, since V is a binary variable that takes on values 0 and 1, equation (4) needs to be modified (Quandt and Young, 1969). Quandt and Young (1969) proposes a modification that combines the multiplicative form in (4) with the exponential form in (5). The hybrid form is thus given by

$$R = \alpha \cdot \exp(\beta_1 V)\, Eff^{\beta_2} \cdot F^{\beta_3} \cdot Z_1^{\gamma_1} \dots Z_K^{\gamma_K}.$$

---

[13] Demand functional forms and features are discussed in depth in Appendix A.

[14] The resulting elasticity measures in equation (4’) are constant, while the elasticity values resulting from equation (5) depend on the value of the variable in question. Appendix A provides the details.

To estimate the parameters, equation (6) can be log-transformed (Quandt and Young, 1969) into

$$\ln(R) = \ln\alpha + \beta_1 V + \beta_2 \ln Eff + \beta_3 \ln F + \gamma_1 \ln Z_1 + \cdots + \gamma_K \ln Z_{K.} \tag{2.6}$$

Equation (2.6) is a more common demand functional form due to it being less restrictive than equations (2.4) and (2.5) and its ability to incorporate dummy variables as well as variables that have non-positive values (Domencich et al., 1968; Quandt and Young, 1969). Based on equation (2.6), the regression model to examine the relationship between TNC and transit ridership in major cities in the U.S. is thus:

$$\ln(R_{it}) = \beta_0 + \beta_1 TNC_{it} + \beta_2 \ln(Eff_{it}) + \beta_3 \ln(F_{it}) + \sum_{k=1}^{K} \gamma_k \ln Z_k + Year_t + Agency_i + \varepsilon_{it}, \tag{2.7}$$

where $\beta_0 = \ln\alpha$, R_{it} is annual transit ridership of agency *i* in year *t*; the variable Eff_{it} is the sequential transit effectiveness index of agency *i* in year *t;* TNC_{it} is a binary variable, which is equal to 1 if TNCs are present in the metropolitan area served by agency *i* in year *t* and zero otherwise. Officially launched in San Francisco in 2010, Uber was the first TNC in the country. Uber and its major competitor Lyft (launched in 2012) spread rapidly to many metropolitan areas thereafter. By 2014, TNCs had covered major metropolitan areas in the U.S. except a few urbanized areas such as Portland, Oregon, and Las Vegas, Nevada.[15] The variable F_{it} is the average transit fare of agency *i* in year *t*, and it is measured by fare per unlinked passenger trip. The variables Z_k include transit and city characteristics variables; $Year_t$ are year fixed effects; $Agency_i$ are agency fixed effects; ε_{it} are the error term.

[15] Besides the binary variable *TNC*, one may also consider the actual TNC ridership data as an alternative determinant in equation (3). But unlike public transit data, TNC ridership data are proprietary. The authors had contacted Uber and Lyft to request for the data, but we did not receive a response.

The parameter β_1 is of interest, since TNCs could have either a negative or positive effect on ridership, and β_1 yields the semi-elasticity of ridership with respect to a unit change in TNC.[16] The parameter β_2 is expected to have a positive effect on ridership since we expect higher transit effectiveness to draw more passengers. According to demand theory, the parameter β_3 should be less than zero, and it measures the price elasticity of demand, that is the percentage change in transit demand with respect to a percentage change in fare.

Annual transit ridership is measured by annual unlinked passenger trips. Each time a passenger boards a public transit vehicle, it is considered an unlinked passenger trip. The American Public Transportation Association (APTA, 2018) uses unlinked passenger trip as a measure of transit ridership. Other independent variables in Z_k include ln(*employee*) and ln(*vehicle hours*). The variables ln((*employee*) and ln(*vehicle hours*) are transit-related; the former reflects the size of transit operations and the latter captures the extent of transit availability; both variables are expected to have a positive effect on ridership. Other explanatory variables that were considered but dropped subsequently due to the lack of statistical significance include population size, population density, real gasoline price, per capita income, car registrations, average fleet age, subsidy/revenue ratio, etc. Population size and population density are control variables for metropolitan characteristics. Real gas prices are an indirect measure of the cost of driving. We also considered per-capita income as a proxy for car ownership in the metropolitan areas since car ownership tends to be positively associated with income (Dargay, 2001). If income rises, car ownership is expected to go up, leading to lower transit ridership. But we found this variable to be statistically insignificant. We also attempted to use the number of

[16] $\%\Delta Ridership \approx (100 \times \beta_1)\times \Delta TNC.$

vehicle registrations, and it too was insignificant.[17] Hence per capita income and vehicle registrations were not included in our final models. Average fleet age controls for transit equipment reliability and serves as a proxy for service reliability and quality; subsidy/revenue ratio provides a measure of the extent of subsidization on rides. These two transit-related variables were insignificant as well. The variables in Model (7) are summarized in Table 2.1 below.

Table 2.1. Variable descriptions

Variable	Definition	Source
R	Ridership measured by unlinked passenger trips	USDOT National Transit Database
fuel	Measured in BTU. Total usage of diesel, gasoline, liquefied petroleum gas, bio diesel and other fuel by individual transit agencies.	USDOT National Transit Database
empcnt	Total operating employee count	USDOT National Transit Database and transit agencies
vhours	Vehicle hours, which is the hours that a vehicle travels from the time it pulls out from its garage to go into revenue service to the time it pulls in from revenue service.	USDOT National Transit Database
population	Population of each urbanized area	Bureau of Economic Analysis
TNC	Dummy variable indicating if TNCs existed at a certain year or not in each urbanized area of interest	Brazil and Kirk (2016)
Eff	Sequential transit effectiveness	Authors
fare	Average transit fare = Total Fare Revenue/# Passenger Trips	USDOT National Transit Database and authors' calculations

[17] Car ownership could be measured by the number of vehicle registrations. However, metropolitan-level data on the number of car registrations are not publicly available. As an alternative measure, we obtained the number of vehicle registrations at the state level and multiplied that value by the ratio of the population in the metropolitan area to that of the state to get the metropolitan-level estimate.

The use of a TNC dummy variable in equation (2.7) allows us to compare changes in transit ridership in cities where TNCs are present to ridership changes in cities without TNCs. Since TNC's availability in the U.S. metropolitan areas differed by timing, we need to account for its increased popularity and public acceptance over time. In addition, since the effect of TNCs may proliferate at different rates after its initial introduction we also account for its impacts in the long term, and to allow the effects of TNCs to differ by year, the following regression model is specified:

$$\ln(R_{it}) = \beta_0 + \sum_{t=2010}^{2017} \beta_t \,(TNC_i \times Year_t) + \delta \ln(Eff_{it}) + \tau \ln(F_{it}) + \sum_{k=1}^{K} \gamma_k \ln Z_k + Year_t + Agency_i + \varepsilon_{it}, \tag{2.8}$$

where β_t measures the effect of TNCs in year t relative to the period before 2010 or prior to TNC's existence.

The previous two regression models assume the effect of transit effectiveness on ridership to be the same every year. Thus, to examine the effects of transit effectiveness that may vary by year, we also estimate the following:

$$\ln(R_{it}) = \alpha + \sum_{t=2008}^{2017} \delta_t \,(\ln(Eff_{it}) \times Year_t) + \beta TNC_{it} + \tau \ln(F_{it}) + \sum_{k=1}^{K} \gamma_k \ln Z_k + Year_t + Agency_i + \varepsilon_{it}, \tag{2.9}$$

where the coefficients δ_t measures the impact of effectiveness on ridership for each year relative to the base year, 2007.

2.4. Empirical Data

The majority of the data was obtained from the FTA's National Transit Database (NTD), which was established in 1974 to serve as a repository of data on financial, operating and asset information of transit systems in the U.S. Transit agencies who are recipients or beneficiaries of grants from the FTA are required to report their operating financial and asset information for inclusion in the NTD. Currently, over 850 transit providers report their data online. According to Schaller (2018), 70% of TNC trips are concentrated in large, densely populated areas. Thus, the 50 largest transit agencies based on ridership size were considered in this study. The panel data used in this analysis are from 2007 to 2017. Out of the top 50 transit agencies, we separated the data according to the service mode.

Forty-five transit agencies which provided bus services were considered as one category. MTA Long Island Rail Road, Northeast Illinois Reg. Commuter Rail Corp., Port Authority Trans-Hudson Corp., and San Francisco Bay Area Rapid Transit District were dropped since they did not provide bus services in the sample. Puerto Rico Highway and Transportation Authority was dropped due to data unavailability. The 45 agencies are listed in Table B1 in Appendix B. Separately, we also study transit agencies that provide rail services in the U.S. Thirty-two of the top transit agencies were providers of light rail (LR), commuter rail (CR) and heavy rail (HR) services. These agencies are listed in Table B2 in the same appendix.

Figure 2.1 displays the total annual ridership of these agencies by transit mode. Both rail and bus ridership appear to move in locked steps before 2010, the year corresponding to the introduction of TNCs. Figure 2.2 reports the annual percentage changes in transit ridership. An increase of 10.2% in rail ridership was observed between 2007 and 2017, however negative rail ridership changes were observed in 4 of the 10 years. Rail transit ridership appeared to have peaked at 4.8 billion unlinked passenger trips in 2014, with an annual growth rate of about 3% in the same year. But rail transit ridership declined subsequently for 3 consecutive years from 2015 to 2017. Bus transit ridership, on the other hand, was down by 15.7% between 2007 and 2017. In fact, bus transit agencies had fewer riders in 2017 than they did in all previous years in the study period. Annual percentage changes in bus ridership were negative in 8 of the 10 years (see Figure 2.2), and the largest single-year decline (-5.5%) was observed in 2017.

Table 2.2 provides the summary statistics of the data for the sampled bus and rail transit agencies in metropolitan areas with and without TNCs. For both bus and rail modes, the average ridership is larger in metropolitan areas with TNCs. Additionally, the average population size of metropolitan areas with TNCs are also considerably larger. This is possibly due to the strategy of TNCs such as Uber who prioritize entry into markets with larger populations (Hall et al., 2018). In this regard, these metropolitan areas tend to have larger transit operations as evidenced by the vehicle hours in operations and the transit employee counts.

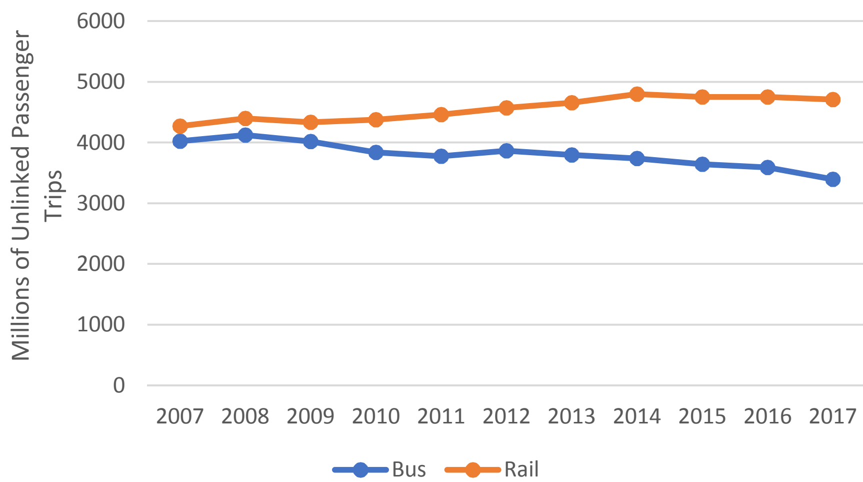

Figure 2.1. Annual ridership by mode, 2007 – 2015

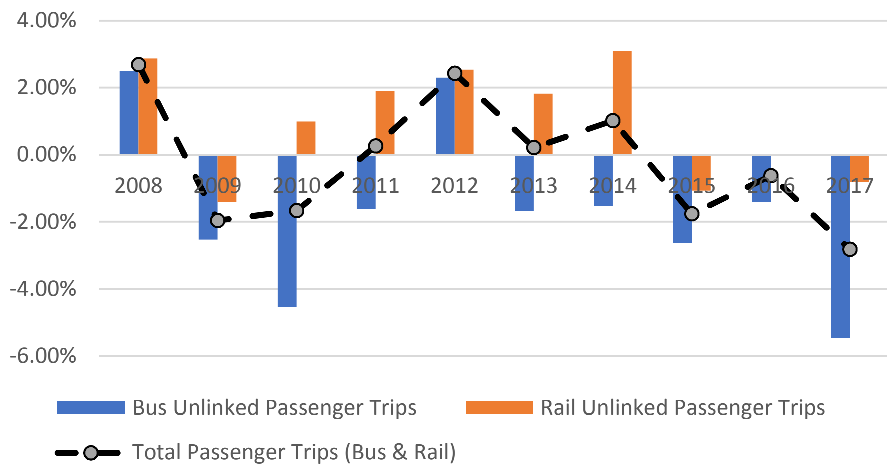

Figure 2.2. Percentage change in transit ridership by mode and year

Table 2.2. Summary statistics for agency-year sample by mode, 2007-2017

	Bus			
	Without TNC (NOBS = 250)		**With TNC (NOBS = 245)**	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
Passenger Miles (mil)	291.00	319.00	318	350
Unlinked Passenger Trips (mil)	84.80	126.00	101.0	141
vhours	2245808	2267693	2459543	2544487
empcnt	2993.36	5443.24	4146.16	7897.89
fuel (mil)	999.00	986.00	1020	1120
fare	1.435	0.921	1.892	1.371
income	45393.71	6824.77	55886.96	9777.38
population	5658555	5470232	8158601	7099496

	Rail			
	Without TNC (NOBS = 169)		**With TNC (NOBS = 183)**	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
Passenger Miles (mil)	702.00	1570.00	1120.00	2080.00
Unlinked Passenger Trips (mil)	109.00	364.00	176.00	499.00
vhours	1244999	3084347	1874259	3808982
empcnt	1594.01	2591.25	3312.46	5913.50
fuel (mil)	733.00	1260.00	1140.00	1430.00
fare	4.373	2.630	3.966	2.155
income	47024.23	6838.68	57781.88	9867.421
population	5789576	5592331	7814769	6576105

2.5. Results and Discussion

We solved the mathematical programming problems in equations (1) and (2) to develop the sequential transit effectiveness indices. These indices are sequential as they were derived using data from all past and current periods and are therefore indicative of the agency's historical transit effectiveness. Figure 2.3 displays the total passenger miles of the top 45 bus agencies as well as the sequential input-oriented transit effectiveness index (*effi*) and the sequential output-oriented transit effectiveness index (*effo*) from 2007 to 2017. Total passenger miles of the top 45 agencies declined by 17.3% during this period. We also observed considerable declines in *effi* and *effo*. In 2017, the average *effo* was 0.54, suggesting that on average, for the same level of input use, an averaged transit agency could achieve 46% more transit service. Compared to 2007, the shortfall of rail transit output was roughly 28%.

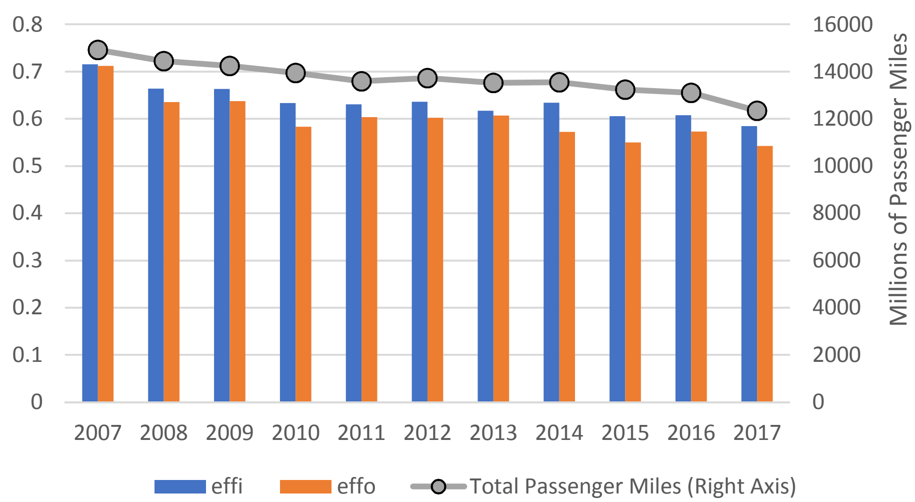

Figure 2.3. Effectiveness of bus transit and total bus passenger miles by year

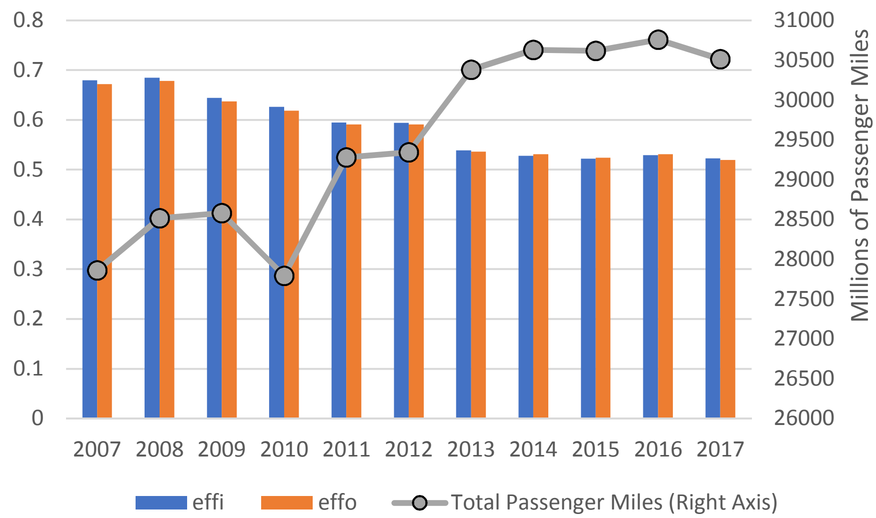

Figure 2.4. Effectiveness of rail transit and total rail passenger miles by year

In Figure 2.4, we also observed a decline in sequential rail transit effectiveness, from around 0.68 in 2007 to 0.52 (for both *effi* and *effo*) in 2017. Total rail passenger miles were down in 2010, but started to rise after that year. Notice that the sequential indices gradually but consistently declined for both bus and rail transits. The declines in sequential effectiveness could be a result of operational and managerial issues that accumulated over time.

Transit effectiveness is expected to have a positive effect on ridership. On the other hand, the effect of TNCs on ridership could be positive or negative. If TNCs effect is positive (or negative), then TNCs are a complement to (or a substitute of) public transit. We estimate equation (2.7) using the data associated with each transit mode. The regression results of equation (2.7) are reported in Table 2.3 below.[18, 19]

[18] The panel data is composed of cross-sectional data on 45 bus agencies and 32 rail agencies over a period of 11 years. As a precaution, we conducted a Levin-Lin-Chu (LLC, 2002) test for unit roots in panel data. The LLC test results rejected the null hypothesis that the panels contain unit roots. Hence the panels are stationary. The LLC test results are available from the authors upon request.

[19] We conducted a Chi-squared test on the joint significance of the year fixed effects to determine if equation (7) were over specified. The null hypothesis that the year effects are jointly insignificant was rejected for all 4 models in Table 3. The Chi-squared statistics are reported at the bottom of Table 3.

Table 2.3. Equation (7) regression results[ǂ], §

	(1) Bus	(2) Bus	(3) Rail	(4) Rail
Constant	12.24***	12.72***	12.72***	12.88***
	(1.208)	(1.089)	(1.635)	(1.586)
TNC	-0.0001	-0.00271	-0.0160	-0.0183
	(0.0188)	(0.0186)	(0.0156)	(0.0158)
leffi	0.0903**		0.457***	
	(0.0380)		(0.101)	
leffo		0.0907***		0.451***
		(0.0320)		(0.0917)
lfare	-0.103*	-0.108*	-0.580***	-0.591***
	(0.0548)	(0.0535)	(0.0990)	(0.0972)
lvhours	0.178***	0.164***	0.390***	0.386***
	(0.0604)	(0.0549)	(0.118)	(0.116)
lempcnt	0.421***	0.383***	0.0771*	0.0642*
	(0.0947)	(0.0904)	(0.0418)	(0.0347)
2008	0.0323***	0.0367***	0.0453***	0.0443***
	(0.0101)	(0.00914)	(0.0115)	(0.0113)
2009	0.0178	0.0227	0.0891***	0.0900***
	(0.0179)	(0.0172)	(0.0199)	(0.0204)
2010	-0.0219	-0.0125	0.0981***	0.102***
	(0.0223)	(0.0228)	(0.0215)	(0.0218)
2011	-0.000195	0.00593	0.167***	0.169***
	(0.0321)	(0.0324)	(0.0328)	(0.0321)
2012	0.0109	0.0184	0.183***	0.185***
	(0.0330)	(0.0334)	(0.0309)	(0.0305)
2013	0.000236	0.00553	0.229***	0.236***
	(0.0343)	(0.0344)	(0.0426)	(0.0424)
2014	-0.00855	0.00536	0.236***	0.240***
	(0.0348)	(0.0343)	(0.0408)	(0.0399)
2015	-0.0374	-0.0233	0.235***	0.240***
	(0.0343)	(0.0336)	(0.0433)	(0.0423)
2016	-0.0539	-0.0424	0.242***	0.247***
	(0.0377)	(0.0380)	(0.0446)	(0.0436)
2017	-0.106***	-0.0927**	0.214***	0.224***
	(0.0392)	(0.0398)	(0.0492)	(0.0480)
Observations	495	495	352	352
R-squared	0.379	0.396	0.803	0.808
#Agencies	45	45	32	32
Year Effects (X^2)	11.13***	10.92***	6.48***	7.29***

[ǂ] Other variables considered include subsidy to fare revenue ratio, average fleet age, real gasoline prices, per capita income, vehicle registrations, population size, and population density. However, these variables were insignificant and were not included in the final model.

§ Values in parentheses are clustered standard errors. ***, **, * denote 1%, 5% and 10% significance levels, respectively.

As displayed in columns (1) and (2) in Table 2.3, *TNC* has a negative effect on bus ridership, but the effect is not significant. The relatively low R-squared values in columns (1) and (2) suggest that the overall regression models for bus transit ridership performed rather poorly compared to the models for rail transit. Transit effectiveness has a positive and significant effect on both bus and rail ridership, but the effect on bus transit is smaller. For rail transit, a 1 percent increase in effectiveness is predicted to increase ridership by roughly 0.45%. TNC's availability is insignificant for public transit, meaning it does not complement nor compete with transit services. The coefficients on bus and rail transit are negative as predicted by demand theory, and demand for both rail and transit is relatively inelastic with respect to price. In particular, compared to rail transit, bus ridership is less responsive to any fare changes. A 1% reduction in fare would lead to a ~0.6% increase in rail ridership and a ~0.1% increase in bus ridership. This implies that any policy aiming to reduce transit fare would see a smaller increase in bus ridership when compared to the increase in rail ridership.

The results thus far suggest that there is no statistically significant evidence of declined bus ridership attributable to TNCs. In addition, changes in rail ridership could not be attributed to TNCs, but transit effectiveness played a vital role in rail transit. Because TNC's popularity within each metropolitan area may spread at different paces after its initial introduction, we controlled for such variations using interaction terms of *TNC* and year-dummies as in equation (2.8). Because large-scale TNC service did not exist prior to Uber's start in 2010, the interaction terms only include year dummies from 2010 to 2017; their associated parameters indicate the effect of TNCs availability at a given year relative to the period 2007-2009. The results are displayed in Table 2.4.[20]

Table 2.4. Equation (8) results§

	(1) Bus	(2) Bus	(3) Rail	(4) Rail
Constant	12.17***	12.67***	12.66***	12.84***
	(1.231)	(1.109)	(1.628)	(1.563)
TNC*2010	0.00212	-0.000559	0.00443	0.00396
	(0.0204)	(0.0205)	(0.0429)	(0.0437)
TNC*2011	0.0192	0.0136	0.00465	0.00411
	(0.0258)	(0.0255)	(0.0285)	(0.0275)
TNC*2012	-0.0137	-0.0155	-0.0334*	-0.0292
	(0.0206)	(0.0212)	(0.0189)	(0.0188)
TNC*2013	-0.0156	-0.0175	-0.0389	-0.0427
	(0.0189)	(0.0186)	(0.0283)	(0.0301)
TNC*2014	0.0528	0.0526	-0.00779	-0.0320
	(0.0520)	(0.0465)	(0.0357)	(0.0469)
TNC*2015	-0.0151	-0.0134	0.0696*	0.0331
	(0.0199)	(0.0202)	(0.0358)	(0.0399)
TNC*2016	-0.0538	-0.0450	0.224***	0.228***
	(0.0418)	(0.0422)	(0.0433)	(0.0424)
TNC*2017	-0.106**	-0.0953**	0.196***	0.204***
	(0.0432)	(0.0438)	(0.0480)	(0.0471)
leffi	0.0926**		0.456***	
	(0.0393)		(0.101)	
leffo		0.0918***		0.450***
		(0.0325)		(0.0933)
lfare	-0.102*	-0.108**	-0.570***	-0.584***
	(0.0542)	(0.0531)	(0.102)	(0.0982)
lvhours	0.180***	0.165***	0.393***	0.388***
	(0.0615)	(0.0559)	(0.117)	(0.114)
lempcnt	0.427***	0.388***	0.0777*	0.0647*
	(0.0970)	(0.0922)	(0.0423)	(0.0351)
2008	0.0324***	0.0367***	0.0448***	0.0440***
	(0.0101)	(0.00918)	(0.0114)	(0.0112)
2009	0.0179	0.0227	0.0881***	0.0894***
	(0.0180)	(0.0173)	(0.0199)	(0.0202)
2010	-0.0219	-0.0125	0.0955***	0.0998***
	(0.0223)	(0.0227)	(0.0213)	(0.0215)
2011	-0.00597	0.000975	0.157***	0.159***
	(0.0317)	(0.0322)	(0.0318)	(0.0308)
2012	0.0183	0.0254	0.191***	0.190***
	(0.0330)	(0.0338)	(0.0321)	(0.0312)
2013	0.0111	0.0157	0.244***	0.253***
	(0.0356)	(0.0349)	(0.0476)	(0.0496)
2014	-0.0578	-0.0461	0.226***	0.251***
	(0.0614)	(0.0574)	(0.0600)	(0.0658)
2015	-0.0229	-0.0131	0.150**	0.189***
	(0.0319)	(0.0322)	(0.0654)	(0.0666)
Observations	495	495	352	352
R-squared	0.382	0.398	0.804	0.810
#Agencies	45	45	32	32
Year Effects (χ^2)	5.72***	7.41***	9.67***	7.54***

§ Values in parentheses are clustered standard errors. ***, **, * denote 1%, 5% and 10% significance levels, respectively.

[20] The null hypothesis that the year effects are jointly insignificant was rejected. The Chi-squared statistics are reported at the bottom of Table 4.

For bus transit, we observed a negative and significant effect of TNCs on bus ridership in 2017 (columns 1 & 2). Although the effect of TNCs appeared significant, it is important to note that, since 2016 TNC services became ubiquitous in the U.S. and they were available in all the metropolitan areas in our data. Thus, including the interaction terms between TNCs and year dummies led to a necessary omission of the 2016 and 2017 year dummies from the regression model to avoid perfect collinearity. Consequently, the *TNC*2016* and *TNC*2017* interaction terms may be capturing the 2016 and 2017 year effects.

For rail transit, although there was an initial negative TNC effect in 2012, the effects of TNC were positive and significant from 2015 through 2017 (see column 3). Relative to the period 2007-2009, rail ridership in year 2015 in metropolitan areas with TNCs was about 7% higher than those without. The effect was positive and even larger in 2016 (22%), but the positive effect of TNC shrank in 2017. Although the positive effect of TNC was significant in 2016 and 2017, the coefficients on the interaction terms may be capturing the year effects of 2016 and 2017. To the extent that this positive effect of TNCs may be sensitive to the presence of New York City in the analysis, we re-estimated equations (2.7) and (2.8) without rail transit agencies serving New York City. The results, reported in Table 5, are largely consistent with those in Tables 3 and 4. That is, we continue to find the effect of TNCs on rail ridership to be positive and significant in 2015 in metropolitan areas excluding New York City.

Table 2.5. Results without New York City rail transit agencies§

	(1)	(2)	(3)	(4)
Constant	11.10***	11.64***	11.04***	11.55***
	(1.779)	(2.035)	(1.827)	(2.060)
TNC	-0.0230	-0.0116		
	(0.0168)	(0.0159)		
TNC*2010			-0.0116	-0.0213
			(0.0436)	(0.0380)
TNC*2011			-0.0292	0.00653
			(0.0317)	(0.0329)
TNC*2012			-0.0316	-0.0198
			(0.0217)	(0.0210)
TNC*2013			-0.0337	-0.0376
			(0.0364)	(0.0284)
TNC*2014			0.00508	0.0136
			(0.0359)	(0.0441)
TNC*2015			0.0936**	0.0974*
			(0.0371)	(0.0535)
TNC*2016			0.186***	0.140**
			(0.0486)	(0.0565)
TNC*2017			0.158***	0.108*
			(0.0508)	(0.0590)
leffi	0.551***		0.550***	
	(0.105)		(0.105)	
leffo		0.322**		0.322**
		(0.149)		(0.149)
lfare	-0.500***	-0.478***	-0.489***	-0.464***
	(0.120)	(0.133)	(0.126)	(0.140)
lvhours	0.480***	0.395**	0.483***	0.400**
	(0.130)	(0.149)	(0.134)	(0.150)
lempcnt	0.106**	0.171*	0.106**	0.173*
	(0.0445)	(0.0891)	(0.0451)	(0.0902)
2008	0.0449***	0.0478***	0.0444***	0.0471***
	(0.0138)	(0.0130)	(0.0140)	(0.0133)
2009	0.101***	0.0911***	0.0997***	0.0898***
	(0.0266)	(0.0259)	(0.0271)	(0.0265)
2010	0.103***	0.0882***	0.101***	0.0871***
	(0.0275)	(0.0302)	(0.0273)	(0.0300)
2011	0.111***	0.106***	0.111***	0.0988***
	(0.0270)	(0.0300)	(0.0263)	(0.0305)
2012	0.145***	0.136***	0.148***	0.138***
	(0.0346)	(0.0367)	(0.0340)	(0.0374)
2013	0.177***	0.140**	0.183***	0.156**
	(0.0524)	(0.0562)	(0.0651)	(0.0613)
2014	0.172***	0.133**	0.144**	0.107
	(0.0497)	(0.0563)	(0.0670)	(0.0794)
2015	0.181***	0.134**	0.0670	0.0263
	(0.0538)	(0.0623)	(0.0734)	(0.0918)
2016	0.211***	0.153**		
	(0.0541)	(0.0636)		
2017	0.182***	0.122*		
	(0.0557)	(0.0660)		
Observations	297	297	297	297
R-squared	0.862	0.807	0.864	0.808
#Agencies	27	27	27	27
Year Effects (X^2)	6.36***	7.40***	8.81***	8.82***

§ Values in parentheses are clustered standard errors. ***, **, * denote 1%, 5% and 10% significance levels, respectively.

Next, we examine the influence of transit effectiveness year-by-year as specified by equation (9). For each transit mode, we estimate equation (9) separately using the two effectiveness indices. The results are presented in Table 2.6.[21]

For bus transit, the results suggest that transit effectiveness indices do not appear to have any significant impact on transit ridership compared to 2007. On other hand, the results in columns (3) and (4) suggest unambiguously that transit effectiveness was positive and significant in every year for rail transit. This means that rail transit agencies with higher effectiveness compared to 2007 tended to have higher ridership. Rail agencies could improve ridership through effectiveness enhancement, internal managerial adjustments, operational improvements and innovations.

Equations (7) through (9) are fixed effects panel regression models which explicitly account for the unobserved cross-sectional fixed effects, $Agency_i$, which capture agency-specific unobserved factors that may be correlated with other right-hand-side variables in the equations. If $Agency_i$ was not correlated with the other control variables, then a random effects model would be more appropriate and can be estimated without the cross-sectional agency dummies.[22] For comparisons, we estimated the random effects version of equations (7) and (9) by leaving out the agency fixed effects. The results, reported in Tables B4 to B6 in Appendix B, are by and large similar to those of the fixed effects models.

[21] The null hypothesis that the year effects are jointly insignificant was rejected. The Chi-squared statistics are reported at the bottom of Table 5.

[22] If the agency effects are correlated with the explanatory variables, then the estimates in a random effects models are inconsistent.

Table 2.6. Equation (9) results§

`	(1) Bus (Input-oriented)	(2) Bus (Output-oriented)	(3) Rail (Input-oriented)	(4) Rail (Output-oriented)
Constant	14.36***	14.25***	13.85***	14.02***
	(1.103)	(1.045)	(1.118)	(1.104)
leff*2008	-0.0441	-0.213	0.154***	0.150***
	(0.0742)	(0.169)	(0.0408)	(0.0371)
leff*2009	-0.0361	-0.267	0.179***	0.167***
	(0.0852)	(0.186)	(0.0540)	(0.0511)
leff*2010	0.000772	-0.345	0.177***	0.164***
	(0.0473)	(0.262)	(0.0568)	(0.0540)
leff*2011	-0.655	-0.721	0.361***	0.324***
	(0.692)	(0.704)	(0.0983)	(0.0865)
leff*2012	0.0560	-0.0735	0.239***	0.224***
	(0.0717)	(0.0673)	(0.0708)	(0.0671)
leff*2013	0.142*	-0.0443	0.214***	0.194***
	(0.0824)	(0.0664)	(0.0683)	(0.0614)
leff*2014	0.0359	-0.184	0.250***	0.227***
	(0.0807)	(0.233)	(0.0745)	(0.0651)
leff*2015	0.0991	-0.121	0.302***	0.274***
	(0.0749)	(0.209)	(0.0841)	(0.0735)
leff*2016	-0.137	-0.199	0.381***	0.342***
	(0.227)	(0.254)	(0.104)	(0.0915)
leff*2017	-0.109	-0.156	0.420***	0.385***
	(0.217)	(0.247)	(0.104)	(0.0914)
TNC	-0.147	-0.115	-0.0230	-0.0265
	(0.135)	(0.100)	(0.0183)	(0.0192)
lfare	-0.252**	-0.212**	-0.692***	-0.706***
	(0.123)	(0.0973)	(0.0764)	(0.0768)
lemp	0.455***	0.469***		
	(0.145)	(0.139)		
lvhours			0.337***	0.325***
			(0.0852)	(0.0844)
2008	0.0111	-0.0802	0.125***	0.127***
	(0.0311)	(0.0945)	(0.0229)	(0.0218)
2009	0.00596	-0.118	0.169***	0.168***
	(0.0335)	(0.107)	(0.0338)	(0.0327)
2010	-0.00497	-0.222	0.182***	0.182***
	(0.0334)	(0.158)	(0.0352)	(0.0358)
2011	-0.430	-0.523	0.345***	0.334***
	(0.443)	(0.511)	(0.0725)	(0.0680)
2012	0.127	0.0301	0.298***	0.298***
	(0.121)	(0.0644)	(0.0506)	(0.0508)
2013	0.185	0.0523	0.322***	0.320***
	(0.145)	(0.0747)	(0.0580)	(0.0557)
2014	0.167	-0.00683	0.353***	0.347***
	(0.148)	(0.0830)	(0.0596)	(0.0558)
2015	0.179	0.00146	0.389***	0.380***
	(0.151)	(0.0774)	(0.0644)	(0.0603)
2016	0.0300	-0.0661	0.452***	0.437***
	(0.0769)	(0.0864)	(0.0791)	(0.0739)
2017	-0.0134	-0.102	0.449***	0.442***
	(0.0805)	(0.0940)	(0.0846)	(0.0804)
Observations	495	495	352	352
R-squared	0.131	0.146	0.801	0.802
#Agencies	45	45	32	32
Year Effects (X^2)	1.95*	1.95*	6.16***	7.45***

§ Values in parentheses are clustered standard errors. ***, **, * denote 1%, 5% and 10% significance levels, respectively.

2.6. Conclusions

Public transit ridership in the U.S. has been declining in recent years. Agencies and policymakers are looking for possible explanations for the declines. Given that the period of ridership decline coincides with the introduction of TNCs in major cities, and TNCs in general have been blamed for undermining the taxi industry in recent years, this study set out to examine whether TNCs availability had an effect on public transit. In this regard, we also felt that the operational performance of transit services should also be examined, since ineffective transit services could steer riders away to other transportation options.

While we observed that transit effectiveness declined during 2007-2017 for both rail and bus transits, our regression results suggest that transit effectiveness was highly important for rail ridership. Although the effect of TNCs on rail ridership was positive in 2014 and 2015, the influence of transit effectiveness clearly trumped that of TNCs. This suggests the importance of enhancing transit effectiveness in rail transit. Innovations in rail transit systems in major cities are much needed. Enhanced on-time performance, improved service and infrastructure reliability, and better service quality and safety are important to riders. While many external and internal factors may be driving the use of public transit, enhancing the overall service and attractiveness of public transit in the next 10 to 20 decades are important for the transit system (Mallett, 2018). Our results showed that the effect of TNC on rail ridership shrank in 2017, and that the positive coefficient could be capturing the year specific effect and not the actual effect of TNC. Thus, transit agencies should approach the plans to collaborate with TNCs for first-mile/last-miles service with more careful deliberation and should focus on addressing internal issues to enhance transit effectiveness. A 2018 SUMC study found that people use transit as part of a routine, and trains remain the top shared mode in regions with an extensive system of commuter or heavy rail service. On the other hand, TNC trips are usually short[23] and concentrated in core downtown areas, with the exceptions of airports, in the survey study region. TNC is not the major transportation mode for most users; it is used only to fill occasional needs (SUMC, 2018).

In addition, although current TNC service charges are considered low, the existing pricing model of TNCs may not be sustainable in the long run because their ride services are heavily subsidized by investors who are willing to tolerate short-term losses with the expectations of longer-term financial gains. Uber, for example, has been an unprofitable business (McDermid, 2016; Winkler, 2018; Bond, 2018). Future paths to profitability may require TNCs to raise their charges, and consequently, their ride services may no longer be as attractive as they are (Mallett, 2018; Business Insider Intelligence, 2016). Cities and transit authorities' increasing reliance on TNCs to provide first-mile/last-mile services could spur more demand for TNC services and strain TNC capacity. This in turn could also lead to higher TNC service charges particularly during peak periods.

In addition, although the effect of TNC on bus ridership was negative in all three models, it was insignificant. Thus, there was a lack of significant evidence that TNCs were in direct competition with bus transit, and it is noteworthy that, TNCs were not a complement to bus transit either. In recent years, besides TNCs, micro-mobility options like dock-less bicycles and e-scooters offer users affordable, flexible and convenient on-demand services for short-distanced travels within a city. While these options allow people to get to or return from transit facilities, micro-mobility users may be less inclined to use public transit and may be substituting short-distanced bus transit with a flexible bicycle or scooter ride (Mallett, 2018). Our findings, and the

[23] Averaged between 2 and 4 miles per TNC trip.

emergence and rising popularity of other micro-mobility options, call for further and more in depth examinations of the problem of declined bus ridership in the U.S.

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CHAPTER 3. PRODUCTIVITY GROWTH OF URBAN TRANSIT AGENCIES IN THE U.S.

3.1. Abstract

This essay assesses the productivity of U.S. urban public transit using data from the 45 largest bus agencies and 32 rail agencies in from years 2007 through 2017. The study shows that both bus and rail transit agencies have experienced declining cumulative productivity growth during the study period. The Malmquist productivity index was decomposed into technical efficiency change and technological change components. The findings indicate that, for bus transit agencies, outsourcing or purchased transportation is associated with negative efficiency change. Although purchased transportation has a positive effect on technological change for bus transit, the effect is not significant. The results suggest that transit agencies that seek to partner with shared-mobility service providers or to integrate shared-mobility with transit service must address challenges that hinder transit efficiency, and that transit technology has yet to keep up with technological progress in urban mobility.

3.2. Introduction

Public transportation in the U.S is the second most common transportation mode after private automobiles for passenger transportation (Sprung et al. 2018). After reaching 10.6 billion passenger trips in 2014, transit ridership in the U.S. has been on the decline and has reached 9.8 billion passenger trips in 2018 (APTA 2019). Efficient and effective public transportation is crucial in recent years when there has been increasing concerns about congestion, global warming and other environmental issues, which are in large part related to transportation (Watkins et al. 2019).

Although public transportation serves approximately 5 percent of total commuters in the U.S., it plays an important role in facilitating urban mobility in some of the largest metropolitan areas in the country (McKenzie and Rapino 2011). While public transit agencies are government owned and operated in the U.S., a portion of the transit service is outsourced to third-party providers in the form of purchased transportation. In terms of vehicle revenue hours provided by all public transit modes, approximately 28 percent of public transit services were considered purchased transportation in 2017, and it accounted for nearly 14 percent ($6.8 billion) of the total operating expenses for transit agencies; 18 percent of bus service revenue hours and 6 percent of rail service revenue hours were provided by contractors in the same year. The percentage of service contracted for operation for bus service has increased in the past decade from 15 percent to 18 percent (APTA 2019).

In recent years, TNCs, such as Uber and Lyft, have become a key transportation options in major metropolitan areas in the U.S. As new mobility service providers emerge, many public transit agencies in the U.S. have partnered, or are in the process of partnering, with them. Table 3.1 provides a summary of the latest partnerships between public transit agencies and external partners. The reasons for such partnerships can vary between increasing cost effectiveness, application of innovative ideas, avoiding large capital investments in park-and-ride facilities and providing more transportation options for existing and/or new transit customers (Curtis et al. 2019). When these partnerships are formed and implemented in transit service provisions, they are reported to the Federal Transit Administration as purchased transportation for the specific transit agency (NTD 2019).

Table 3.1. Transit and TNC partnerships

Transit Agency	External Partners	Start Date
Des Moines Regional Transit Authority, Des Moines, IA.	Uber and YellowCab	November 2019
MetroLink, St. Louis, MO.	Lyft	October 2019
Regional Transportation District (RTD), Denver, CO.	Uber	May 2019
Big Blue Bus (BBB), Santa Monica, CA.	Lyft	July 2018
Capital Metro (CapMetro), Austin, TX.	RideAustin	June 2018
Central Pennsylvania Transportation Authority, central Pennsylvania counties, PA.	Lyft and Uber	May 2017
Denton County Transportation Authority, Denton, TX.	Lyft and Uber	October 2016
Livermore Amador Valley Transit Authority, Livermore, CA.	UberPOOL, Lyft Line, or DeSoto	January 2017
Metropolitan Atlanta Rapid Transit Authority (MARTA), Atlanta, GA.	Lyft and Uber	July 2015
Los Angeles County Metropolitan Transportation (LA Metro), Los Angeles County, CA.	Via rides	January 2018
Massachusetts Bay Transportation Authority (MBTA), Boston, MA.	Lyft and Uber	September 2016
Omnitrans, San Bernardino, San Bernardino, CA.	Lyft and RIDE Taxi	July 2016
Pierce County Transit, Pierce County, WA.	Lyft	May 2018
Pinellas Suncoast Transit Authority, Pinellas County, FL.	Uber, United Taxi and Care Ride	August 2016
Sacramento Regional Transit (SacRT), Sacramento, CA.	Lyft, Uber and Yellow Cab Company	May 2018
Cascades East Transit (CET), Central Oregon, OR.	Uber	June 2017
Southeastern Pennsylvania Transportation Authority (SEPTA), Philadelphia, PA.	Uber	May 2016
Southwest Ohio Regional Transit Authority (SORTA), Cincinnati, OH.	Uber	March 2016
Solano Transportation Authority (STA), Solano, CA.	Lyft	May 2017

Source: APTA 2019b, Curtis et al. 2019.

Metropolitan Atlanta Rapid Transit Authority (MARTA) has had stable partnerships with Uber and Lyft since 2015. This partnership included discounts, ranging from 20 to 50%, for trips that began or ended at MARTA rail stations with the intention of encouraging transit use to destinations such as the Hartsfield-Jackson Atlanta International Airport. Los Angeles County Metropolitan Transportation (LA Metro) is currently implementing a pilot project in which customers whose origin or destination is one of three selected rail and bus rapid transit stations (North Hollywood, Artesia, or El Monte) will receive first mile/last mile discounts on TNC's service if they are willing to share the ride (APTA 2019b). SEPTA Philadelphia had a temporary partnership program with Uber in the summer of 2016. Under this program, Uber fares are discounted by 40% with a maximum of $10 per ride for rides to-and-from selected regional rail stations.

Hence, outsourcing transit service or purchased transportation play an increasingly important role in urban mobility. However, the implications of purchased transportation on transit productivity has not been previously examined. The aim of this paper is to examine the productivity, efficiency and technological changes in urban public transit agencies in the U.S. focusing on the 50 largest transit agencies in the U.S. from 2007 to 2017. The transit productivity was examined by calculating the Malmquist productivity index and decomposing the index into efficiency and technological changes. Finally, a regression analysis is conducted to determine if purchased transportation and other factors affect productivity growths of these transit agencies.

3.2.1. Transit Efficiency and Productivity

A lot of interest has been expressed over the years in terms of measuring and improving efficiency in public transportation (Holmgren 2013). Selecting the most suitable efficiency measure mainly depends on the nature of the industry being considered. Although profit maximization may be the natural objective of most firms and industries in the U.S., this is not necessarily the case for urban transit systems. As urban transit systems are generally managed as a public service, despite the presence of a marketed transit output, profitability cannot be used as the only measure of performance (Fielding et al. 1985). Pestieau and Tulkens (1990) and Button and Weyman-Jones (1992) suggest that one way to evaluate the performance of public industries is technical efficiency, especially since how efficiently public firms convert inputs into a public output/service is a critical question, technical efficiency is of interest from a public policy perspective (Viton 1998). Besides serving the public interest, firms can effectively address any cost concerns after technical efficiency has been achieved. Hence, in order to evaluate and compare the success and potential of individual operators, measuring public transit efficiency is crucial.

According to De Borger et al. (2002, page 3), there are at least two reasons for this. “First, a transparent framework for productivity and efficiency measurement has been developed, unlike for the other objectives. Second, it has been forcefully argued that, independent of the other objectives, a first and indispensable demand for all public-sector activities is to operate technically efficient.” The measurement of efficiency, the notion of best-practice frontiers was first introduced by Farrell (1957). Since then various frontier estimation techniques have been developed. Frontier methods enable one to distinguish between efficient and inefficient production and the estimation of the extent of (in)efficiency. In the transportation literature, frontier methods have been used in efficiency studies on almost all transport modes (De Borger et al. 2002).

Productivity is a representation of firm performance which is measured as a ratio of outputs relative to the inputs used in the production process. Profitability ratio (revenue/input cost) is an example for the simplest productivity measure. In such cases, productivity growth therefore implies lower average costs. When multiple inputs and outputs are productivity may be measured using the index number approach, under which output and input quantity indexes are created using disaggregated data on the quantities of outputs and inputs, which are weighted respectively by output and input prices. In other words, multiple inputs and outputs have to be adjusted by input and output price indexes. However, price data may not be available for all output and input prices. Alternatively, the distance function approach can be used to measure total factor productivity. The productivity index derived from distance functions does not require price information. This paper thus uses the distance function approach to calculate the

Malmquist productivity index which accommodates multiple outputs and inputs, and it does not require price information (De Borger and Kerstens 2000; Shi et al. 2011).

Transit productivity and efficiency studies in the past two decades have largely overlooked the performance of agencies in the U.S. Among other studies carried outside U.S., a stochastic cost frontier model was estimated to identify if there were differences in efficiency between privately and publicly owned operators for the Norwegian bus industry by Jorgensen et al. (1997). Results suggested that these was no significant differences between the two operators in Norway. Another cost frontier model was estimated on 44 Italian transit companies in order to determine how subsidization affects the cost efficiency of public transit systems (Piacenza, 2006). An overall performance index was developed by Yeh et al. (2000) using a multi-criteria analysis to assess bus system performance in Taiwan.

Lave (1991), Chu et al. (1992) and Viton (1998) are among the few studies that focused on transit performance in the U.S. Looking into transit performance from the 1950 to 1985, Lave (1991) considered a number of performance measures like the revenue to operational expense ratio, revenue per passenger, operating expense per bus hour, bus hour per employee, etc. The study found that a decline in productivity and increases in deficits were inevitable because of transit subsidization that started in the 1960s. Using a different method, Chu et al. (1992) employed data envelopment analysis (DEA) to measure the efficiency and effectiveness of transit service. According to Chu et al. (1992), transit efficiency is evaluated in a DEA model in which revenue vehicle hours or service produced is used as the output variable. On the other hand, effectiveness is evaluated in a model in which transit service consumption, like the number of passengers of passenger trips, are used as the output measure. Besides Chu et al. (1992), Viton (1998) also used DEA to measure productivity changes in bus transit between 1988 and 1992.

3.2.2. Transportation Outsourcing and Partnerships

Transportation outsourcing is a common practice in the U.S. For example, since trucking deregulation in 1980, large carriers were able to expand their network (He and Nickerson, 2003). He and Nickerson (2003) found that trucking companies hired third-party truckers when the origin or destination of a shipment is outside their network and when their trucks have no backhauls. Thus, outsourcing not only allows trucking companies to maintain strong relationships with clientele through a wider network, it enables them to achieve greater efficiency by lower operating costs (Nickerson and Silverman 2003).

Besides trucking, major U.S. airlines also subcontract regional services to smaller feeder airlines, which some of them are subsidiaries of the major carriers. Feeder airlines typically serve the low-density, short- and medium-haul service routes in the country, transporting passengers from smaller airports to hub airports of major carriers. They operate under codeshare agreements with major carriers who sell tickets of the contracted flights under the latter's flight designator codes and business names (Forbes and Lederman, 2009). Major carriers who use external feeder airlines as opposed to their own subsidiaries may incur higher transaction costs associated with haggling and incomplete contracts since non-contracted flight schedule or service adjustments are difficult. Thus, Forbes and Lederman (2009) concluded that major carriers tend to use their own subsidiary feeder airlines to serve routes with adverse weather and to serve city pairs that are more integrated within their existing networks, since more integrated city pairs tend to be affected by unexpected disruptions elsewhere in the network.

Outsourcing is also ubiquitous in the public transit sector. The case of public transit outsourcing differs from other transportation subcontracting because U.S. transit services are under the control of government agencies funded by public monies. Transit agencies contract out their services due to reasons such as, limited/reduced funding. The purpose of contracting out such services is increasing productivity and cost efficiency (Iseki 2010). Outsourcing of public transit is closely related to the analysis of the make-versus-buy decision for these transit agencies. Since these buying decisions must be carried out with public money, many restrictions and regulations must be followed accordingly. Transit agencies or authorities are also legally obliged to issue calls for tender for all public transportation services they plan on contracting to private agencies (Andersson et al. 2019). In theory, under specific conditions, such as highly competitive bidding, well organized contracts and sufficient oversight, contracting enables transit agencies or authorities to provide transit service at a lower costs compared to creating such services in-house. However, certain conditions such as, insufficient competition, inadequately designed contracts and inadequate oversight, could result in decreased efficiency if public transit is contracted out (Savage 1986).

A study conducted by the Transportation Research Board (TRB, 2001) found that compared to smaller agencies, large agencies, such as those with more than 50 vehicles, would be more likely to outsource some transit services. However, smaller agencies would be more likely to outsource all services when they use external providers since many of these agencies are operated by small city or county agencies that do not specialize in transit. Besides agency size, Iseki et al. (2006) found that older and larger agencies tend to contract out a portion of their services, compared to newer and smaller agencies that contract out all services because older agencies have a longer history of providing services using unionized employees. Most transit agencies use contractors or external providers to produce demand-responsive transit service, and some smaller agencies contract all fixed-route bus services (TRB, 2001). In addition, transit agencies outsource services to external providers to fill niches or expand service, and outsourcing allows agencies to provide new services, lower costs, and improve service cost-efficiency. From a cost's standpoint, agencies are able to take advantage of the differences in labor cost where private sector's hourly wages tend to lower than those of public sector's unionized employees; outsourcing also encourages competition between private bidders, and enables agencies to enhance service efficiency by contracting less-efficient services to external providers (TRB, 2001; Frick et al., 2006). Transit outsourcing is particularly preferred when an agency desires additional flexibility and wants to test new services before hiring public employees (Frick et al., 2006).

However, some agencies may choose not to outsource because they would like to retain control over their operations, in some cases, the expected cost savings may not be high enough, and some agencies may see no reason to change their operations (TRB, 2001). Frick et al. (2006) concluded that outsourcing transit service does not necessarily lead to improved efficiency, and cost savings maybe achieved at the expense of service quality. Thus, more evaluations should be conducted on the implications of outsourcing on transit productivity.

In the last few years, the rise of TNCs and other micro-mobility options has fueled transit partnerships with these transportation modes. According to Curtis et al. (2019), partnerships with TNCs can be driven by different motivations which can be grouped into three categories such as using TNCs to provide very specific services, to meet or address specific policy goals, or to display innovative qualities and flexibility of transit agencies. Some benefits transit agencies gain by partnering with TNCs include, increasing service accessibility and reducing operation costs. Additionally, such partnerships can increase ridership by connecting potential passengers to transit stations as well as developing first and last mile connections in regions with limited transit availability/ frequency and/or areas with low density residential neighborhoods. Besides offering first-last mile connections, such partnerships also provide certain demand-response services (such as micro transit[24]), late night service and sharing technological platforms; transit providers can focus resources on modernizing top-performing routes, serving commuters, and other core strengths such as service reliability and timeliness (Todd et al. 2018; Mallett 2018). A study carried out by Feigon and Murphy (2018) suggests that although TNC use did not impact transit ridership use in the peak-hour commute times, TNCs were used most heavily for short distances during off peak-hours in concentrated downtown neighborhoods closer to transit stations, especially on weekend nights (Feigon and Murphy 2018).

Despite having different motivations for creating partnerships, Curtis et al. (2019) indicate that these motivations are not linked to specific performance indicators which could have helped the transit agency to have more control over the process. In the survey carried out by them on public transit agency partnerships with TNCs, respondents expressed concerns on providing accessibility to disabled users, barriers faced by customers without smart phones and limiting liability to the transit agency. Furthermore, Curtis et al. (2019) identify that issues related to data sharing between transit agencies and TNCs may hinder the process of developing a solid partnership between the two parties. One major reason for TNCs' unwillingness to share

[24] "Micro transit is an emerging service model providing demand responsive or flexible-route trips in a defined service zone by matching customers to vehicles through real-time trip requests. It is intended to serve areas that are typically difficult for fixed-route transit to serve, such as low-density suburban development, and provide improved quality of service for riders" (Todd et al. 2018. Pg. 2).

data is the Sunshine Laws which mandate information held by governments to be publicly available. Such information openness may expose TNCs' customers' personally identifiable information as well as information of the companies (Curtis et al. 2019).

In recent years, the need to assess transit outsourcing is critically important in the face of increased urban micro-mobility options and agencies' interest in partnering with first-mile/last-mile external providers. Malalgoda and Lim (2019) cautioned that any agencies should approach this strategy carefully. They pointed out that while current TNC charges low (compared to taxi fares), the pricing models may not be sustainable because TNC riders usually do not pay full prices to cover the actual cost of their trips because a sizeable portion of the trips' cost is subsidized by TNC investors who prioritize long-term profits over short-term losses of TNCs.

3.3. Methods

In this study, an agency uses N inputs represented by the input quantity vector $X = (x_1, \ldots, x_N)$ to produce M outputs represented by the output quantity vector $Q = (q_1, \ldots, q_M)$. Productivity in simpler terms is comparing outputs to its inputs. When the output growth is larger than the input growth, an increase in productivity was observed. For public transit agencies, productivity growth measurement is an important issue especially in the 1970s and the late 1980s. But since then very little attention has been put on the area of public transit productivity in the U.S. (Boame and Obeng 2005).

Past studies have discussed limitations related to partial (single) productivity measures and have shown the importance of using comprehensive measures in calculating productivity (Obeng et al.1992). When considering the productivity of public transit agencies, total factor productivity (TFP), which incorporates multiple outputs and inputs across firms needs to be taken into account. This can also be defined as a ratio of aggregate outputs to aggregate inputs.

Hence a change in TFP is considered as a change in total outputs relative to a change in total inputs.

In this study, the Malmquist productivity index (MPI) was used to measure transit productivity. The MPI is a measurement of total factor productivity in two data points by calculating the ratio of the distances of the specified data compared to a common technology using panel data. As shown by Färe et al. (1989), the MPI can be decomposed into efficiency and technological change components to identify the sources of productivity growth. The MPI is preferred over the index number approach because it does not require input and output price data (Boame and Obeng 2005).

In this study output-oriented productivity measures were chosen over input-oriented measures arbitrarily since transit inputs tend to be fixed, and agencies are to maximize output given the available inputs. This is particularly the case for public transit service considering the fixed-route services and schedules they are expected to follow regardless of riders. If agencies had more control or flexibility with regard to input use, then an input-oriented measure would be more appropriate. However, if production exhibits constant returns to scale in the two time periods in question, the input-oriented and output-oriented Malmquist indices are the same.

When deriving the output-oriented MPI, the productivity change for two subsequent time periods *s* and *t*, where technology used for period *t* is used as the reference technology, can be written as:

$$m_0^t(q_s, x_s, q_t, x_t) = \frac{d_0^t(q_t, x_t)}{d_0^t(q_s, x_s)}, \tag{3.1}$$

where $d_0^t(q_t, x_t)$ is a period *t* distance function, and $d_0^t(q_s, x_s)$ is a mixed-period distance function where a period-*s* production point is compared against the reference technology in period *t*. Similarly, the output-oriented MPI in period *s* under constant returns to scale technology is:

$$m_0^s(q_s, x_s, q_t, x_t) = \frac{d_0^s(q_t,x_t)}{d_0^s(q_s,x_s)}, \tag{3.2}$$

where $d_0^s(q_s, x_s)$ is a period *s* distance function, and $d_0^s(q_t, x_t)$ is a mixed-period distance function where a period-*t* technology is compared to the reference technology in period *s*.

Individually, the MPI in (3.1) and (3.2) may yield a value greater than, equal to, or less than one. An output-oriented MPI greater than one represents a positive total factor productivity change (TFP); while a lower value than one indicates a TFP decline. When two time periods (*s* and *t*) are involved in an MPI calculation, it is necessary to utilize two single-period and two mixed-period measures (Chen and Ali 2004). Since the MPI has the ability to use either technology period (*s* or *t*) as the benchmark technology, it could also be defined as the geometric mean of two indices based on the two time periods:

$$m_0(q_s, x_s, q_t, x_t) = \left[\frac{d_0^s(q_t,x_t)}{d_0^s(q_s,x_s)} \times \frac{d_0^t(q_t,x_t)}{d_0^t(q_s,x_s)}\right]^{1/2}. \tag{3.3}$$

If the value of the MPI in Equation (3) is equal to one, then no productivity growth occurs between these two periods. A value of $m_0(q_s, x_s, q_t, x_t)$ less than 1 suggests a productivity decline, and a value greater than 1 suggests productivity growth between periods *s* and *t*. The MPI in equation (3.3) can be decomposed into two main components. The first component is the change in efficiency, and the other component is the change in the frontier technology (Bjurek 1996; Chen and Ali 2004). Specifically, the MPI can be rearranged to show the product of a technical efficiency change index and an index of technical change:

$$m_0(q_s, x_s, q_t, x_t) = \frac{d_0^t(q_t,x_t)}{d_0^s(q_s,x_s)} \left[\frac{d_0^s(q_t,x_t)}{d_0^t(q_t,x_t)} \times \frac{d_0^s(q_s,x_s)}{d_0^t(q_s,x_s)}\right]^{1/2} \tag{3.4}$$

where the first part of equation (3.4), $\frac{d_0^t(q_t,x_t)}{d_0^s(q_s,x_s)}$, represents the technical efficiency change (EFFCH) between periods *s* and *t*. The second part of Equation (3.4), $\left[\frac{d_0^s(q_t,x_t)}{d_0^t(q_t,x_t)} \times \frac{d_0^s(q_s,x_s)}{d_0^t(q_s,x_s)}\right]^{1/2}$, represents the technical change (TECH) component which measures the geometric mean of the shifts in the production possibility frontier. When the TECH measure is less than, equal to or greater than one, the technological best practice is deteriorating, unchanged or improving, respectively.

The MPI can be calculated using data envelopment analysis (DEA) linear programming methods to estimate a production technology and thereby estimate distance functions that form the MPI. The single- and mixed-period distance functions associated with equation (3.4) are given below (Coelli et al. 2005):

$$\begin{aligned} [d_0^s(q_s, x_s)]^{-1} &= max_{\phi,\lambda}\phi, \\ st \qquad & -\phi q_{is} + Q_s\lambda \geq 0, \\ & x_{is} - X_s\lambda \geq 0, \\ & \lambda \geq 0, \end{aligned} \tag{3.5}$$

$$\begin{aligned} [d_0^t(q_t, x_t)]^{-1} &= max_{\phi,\lambda}\phi, \\ st \qquad & -\phi q_{it} + Q_t\lambda \geq 0, \\ & x_{it} - X_t\lambda \geq 0, \\ & \lambda \geq 0, \end{aligned} \tag{3.6}$$

$$\begin{aligned} [d_0^t(q_s, x_s)]^{-1} &= max_{\phi,\lambda}\phi, \\ st \qquad & -\phi q_{is} + Q_t\lambda \geq 0, \\ & x_{is} - X_t\lambda \geq 0, \\ & \lambda \geq 0, \end{aligned} \tag{3.7}$$

and

$$[d_0^s(q_t, x_t)]^{-1} = max_{\phi,\lambda}\phi,$$

$$st \qquad -\phi q_{it} + Q_s\lambda \geq 0,$$

$$x_{it} - X_s\lambda \geq 0,$$

$$\lambda \geq 0. \tag{3.8}$$

Solving for equations (3.5) and (3.6) yield the technical efficiency scores of transit agencies for periods *s* and *t*, respectively. The solutions to equations (3.5) through (3.8) are used to calculate the MPI and its two components. Following this, panel data regression models will be used to identify factors which may be contributing towards changes in transit productivity, efficiency and technology.

3.4. Data

Most of the data were obtained from the U.S. Department of Transportation's National Transit Database (NTD). The NTD database consists of data from most individual public transit operators in the nation. Public transportation services provided by transit agencies themselves are reported as directly operated (DO), and those provided by third-party contractors are reported as purchased transportation (PT). Under a PT agreement, a transit agency (known as the buyer) pays an external party (who is the seller) the full costs of service provided by the latter. Some cities may have only DO transit systems, but most of them have both DO and PT transit services. Agencies report PT data as required by the Federal Transit Administration (FTA) in their annual reports to the NTD; the information includes the allocated costs and service, assets and resource data of operating the service (NTD 2019). In this study, the transit productivity of the 50 largest U.S. metropolitan transit agencies based on ridership size are examined. Among these agencies, 45 of them are bus transit operators and 32 of them also operate rail transit services. The analysis is performed using a panel data-set from years 2007 to 2017.

Selecting suitable inputs and outputs is one of the crucial steps of productivity analysis. According to De Borger et al. (2002), due to the wide variability of inputs and outputs in urban transit systems, which is a notably important feature of urban transit, there is not a generally accepted set of variables specific to the transit industry. Thus, following Malalgoda and Lim (2019), four inputs and one output were chosen for this analysis (Table 3.2). The inputs include the fleet size, fuel, total number of employees and the amount of governmental subsidy received by individual public transit agency.

Table 3.2. Variable definitions and sources

Variable	Definition	Source
Transit Outputs		
Pass Trips	Unlinked passenger trips. Used to measure ridership.	USDOT National Transit Database
Transit Inputs		
Fleet Size	Total number of vehicles operated in maximum service for each transit agency	USDOT National Transit Database
Fuel BTU	Total usage of diesel, gasoline, liquefied petroleum gas, bio diesel and other fuel by individual transit agencies	USDOT National Transit Database
Employee Count	Total operating employee count	USDOT National Transit Database
Subsidy	Sum of Federal, State and Local government funding	USDOT National Transit Database
Determinants		
Population	Population of each urbanized area	Bureau of Economic Analysis
Partnership	Dummy variable indicating if agency has a partnership with TNCs	APTA (2019)
PT	Dummy variable indicating if agency has purchased transportation	USDOT National Transit Database
PTCost	Dollar amount spent by individual agencies on purchased Transportation	USDOT National Transit Database

By definition, fleet size refers to the number of revenue vehicles operating in the agency to meet annual service requirements. In other words, it is the revenue vehicle count at the annual peak season, on the peak week and the specific day that maximum service is provided. This count excludes unique days and exceptional one-time events (NTD 2017). Fuel is the total fuel consumption of the transit agency. All consumption units of fuel, biodiesel and kWh of electricity were converted into BTU's. The number of employees include any individual who is compensated by the transit agency either in DO or PT operations. Governmental subsidy for each public transit agency includes the total funds received from the government at local, state and federal levels.

According to Viton (1998), the two most common measures for transit output are vehicle-miles and number of trips. In this paper, unlinked passenger trips (Pass Trips) for all bus and rail modes representing the demand for public transit was the output variable. An unlinked passenger trip is a passenger boarding a public transit vehicle. On the other hand, vehicle hours is also another appropriate measure of output with regard to efficiency consideration (Chu et al. 1992). The choice between demand-related indicators (like passenger miles, passenger trips, or number of passengers) and supply indicators (like vehicle miles or seat miles) is arbitrary. However, Croissant et al. (2012) advised against using a supply measure since it may lead to a wrong conclusion that the most efficient transit agencies are those with the most number of empty seats. Hence, the use of a demand-side output measure is more appropriate.

In the regression model, three outsourcing measures: Partnership, PT and PTCost were considered. The variable Partnership captures the effect of agency's partnership with TNCs on transit productivity, efficiency and technical changes. During the study period (2007-2017), Metropolitan Atlanta Rapid Transit Authority (MARTA) has partnered with Lyft and Uber starting 2015, and Massachusetts Bay Transportation Authority (MBTA) has partnerships with Lyft and Uber starting 2016 (APTA 2019b). Partnership between MARTA and TNCs (Uber and Lyft) are currently identified as a promotional partnership in which MARTA transit users are given direct discounts on Uber and Lyft in exchange for free advertising allowance given for these TNCs on the MARTA mobile application (GAO 2018). MBTA partnership with Uber and Lyft is limited to customers with disabilities. They have allocated a maximum number of subsidized trips per individual customer based on his/her ride history. Partnerships at initial stages or pilot studies may not be considered as purchased transportation. But when TNCs' partnership with transit agencies is regular and continuing, it is reported as PT (NTD 2019). Thus, partnerships as such resemble PT, and we expect them to behave in a similar manner to outsourcing or purchased transportation. PT is a binary variable for transit agencies that outsource regular services to external providers. PTCost is the agencies' total payments to external PT providers. Population is included as a control variable for city size.

Tables 3.3 and 3.4 display the summary statistics for bus and rail transit agencies in our samples. The total sample sizes for bus and rail transit agencies were 495 and 352 respectively. Mean values indicate that the number of passenger trips consumed is higher for rail transit compared to bus. The fuel consumption and employee size have lower mean values for rail agencies indicating the considerable economies of scale rail transit has over bus.

Table 3.3. Summary statistics for bus transit agencies

	Observations	Mean	Standard Deviation	Minimum	Maximum
Pass Trips (Millions)	450	92.33	132.75	10.21	902.64
Fleet Size	450	721	689	70	4431
Fuel BTU (Millions)	450	1022	1133	5.71	7402
Employee	450	3284	6614	480	48500
Subsidy	450	0.6221	0.2234	0.0064	0.9625
Population (Millions)	450	6.94	6.49	0.80	36.70
Partnership	450	0.0289	0.1677	0	1
PT	450	0.5733	0.4951	0	1
PTCost (Millions)	450	15.61	29.59	0	207.64

Table 3.4. Summary statistics for rail transit agencies

	Observations	Mean	Standard Deviation	Minimum	Maximum
Pass Trips (Millions)	320	144.76	443.23	2.26 M	2743
Fleet Size	320	557	991	23	6375
Fuel BTU (Millions)	320	971.30	1376	1.86	6153.20
Employee	320	2571	4880	114	33291
Subsidy	320	0.5283	0.2370	0.0366	0.8950
Population (Millions)	320	6.87	6.21	1.05	21.35
Partnership	320	0.0313	0.1743	0	1
PT	320	0.775	0.4182	0	1
PTCost (Millions)	320	10288.79	56450.33	0	383632.70

3.5. Results and Discussion

The output-oriented annual MPI was calculated for bus and rail transit agencies in the U.S. from year 2007 to 2017 under the assumption of constant returns to scale. Linear programming equations (3.5)-(3.8) were used in calculating the MPI index. First, the DEA efficiency scores for bus and rail transit agencies in Table 3.5 are reported. The DEA model considers the number of unlinked passenger trips as a demand-side output measure.[25] DEA

[25] Efficiency scores and productivity index from the model considering passenger miles as the output are similar to the ones reported in this study, and they are available from the authors upon request.

efficiency scores range from 0 to 1. The overall average DEA score for the bus transit agencies was approximately 0.6, while rail transit agencies reported a lower average of 0.56.

Table 3.5. DEA scores summary for bus and rail transit agencies 2007-2017

	Bus Agencies				Rail Agencies			
Year	Mean	SD	Min	Max	Mean	SD	Min	Max
2007	0.581	0.250	0.246	1	0.583	0.271	0.217	1
2008	0.578	0.249	0.231	1	0.586	0.274	0.212	1
2009	0.584	0.248	0.218	1	0.585	0.281	0.177	1
2010	0.556	0.247	0.227	1	0.541	0.265	0.154	1
2011	0.606	0.234	0.259	1	0.560	0.276	0.205	1
2012	0.635	0.234	0.267	1	0.550	0.267	0.199	1
2013	0.642	0.240	0.211	1	0.527	0.252	0.198	1
2014	0.641	0.244	0.215	1	0.536	0.265	0.218	1
2015	0.608	0.249	0.208	1	0.591	0.251	0.231	1
2016	0.608	0.251	0.212	1	0.602	0.246	0.242	1
2017	0.524	0.245	0.184	1	0.506	0.278	0.156	1
Overall	0.601	0.245	0.225	1	0.561	0.266	0.201	1

After solving the single-period and mixed-period linear programming problems, the annual MPI for bus and rail transit agencies for the period 2007-2017 is calculated. The index is decomposed into efficiency change (EFFCH) and technical change (TECH) components. The results are reported in Table 6 below. MPI values greater than one imply improvements in productivity; MPI values less than one suggest a deterioration in performance for transit agencies, and when the MPI value equals one, it means no productivity change.

In summary, Table 3.6 shows that only 2 out of the ten periods considered have resulted in a slight productivity growth of about 1 percent for bus transit agencies. Productivity declines are observed in most time periods, with the largest decline, -9.1%, observed in 2009-2010. This decline was due to an efficiency and a technological decline during the year. A 3% decline in bus ridership was noted between 2009 and 2010. Another large efficiency decline for bus transit was observed for 2016-2017; this was possibly due to a decline in bus ridership that year (APTA

2019). Technological change for bus transit was negative, and between -5.4% and -2.3%, in seven of the 10 years studied. Annual bus transit productivity averaged 0.971 for the period 2007-2017. This implies that bus transit productivity declined by 2.9% per year.

Table 3.6. Geometric annual means: Malmquist Index and its components, 2007-2017

	Bus Agencies			Rail Agencies		
Year	EFFCH	TECH	MPI	EFFCH	TECH	MPI
2007-08	0.995	1.001	0.996	1.005	0.996	1.000
2008-09	1.012	0.952	0.964	0.996	1.003	0.999
2009-10	0.946	0.961	0.909	0.989	0.873	0.863
2010-11	1.111	0.886	0.984	1.013	0.987	1.000
2011-12	1.052	0.963	1.013	0.989	1.012	1.001
2012-13	1.008	0.948	0.955	0.998	0.927	0.926
2013-14	0.997	0.977	0.974	0.996	1.010	1.004
2014-15	0.929	1.085	1.018	1.055	1.011	1.067
2015-16	1.010	0.946	0.946	1.023	0.97	0.993
2016-17	0.852	1.113	0.948	0.854	1.142	0.975
2007-17	**0.991**	**0.983**	**0.971**	**0.992**	**0.993**	**0.983**

As for rail transit agencies, the largest productivity decline was also seen in 2009-2010 due to declines in both efficiency and technology. A 6% rail transit productivity growth was observed in 2014-2015, and rail transit productivity was rather stagnant for most time periods. Overall, compared to bus transit, rail transit experienced slightly less productivity declines throughout the years of study. One contributing factor towards this decline of productivity for transit agencies in 2009-2010 can be due to the decrease in ridership of commuter and light rail users within this time frame. A major factor contributing towards the productivity decline was the effect the 2008 recession on public transit agencies. Public transit agencies were facing declines in funding from state and local sources, and they were forced to take drastic actions including layoffs, service cuts, and fare increases in 2009 (APTA 2010). Overall rail transit agency productivity averaged 0.983 per year, which means rail agencies experienced an average productivity decline of 1.7% per year.

The cumulative productivity for both transit modes are displayed in Figure 3.1. The cumulative productivity growths for bus and rail transit agencies have been on the decline since 2008.

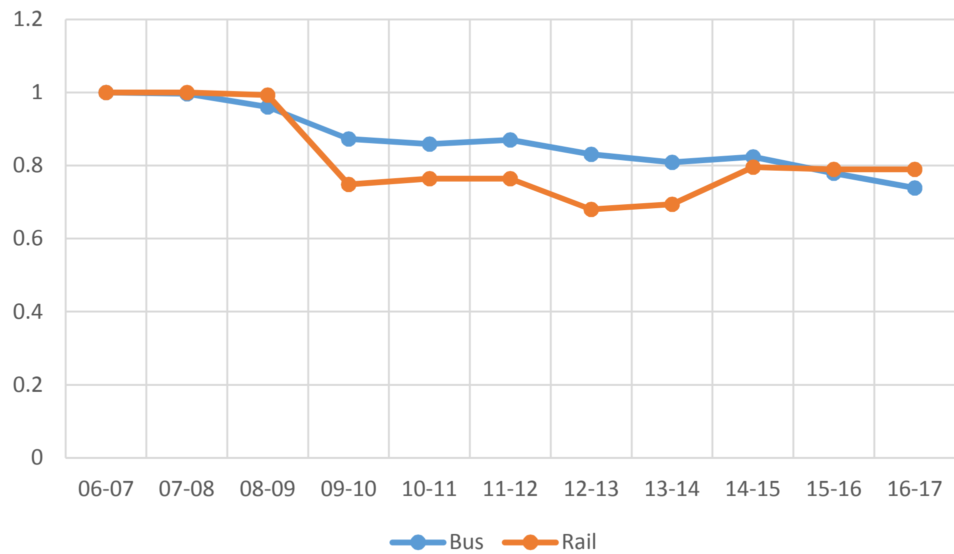

Figure 3.1. Cumulative productivity for bus and rail transit agencies

Next, the changes in productivity, efficiency and technology are further analyzed using a regression model to identify the possible determinants of transit performance. It is of importance to understand the factors which may cause the MPI and its components to change over the years for U.S. public transit. In this study, fixed effects (FE) panel data regression models with EFFCH, TECH and MPI as dependent variables is performed. After conducting the Hausman test (Greene 2008), the fixed effects model was preferred over the random effects model. Table 3.7 displays the results for bus transit agencies. For bus transit agencies, purchased transportation or outsourcing is significantly and negatively associated with efficiency change. This is evidenced by the negative coefficients on PT and ln(PTCost). Bus agencies that outsourced had an approximately 3.6 percentage points lower efficiency change and a 1% increase in purchased transportation expenditure is associated with 0.25 percentage point reduction in efficiency change. Although outsourcing has a positive effect on technological change for bus transit, the effect is not significant.

Table 3.7. Factors affecting MPI and its components for bus transit agencies

	Efficiency Change		Technological Change		Productivity change	
	(a)	(b)	(a)	(b)	(a)	(b)
PT	-0.0362**		0.0071		-0.0277	
	(0.0165)		(0.0130)		(0.0172)	
ln(PTCost)		-0.0025**		0.0006		-0.0019
		(0.0011)		(0.0009)		(0.0012)
Partnership	-0.0803**	-0.0805**	0.0333	0.0332	-0.0728***	-0.0730***
	(0.0359)	(0.0360)	(0.0527)	0.5273	(0.0124)	(0.0126)
ln(Population)	-0.0557*	-0.0559*	-0.0017	-0.008	-0.0645**	-0.0639**
	(0.0288)	(0.0292)	(0.0325)	(0.0325)	(0.0400)	(0.0279)
Year	-0.0071***	-0.0070***	-0.0106***	-0.0104***	0.0025	0.0253
	(0.0017)	(0.0017)	(0.0013)	(0.0013)	(0.0018)	(0.0019)
Constant	16.3075***	16.0883***	-20.2455***	-19.9811***	-3.1032	-3.1040
	(3.2358)	(3.2856)	(2.6792)	(2.6770)	(3.6371)	(3.7856)
N	450	450	450	450	450	450
R-sq	0.1132	0.1141	0.1134	0.1137	0.1018	0.1017
F-Stat	21.83***	24.51***	21.34***	21.22***	23.30***	1.32***

*** Denotes 1% significance level, ** Denotes 5% significance level, and * Denotes 10% significance level.

Partnerships is a dummy variable for transit agency's partnerships with TNCs. This study shows that such partnerships had a significantly negative effect on efficiency and productivity changes. Additionally, the effect of partnerships is negative on efficiency change and productivity change in a fashion similar to purchased transportation. Furthermore, a positive effect of partnership on technological change was noticed for bus transit, but it is not significant.

Table 3.8 displays the results for regression results for rail transit agencies. For rail transit agencies, PT and ln(PTCost) are insignificant in explaining variations in efficiency, technical and productivity growths. The partnership variable has a significant negative effect on productivity change, suggesting a productivity decline for agencies that had partnerships with TNCs. Since transit agencies reimburse for TNCs for reduced fares for transit riders, the result here suggests that the ridership increase may be less than the payments made towards TNCs by these agencies.

Table 3.8. Factors affecting MPI for rail transit agencies

	Efficiency Change		Technological Change		Productivity change	
	(a)	(b)	(a)	(b)	(a)	(b)
PT	-0.0477		0.0091		-0.0493	
	(0.0327)		(0.0377)		(0.0341)	
ln(PTCost)		-0.0020		0.0000		-0.0017
		(0.0016)		(0.0019)		(0.00147)
Partnership	-0.0850	-0.0839	0.0158	0.0175	-0.0765**	-0.0740**
	(0.0529)	(0.0529)	(0.0806)	(0.0804)	(0.0304)	(0.0298)
ln(Population)	0.00383	0.0026	-0.0025	0.0001	-0.0050	0.0015
	(0.0250)	(0.0249)	(0.0378)	(0.0373)	(0.0267)	(0.0267)
Year	-0.0026	-0.0026	0.0215***	0.0213***	0 .0129***	0.0129***
	(0.0032)	(0.0032)	(0.0043)	(0.0041)	(0.0045)	(0.0045)
Constant	6.2506	6.2469	-42.1317***	-42.0526***	-25.0342**	-24.9636**
	(6.2507)	(6.3892)	(8.1711)	(8.7043)	(9.0324)	(9.0318)
N	320	320	320	320	320	320
R-sq	0.0900	0.0709	0.1155	0.1156	0.0922	0.0916
F-Stat	1.64***	1.49***	7.13***	7.22***	2.45***	2.4***

*** Denote 1% significance level, ** Denote 5% significance level, * Denote 10% significance level.

3.6. Conclusions

In this study, changes in total factor productivity of bus and rail transit agencies in the U.S were measured. The productivity index was decomposed into an efficiency change component and a technical change component. Some changes were observed in efficiency, technology and productivity annually throughout the period of study, and the cumulative productivity declines were observed for both bus and rail transit agencies.

The current study shows that, for bus transit agencies, outsourcing is associated with negative efficiency and productivity changes. Although outsourcing has a positive effect on technological change for bus transit, the effect is not significant. Most importantly, TNC partnerships also have a negative effect on efficiency and productivity changes in bus transit. In recent years, urban consumers in the U.S. have seen an increase in on-demand transportation choices like ride-hailing services and micro-mobility options. There is an increasing trend of transit agencies partnering up with TNCs. The results suggest that transit agencies that seek to partner with shared-mobility service providers or to integrate shared-mobility with transit service must address challenges that hinder transit efficiency, and that transit technology has yet to keep up with technological progress in urban mobility. Sunshine Laws and organizational structural differences (Curtis et al. 2019) between transit agencies and TNCs must be thoroughly considered prior to forming these partnerships to avoid the negative impact on productivity of transit agencies.

This study also demonstrated that a negative effect of TNC partnerships on rail transit productivity. Since most partnerships have begun especially after 2018, it will be of great importance for future studies to further examine this using the latest data available. If public transit system is increasingly utilized, it could both improve mobility options and decrease transportation energy use, which could lead to decreased greenhouse gas emissions.

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CHAPTER 4. ONLINE SHOPPING, BRICK-AND-MORTAR OUTLETS AND TRANSIT RIDERSHIP IN THE U.S.

4.1. Abstract

With increasing trends in online shopping, brick-and-mortar outlets have experienced declines in businesses forcing them to close down completely, downsize or go online. Shopping malls and strip malls, for example, have been faced with less foot traffic in recent years, while struggling to retain and attract new businesses to operate in various locations. Similarly, public transit agencies in the U.S have seen declines in ridership. Using a bivariate probit model and examining the inter-relationship between online shopping, mall visits and public transit use, I seek to determine if online shopping activities contribute to the declines in public transit use in the U.S. Results indicate that public transit use is positively associated with mall visits; for consumers who are online shoppers, online shopping creates a negative effect on mall visits thereby reducing their public transit use.

4.2. Introduction

Public transit ridership in American cities has been falling in recent years, and transit agencies have attempted to understand the reasons for this with varying degrees of evidence and uncertainty, such as the growth of TNCs, rising household incomes, falling gas prices, cheap financing and increased personal car use (Hall et al. 2018). This ridership decline is seen in both rail and bus transit systems (Higashide and Buchanan 2019). At the same time, the consumption of public transit in the U.S. is quite dispersed. Consumers living in the largest 42 urbanized areas consume nearly 88.6% of the public transit service provided in the U.S. The ridership per capita varies from 232.5 in New York-Newark to 10.1 in Detroit, MI (NTD 2018; APTA 2018).

Advancements in technology, especially wireless communications, have been successful in substituting travel in many cases (Polzin 2016). The rise of smartphones and the increase use of home computers have intensified competition among retailers as consumers shift their purchases online, leading to a decrease in the need for travelling to specific locations or to buy from a local store. Many traditional retailers have also expanded or taken their businesses online, and merchants who are slow to respond to the online marketplace have either collapsed financially or filed for bankruptcy. For example, Sears in-store sales declined 13.9% and Kmart same-store sales declined 6.9% during 2015. Nearly 12,000 retail store closures in the U.S. was reported in 2015, which were estimated to have impacted 161 million square feet of retail areas (Cavan 2016). On the other hand, online retailers such as Amazon.com[26] have greatly changed how people shop, making it easier to purchase goods on a computer or a smartphone (Pelletier et al. 2011). In the U.S., 10.1 billion trips were made using public transit in 2017 (APTA 2017), and 21% of the trips were made for the purpose of shopping (Clark 2017). It is possible that the effects and the increasing popularity of online shopping, may have potentially negative effects on the use of public transit.

First, the relationship between travels to shopping malls or physical retail stores and the use of public transit will be examined. The possible relationship between the attitudes people have towards online shopping and how the attitudes may affect consumers' decisions to visit shopping malls or traditional retail stores will be explored. If consumers make trips to shopping malls, we can expect a positive relationship between mall visits and the use of public transit. In other words, people will use more public transit if they visit physical retail stores or shopping

[26] The online retail giant Amazon.com has been able to increase its subscribers (Amazon Prime Members) to 65 million by September 2016 (Rutter et al. 2017).

malls. If shopping mall or physical retail store visits are reduced because of the increased tendency to shop online, then online shopping has a negative effect upon mall visits and the use of public transit by consumers.

4.3. Literature Review

4.3.1. The Creative Destruction Effect of the Internet on "Brick-and-Mortar" Businesses

Online shopping is rapidly increasing in popularity and can have significant impacts on traditional forms of shopping, due to the fact that more than 55.6 percent of people (in 2018) in the world now have access to the internet (Internet World Stats 2018). The rise of ecommerce has negatively affected bricks-and-mortar retail[27] stores. Among the hardest hit traditional departmental stores, retail giants such as Sears, Radio Shack, JCPenney, Macy's and many shopping malls in the U.S. have experienced declines in sales, and as a result, employment at their physical stores have shrunk. The massive decline in in-store sales has prompted markets, industries and businesses to transform and adapt to online retailing (Hortaçsu and Syverson 2015). Some retailers, while closing unprofitable stores nationwide, are expanding or focusing their businesses online. For example, Staples, one of the largest office-supply companies in the U.S. aimed to close nearly 10 percent (225 stores), of its North American stores by the end of 2015, while focusing on gaining more online sales with increased numbers and product varieties it sells on Staples.com (Davidson 2014).

Through the internet, businesses now have the opportunity to reach out and communicate with people, who might be potential customers, anywhere in the world (Haubl and Trifts 2000). At the same time, consumers seeking goods and services have increased product information to

[27] Retail stores include facilities such as departmental stores, supermarkets, hypermarkets and others (Jaravaza and Chitando 2013).

make better purchase decisions after considering and comparing all options. Moreover, consumers can easily find merchants, products, and product information by browsing the web, which results in reducing search costs, and reducing the need to travel. Time saving ability of online shopping has made it the preferred choice of busy households (Szymanski and Hise 2000). Consumers' choice to shop online could be influenced by a wide variety of reasons such as product availability (many producers and sellers), products delivered to door step, convenience, peer influence, lower online prices, internet experience and ease of purchasing (Limayem et al. 2000; Swinyard and Smith 2003). The effect of online shopping activities on traditional brick-and-mortar businesses may be irreversible (Hsiao 2009).

According to the U.S. Census Bureau (1999), e-commerce (online sales by retail establishment), which was in its infancy in the late 1990s, accounted for US$ 5.3 billion in the fourth quarter of 1999, which represented a mere 0.64% of all retail sales. In the early 2000's, conventional retail stores in the U.S. accounted for nearly 96.6 % of all retail sales, and online sales had approximately 1.1 % at the time (Mesenbourg 2001). However, by 2015, online sales increased to $340.2 billion, and went up by 14.4 % to $513.6 billion by the end of 2018, increasing its share up to 9.7 % out of total retail sales.

Figure 4.1 displays the gradual increase of the percentage of e-commerce retail sales from 2001 to 2018 and a comparison between retail and e-commerce year-over-year sales growth rate during the same period. E-commerce year-over-year sales growth rate displays an average of 17.5 percent per year within this time frame whereas total retail sales including ecommerce only bring out a 0.03 percent average year-over-year sales growth rate (U.S. Census Bureau 2016; U.S. Census Bureau 2018)

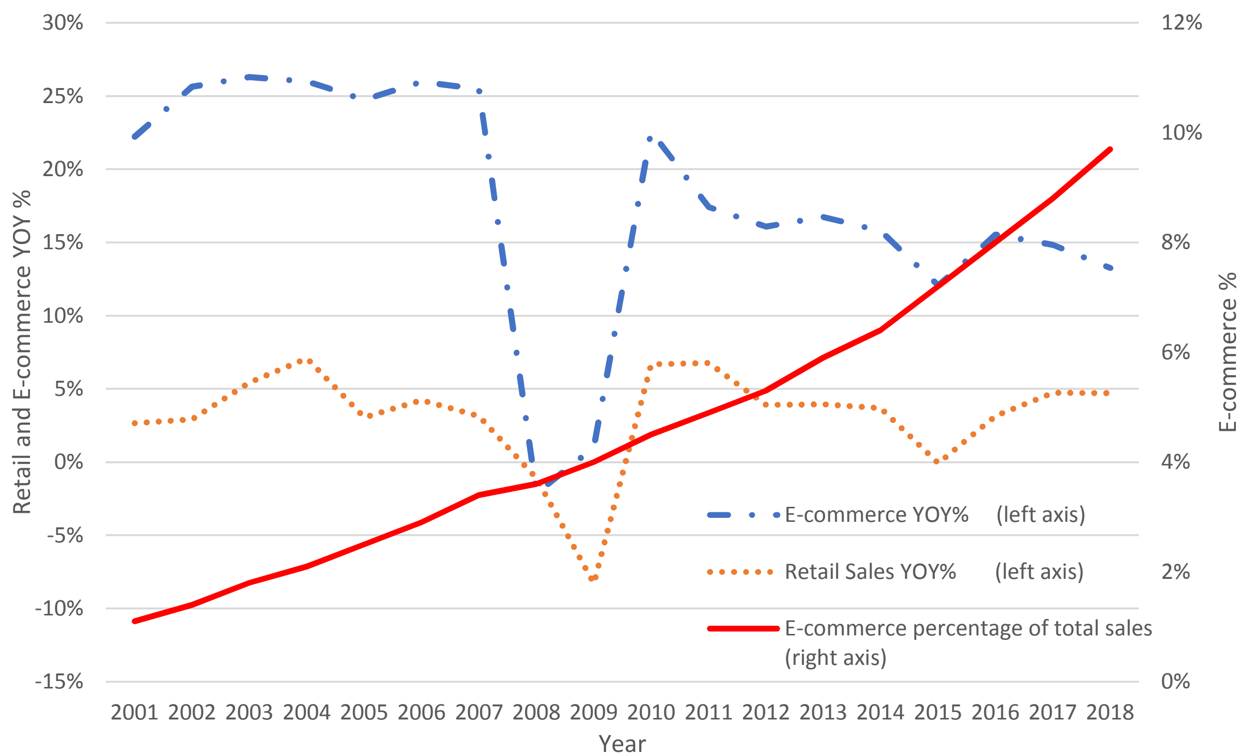

Figure 4.1. Retail and e-commerce year-over-year sales growth rate (left) and e-commerce retail sales as percent of total retail sales (right)
(Source: Raw Data Obtained from the U.S. Census Bureau Quarterly E-Commerce Report Historical Data)

Shaked and Orelowitz (2017) discuss the shift in consumer shopping preferences from brick-and-mortar stores towards online stores, and they find that traditional retail stores nationwide are losing ground to online retailers. The departmental stores in the U.S experienced 23 consecutive months of year-over-year declines resulting in a 7.2 percent drop in store sales by 2016, compared to the previous year. Furthermore, they conclude that with fewer retail staff on the sales floor, even fewer retail sales are the ultimate result for this industry.

4.3.2. Factors Affecting Public Transit

The demand for public transit is affected by factors such as cost, quality of service, income and vehicle ownership (Paulley et al. 2006). The Masabi Foundation (2017) carried out a survey of over 1,000 U.S. residents who had access to public transit; 33 percent of the respondents considered convenience as the top priority, price (24 percent), travel time and necessity (17 percent) followed as the other major factors for taking public transit (Masabi 2017).

I performed a thorough search of past literature on factors affecting public transit ridership. The summary is displayed in Table 4.1 below. I categorized these factors according to the classifications by Taylor and Fink (2013), who provides a broad view of some of the traditional research relevant to factors affecting transit ridership. They break down these factors into macroeconomic factors (employment levels, central business district employment, and household income); spatial factors (population density, employment density, and traffic congestion levels); and internal factors (improvements in service, pricing, schedule reliability).

Macroeconomic factors (such as household income and employment) could have an impact on public transit ridership. Many studies have shown the significant impact of such macroeconomic factors on transit ridership. Gómez-Ibáñez (1996), highlights that per capita income increases are positively correlated with car ownership, which has reduced transit ridership in the U.S. Furthermore, Paulley et al. (2006) also identify income and vehicle ownership as “background factors” affecting public transit ridership in comparison to specific attributes of public transit such as cost/fares and the quality of service, which are directly controlled by the transit operator. According to Paulley et al. (2006), in general, higher income increases the number of trips and the average length/time duration of each trip. However, it is possible that additional travel is divided between using public transit and a personal vehicle. On the other hand, increasing income leads to increased car ownership. Thus, rising income has secondary and negative effects on transit ridership, which further supports the findings of

Gómez-Ibáñez (1996). He further states that employment too plays a major role in transit ridership. In Boston, for example, employment was a key factor driving increase of ridership in 1969-1990 (Gómez-Ibáñez 1996).

Furthermore, according to Taylor and Fink (2013), spatial factors such as population and employment density, congestion levels, land use mix and accessibility and design are key determinants. Population density has a significant positive relationship with transit ridership. It has been shown that higher density in urban areas leads to significantly higher public transit use (Murray et al. 1998). Cervero et al. (2004) finds out that higher employment densities have a positive effect on public transit use. Land use mix too is a crucial determinant of transit ridership, by creating a stable demand for public transit over time and creating the balance of customer flows. Land use designations should contain a proper combination of zoning types (e.g. residential, retail, office, light industrial) to ensure transit oriented development in cities (Cervero et al. 2004). Accessibility and design combined, is another factor which attracts more customers towards transit stations. Locating public transit facilities in the most convenient and suitable areas is of utmost importance in order to gain ridership for transit agencies. Past research have shown that public transit agencies are not able to provide its customers with adequate accessibility to their services, which has created the opportunity for other ride hailing activities to enter the market (Saif et al. 2019). According to a survey by APTA (2017), in 2017, nearly 70% transit riders walked to their stop or station, 11% drove, while another 10% of transit riders had to use another form of transit to get there. Only 0.5% of riders from the survey used a shuttle or taxi to get to their station or stop (APTA 2017). In terms of the transit mode used, there were significant differences among users of bus and rail with regard to accessibility. More bus riders walked (81 %) to the stop compared to rail passengers (55%). More rail passengers (12%) had to use another form of transit service to reach their desired station, whereas for bus riders, it was around 9%. Most importantly, no one in the survey used shuttle or taxi to access bus stations and only 1% of rail passengers used facilities such as shuttle, taxi's or ride share to reach their specific station (APTA 2017).

While external factors such as macroeconomic and spatial factors have extensive influence on transit ridership, internal factors related to transit agencies also play a substantial role. Fares, transit reliability, service quality, transit density and reach of route networks are some of the key internal factors transit agencies focus on to attract more riders (Taylor and Fink 2013).

According to Paulley et al. (2006, pg. 300), the quality of transit service includes "a wide range of attributes which can be influenced by planning authorities and transport operators." The quality of public transit includes accessibility, time taken to exit public transit, time spent in-vehicle, frequency of service, interchanges between different modes of public transit, reliability of service and availability of transit related information. Similarly, Redman et al. (2013) determined that factors affecting ridership is linked to both physical and perceived service quality attributes of public transit. Physical transit service attributes include reliability, frequency, speed, accessibility, price, information availability, ease of transfers and vehicle condition;perceived attributes include comfort, safety, convenience and aesthetics (Renwick et al. 2013).

It is the responsibility of transit agencies to provide a reliable, efficient and productive services to the public (Vuchic 2005). Customers' decision to use public transit greatly depends on the reliability of the mode of transportation, and it is a crucial factor in customer retention as well as ridership gain for transit agencies. Throughout the years, inconvenience, uncertainty, and added time costs of unreliable service in the public transit sector have become factors which have driven away many customers from this industry. Therefore, it is necessary to maintain an efficient and attractive system, which increases user satisfaction and loyalty. Reliability is also a crucial factor for transit agencies in terms of identifying internal inefficiencies, reducing operator costs, and improving revenue (Diab et al. 2015). In a survey carried out by Carrel et al. (2013), the most significant negative experiences that caused a reduction in public transit use were delays perceived to be the fault of the transit agency, long waits at transfer points, and being prevented from boarding due to crowding.

As mentioned earlier, fares are a critical factor affecting ridership. As such, pricing and fare levels are frequently analyzed. In this context, Sale (1976), who studied seven systems found that ridership increased by 5% or more within the time frame of 1971 through 1975 as a result of stable or declining transit fares, although service expansion was the most important factor that increased ridership in the early 1970s. Similarly, Liu (1993) and Kain and Liu (1995) examine the ridership trends in Portland, San Diego and Houston using fare variables in regression models, and they find that fare, along with other internal and external factors such as employment, gas prices and service quality, have a significant effect on the use of public transit in those metropolitan areas. In Portland, reduction in fares and expansion of service served as primary factors that lead to a dramatic increase in public transit use in the 1970s.

In addition, changes in lifestyle and advancements in technology (Chen and Cho 2011), auto ownership and parking availability (Taylor and Fink 2013) also have effects on public transit use. While social factors are not easily quantifiable, there has been some research evaluating how factors such as the growth of e-commerce and new technologies affect the transportation industry in general. With the demand for online shopping and the downfall of traditional brick-and-mortar businesses, it is important to understand how emerging shopping trends affect public transit ridership, as this information is vital for policy decisions on public transit (Chen and Cho 2011).

Table 4.1. Summary of studies

Study	Transit Related Factors	Non-transit Related Factors	Methods	Data
Imaz et al. (2015)	-Service quality -Reliability -Level of crowding of the transit vehicles -Travel and wait times -Punctuality and reducing the number of transfers -Transit fare		Binary logistic regression models to capture customer loyalty toward transit	Commuting Survey for Mode Shift (COSMOS) survey conducted in Toronto, Canada 2012 which include subway, bus and streetcar riders.
Taylor and Fink (2013)	-Internal (improvements in service, pricing, schedule reliability, routing, service frequency, safety, accessibility)	-Macro-economic factors (employment levels, central business district employment, and household income) -Spatial factors (population density, employment density, and traffic congestion levels) -Auto ownership and parking availability	Review of past studies	
Jin, X., (2005)	-Accessibility -Connectivity	-Automobile ownership -Fuel prices	Multinomial regression model to predict transit and auto captivity	Oregon 1994 Household Activity and Travel Diary Survey.
Jou and Chen (2014)	-Average daily frequency -Route lengths and number	-Income levels -Employment -Population density	Unrelated regression equations (SURE) model	Public sector statistics on 336 townships in Taiwan 2010.
Souche (2010)	-Quantity effect (frequency, speed, Network density and network access time)	-Price effect (fuel prices) -Income effect -Spatial effect (population density)	Robust econometric method to determine urban travel demand	International Union of Public Transport (IUTP) Database for 100 of the world's cities in 1995.
Gutiérrez et al. (2011)	-Characteristics of the stations (type, number of lines, accessibility within the network)	-Built environment dimensions (street density, diversity- Land-use mix and design), -Socioeconomic factors (household income, age, race/ethnicity and car ownership)	Rapid response ridership forecast model, on the combined use of Geographic Information Systems, distance-decay functions and multiple regression models	Monthly Transit-station ridership data, Madrid Spain 2004.
Chen and Chao (2011)	-Advancement in technology	-Habitual mode choice -Life style changes	Utility-maximizing of microeconomic theory and psychological behavior theory to identify factors influencing public transit.	Survey data on commuters in Kaohsiung City, Taiwan 2009.

Table 4.1. Summary of studies (continued)

Study	Transit Related Factors	Non-transit Related Factors	Methods	Data
Chu (2004)	-Service Coverage -Scheduling -Transfers -Total trip time -Safety and security -Appearance and comfort -Reliability -Accessibility	-Crime rates -vehicle ownership	Simultaneous equations system with a count-data model and a binary choice model	Transit bus data (Jacksonville, Florida USA) from National Transit Database Data and data provided by Kittelson and Associates, Inc. (KAI) in 2001.
Swimmer and Klein (2010)	-Average distance to station -Commute time -Service availability	-Metropolitan density -Fuel prices -Poverty level -Income -Education level	Linear regression analysis to examine determinants of public transportation	Public transportation ridership data in over 100 U. S. cities in 2007.
Masabi (2017)	-Convenience -Price -Travel time, and even necessity -Technology advancements	-Vehicle ownership -Rideshare	Identifying trends in public transit ridership across North America.	Google surveys poll of 1000 U.S. residents with access to public transit.
Paulley et al. (2006)	-Fares -Quality of service -Technology advancements (pricing, changes in vehicle size, environmental controls on emissions, and developments in ticketing and information provision)	-Income -Car ownership	Review of past studies	
Redman et al. (2013)	Quality attributes -Physical (reliability, frequency, speed, accessibility, price, information, provision, ease of transfers, vehicle condition) -Perceived (comfort, safety, convenience, aesthetics)		Review of past studies	
Chiou et al. (2015)	-Accessibility to public transport (fare rate, station accessibility, service frequency, park and ride space, feeder service)	-Demographic and socio-economic (population, employment, age group, and income level) -Land use (residential, industrial, commercial, or mixed use) -Availability of private transport (car ownership, road length, fuel price, parking fee, parking space)	Global and local regression models to identify the key factors of public transportation usage rates.	Survey data on 48 regions (township or districts) in Taiwan 2010.

Table 4.1. Summary of studies (continued)

Study	Transit Related Factors	Non-transit Related Factors	Methods	Data
Buehler (2011)		-Socio-economic factors (income and automobile ownership) -Demographic factors (household composition and life cycle, gender, and age) -Spatial development patterns (Residential density) -Transport and land-use policies -Culture and attitudes	Bi-variate analysis and regression analysis.	Data from National Household Travel Survey (NHTS 2001) for U.S. and the Mobility in Germany Survey (MiD, 2002) to identify determinants of transport mode choice in U.S. and Germany.
Perk et al. (2008)	-Travel time reliability (on-time performance) -Service quality (safety, convenience, organization, fast travel time, reasonable wait time, information availability, smooth, uncrowded ride, vehicle comfort, vehicle cleanliness, ease of ticket purchasing, staff courtesy, convenient parking convenient stops, and linkage to the local transit system.		Analysis of survey data.	Puget Sound Transportation Panel (PSTP) survey data for 12 years.
Carrel et al. (2013)	- In-vehicle delays - Network congestion - Wait time during transfers - Service frequencies - Transfer reliability		Analysis of survey data.	Current and former user survey data of San Francisco Municipal Transit Authority, (MUNI) in California.
Murray et al. (1998)	-Accessibility to this mode of travel -Fares - Placement of stops and routes - Frequency of operation - Connectivity of the transport network	- Population Density	Review of past studies and discussion related to Brisbane region, Australia.	
Gomez-Ibanez (1996)	-Fares	-Suburbanization -Income -Employment	Deficit accounting model and Statistical analysis of ridership change.	U.S. Census and National Transit Database data on Boston metropolitan area 1970-1990.
Kain and Liu (1995)	-Fares -Service quality	-Employment -Population densities -Suburbanization of jobs -Income -Car ownership -Gas prices	Estimating ridership models using cross section and time series data.	Houston's (METRO) 1993, and San Diego's Metropolitan Transit System (MTS) 1992.

4.3.3. Online Shopping and Changes in Transportation

A traditional retailer's main focus was on the location (physical space), tangible inventory, and customer traffic (Cowles et al. 2002). The location decision of a firm is crucial and influenced by numerous factors. Selecting the most suitable location for any retail business is considered an utmost important decision, and successful companies spend considerable time and effort in choosing the optimal location (Jaravaza and Chitando 2013).

According to the brick-and-mortar model pertaining to retail environments, a retailer's physical location defines the "target geographical market," in which the retailer competes for customers (Ingene and Lusch 1981, pg. 108). In this context, traditional retail norms dictate that the retailer has a very minor opportunity to attract customers beyond its geographical market. Thus, in a traditional retail environment, the success or failure of retailing is directly influenced by the retailer's location (Ingene and Lusch 1981). However, these retail locations were determined by traditional location theories developed in different retail environments. Theoretical frameworks for analyzing store location potential and trading areas include central place theory, and retail gravitation theory (Friske and Choi 2013). According to the central place theory, customers are willing to travel greater distances to retail establishments that carry a relatively wide selection of valuable goods. The gravity theory asserts that groups of customers are drawn to certain locations because of factors, such as the distance to market, distance between markets, market population, the size of the retail establishment, the location of competitors, etc. (Eppli and Shilling 1996).

Living in an era in which consumer preferences have shifted towards online shopping, e-commerce activities have significant impacts on physical stores, and e-commerce is challenging bricks-and-mortar retailers in many ways. Traditional location theories may not apply since websites have become a more appealing alternative to traditional brick-and-mortar stores (Friske and Choi 2013). This shift provides the opportunity to reduce the costs and limitations vendors may have on accessing physical shopping locations, and enables new vendors to enter the market from any location (Fichter 2002). Retailers that perform most of their sales online, such as Amazon.com, have enjoyed great financial success over the last decade; yet most retailers view their websites as a complement to their existing brick-and-mortar stores, not as a replacement (Friske and Choi 2013).

According to Rotem-Mindali and Salomon (2007), online retailers have implications on the organization and structure of retail systems as well as customers' shopping habits. However, they also state that such changes vary by the degree to which consumers respond to technological changes. When using online shopping over conventional shopping, consumers gather information about products, choose a mode of transaction and a mode of delivery to their homes. In the past, accessibility to a certain item was mainly travel-based, where the consumer had to be physically present at a store to make a purchase. However, with advancements in technology and the expansion of e-commerce, accessibility is no longer only travel-based, it is also information technology based. In the retail business, as competition between retailers grow, there is a high premium for accessibility. The demand for accessibility is true mostly for travel-based retail, but it is also relevant to online retail because retailers have to reach their customers through a device or a computer (Rotem-Mindali and Salomon 2007).

In a different study, Edwards et al. (2009) study the carbon footprint of conventional vs. online retailing and found, online retailing on average generated lower carbon dioxide compared to traditional stopping. In the study, small, non-food items, such as books, CDs, clothing and household items were taken into consideration. In this context, with the increasing use of online retail and the possibility of buying food online, it is possible that these effects may be more significant in recent years. Furthermore, Edwards et al. (2009) identify the number of items purchased per trip, mode of transportation, trip chaining as well as grouping purchases to reduce the number of trips and online purchases as critical factors that affect the results of the study. Therefore, these critical factors should be taken into consideration by consumers as well as online retailers to reduce the carbon footprint of their logistical operations. Similarly, Rotem-Mindali and Weltevreden (2009) study the effect of e-commerce on travel in the Netherlands and determined that personal travel decreased slightly due to purchases made online, however an increase in freight travel was observed. The net effect on travel was negative as the increase in freight travel did not fully offset the decrease in personal travel.

In another study, Rotem-Mindali and Weltevreden (2013) discuss factors which affect personal travel in relation to online shopping. E-commerce could reduce personal travel due to the home delivery features of online retail stores, and it could reduce the travel from store to store when consumers look for specific goods which may not be available at one store. In this study, the authors explain that travel may not be affected if consumers link travel trips together (trip chaining), which would mean that the effect of online shopping in the context of travel may not be significant. For instance, if people visit a shopping center after work, eliminating the trip to the store as a result of online shopping will not lead to significant effects on travel. Additionally, most people purchase multiple items in a single shopping trip, therefore buying something online does not necessarily mean that people would not travel to stores. If so, online shopping does not nessarily mean less physical store visits nor less transit use.

In summary, traditional shopping forces customers to visit physical stores, make purchase decisions based on the limited product information from commercials at the store or past experiences. E-commerce provides a complete opposite scenario, in which the customer does not need to travel to any physical location, instead he/she can obtain more product information, make the purchase and get the product delivered to his/her doorstep (Rotem-Mindali and Salomon 2007). If consumers substitute store visits with online shopping, increased online shopping could result in less public transit use due to reduced store visits. In this case, online shopping and physical store visits are substitutes of each other, and the substitutability of the two activities could lead to reduced transit use. However, if online shopping causes consumers to know where to shop or to check out product attributes at a local store site before actually making a purchase online or onsite, or if it causes consumers to go to a local store to pick up an online order onsite[28], then increased online shopping may actually lead to more store visits. This means that online shopping and store visits are complementary to each other, and if so, online shopping may not necessarily lead to reduced public transit use. Thus, the relationship between online shopping and transit use hinges largely on the linkage between online shopping and physical store visits, or on whether they are substitutes or complements. In light of this, online retail activities may or may not reduce the need for store visits and may or may not contribute towards the loss of transit ridership, depending on how online shopping affects physical store visits. This is the motivation for my study.

4.4. Model Development

In this research I would like to examine the effect of online shopping behavior on public transit usage in the U.S. Figure 4.2 displays the conceptual framework for the relationship between consumer's shopping behavior and the demand for public transit. The connection between online shopping behavior (Node 1) and physical store trips (Node 2) is shown by Link 1

[28] For example, instead of shipping items ordered online to consumers' homes, online retailers, like walmart.com, target.com, macys.com, etc., enable consumers to pick up the items at their physical stores.

in Figure 4.2. The outcome of this connection in turn affects the demand for public transit (Node 3); and this relationship is represented by Link 2. As consumers increasingly shop online, if the need to travel to physical stores is reduced (increased), then the reduced (increased) travel leads to a lower (higher) demand for public transit.

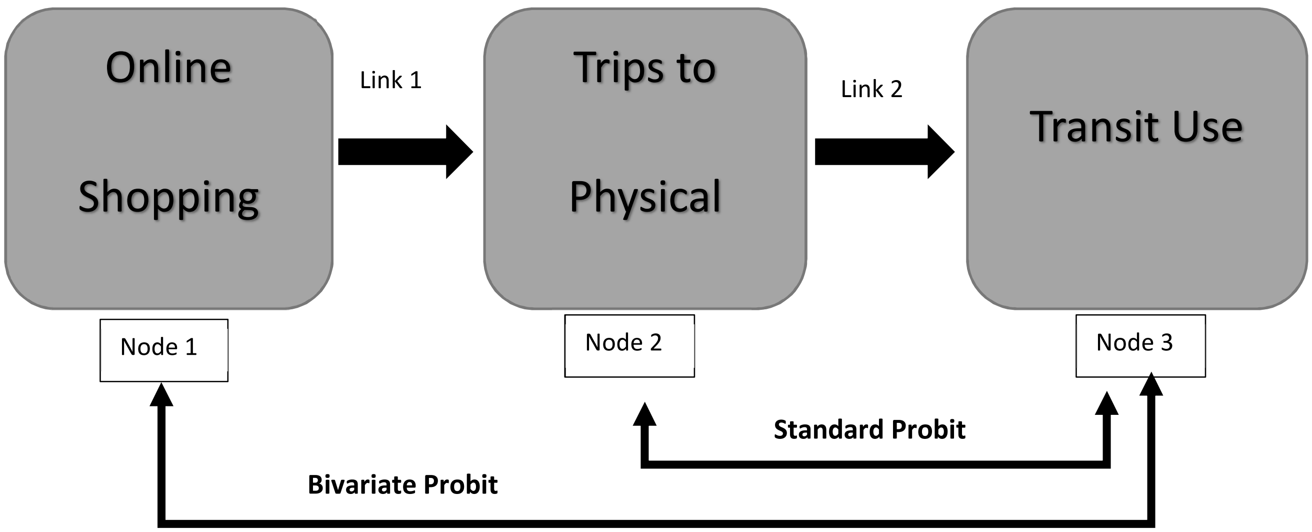

Figure 4.2. Schematic of the model

In this study, I focus on consumers' trips to shopping malls and strip malls since items or products at these places tend to be available online. For example, clothing, electronic devices, cosmetics, nutrition products, etc. are consumer products that can be purchased online or at physical stores.[29] Departmental stores like JCPenney and Macy's have faced considerable competition from online retailers like Amazon.com and other rival online stores. An important assumption for this modeling framework is that I assume the products must be available both online and at a physical store. This allows consumers to either substitute online shopping for physical shopping or complement one with the other.

[29] While grocery items and fresh produce are increasingly available online and delivered to homes, they are not as common online compared to other tactile and durable consumer items.

A bivariate probit model to examine the relationship between consumer shopping behavior and transit use is developed. In the model, there are two binary dependent variables Y_1 and Y_2:

$$Y_1 = \begin{cases} 1 & \text{if } Y_1* > 0 \\ 0 & \text{Otherwise} \end{cases}, \tag{4.1}$$

$$Y_2 = \begin{cases} 1 & \text{if } Y_2* > 0 \\ 0 & \text{Otherwise} \end{cases}, \tag{4.2}$$

where $Y_1 = 1$ indicates a consumer goes to a brick-and-mortar shopping mall or a strip mall, $Y_2 = 1$ indicates a consumer takes public transit, and Y_1* and Y_2* are latent (unobserved) variables which can be modeled as,

$$Y_1^* = \alpha_0 + \alpha_1 Online + \alpha_2 X_1 + \ldots \alpha_k X_k + \varepsilon_1 \tag{4.3}$$

and

$$Y_2^* = \beta_0 + \eta Y_1 + \beta_1 Z_1 + \ldots \beta_j Z_j + \varepsilon_2. \tag{4.4}$$

We assume that

$$\begin{pmatrix} \varepsilon_1 \\ \varepsilon_1 \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}\right],$$

which means the errors in (3) and (4) have a standard bivariate normal distribution with zero means, variances of 1, and the correlation coefficient $\rho \neq 0$. If $\rho = 0$, then equations (4.3) and (4.4) may be estimated as two separate probit regression models that are independent of each other. Bivariate probit assumes a joint normal distribution for the correlation in unobservables affecting the discrete measures of mall visits and transit use (Hutchinson and Wheeler 2006).

Equations (4.3) and (4.4) is a simultaneous-equation system and a recursive bivariate probit model. In equation (4.3), the amount of online shopping would have a negative impact on physical store shopping Y_1, if consumers substituted physical store visits with online shopping, so if the coefficient α_1 is negative, online shopping leads to less store visits. Physical store visit, Y_1, is an endogenous variable in equation (4); it is expected to have a positive effect on transit use Y_2. The variables $(X_1, \dots, X_k)$ and $(Z_1, \dots, Z_j)$ are consumer demographic variables like income, household size, age, education level, car ownership, etc.

4.5. Data

The study uses consumer-level data from the annual Simmons National Consumer Survey (NCS) Respondent Database from years 2012 to 2015. The Simmons NCS database contains basic demographic information and product, lifestyle and media preferences of sampled U.S. population. The Simmons NCS uses a multi-stage stratified probability sample of individuals, oversampling high-income and Hispanic households. The data include weights to account for oversampling and non-response and to match the demographic profile of the American public (Park and Hoy 2015). This research uses the information on American consumers' sociodemographic characteristics, transportation as well as shopping patterns available in the Simmons NCS database. The selected variable list is displayed in Table 4.2.

Table 4.2. Variable definitions

Variable	Definition
Public Transit	Binary variable indicating if consumer used public transit in the past 30 days
Shopping Mall	Binary variable indicating if consumer visited shopping malls in the last 4 weeks
Strip Mall	Binary variable indicating if consumer visited strip malls in the last 4 weeks
Online Shopping Behavior	Binary behavioral variable indicating if consumer agrees a lot on that he/she is doing more online shopping than before
Employed	Binary variable indicating if consumer is employed (full time and part time) or not
Gas Price	State average gas prices obtained from the U.S. Energy Information Administration
High School Grad	Binary variable indicating if consumer has a high school diploma or less
Some College	Binary variable indicating if consumer attended college 3 years or less
College Grad	Binary variable indicating if consumer graduated college
Male	Binary variable indicating if consumer is male or not
White	Binary variable indicating if consumer's ethnicity is White or not
Asian	Binary variable indicating if consumer's ethnicity is Asian or not
Black	Binary variable indicating if consumer's ethnicity is Black or not
Other (Races)	Binary variable indicating if consumer's ethnicity is other than White, Black or Asian
Children	Binary variable indicating if consumer has one or more dependent children
Work at home	Binary variable indicating if consumer works from home or not
Driver's License	Binary variable indicating if consumer has a valid driver's license or not
Auto Insurance	Binary variable indicating if consumer has auto insurance or not
Age	Binary variables indicating 4 categories of age groups. Age categories: 18-21,21-30, 30-44, 45-59, 60 or older
Family	Binary variable indicating 4 categories of household sizes in terms of the number of family members per household. Family categories:1-2, 3-4, 5-6, 7 or more people
Household Income Levels (HINC)	Binary variables indicating different categories of household incomes. Annual HHI Levels: Less than $25,000; $25,000-$44,999; $45,000-$74,999; $75,000 and above.

Source: Simmons National Consumer Survey (2012-2015)

In our model, $Y_1 = 1$ corresponds to a visit to a shopping mall or a strip mall in the last 30 days, otherwise $Y_1 = 0$. In equation (4), $Y_2 = 1$ if the consumer used public transit in the last 30 days prior to the survey, and 0 otherwise.[30] The analysis was performed on different samples extracted from the main dataset. The first dataset is the full sample(101,206 sampled individuals), while we narrow the next three samples by considering only (I) online browsers (or online information gatherers) – these are individuals who in the last 30 days prior to the survey used the internet or visited websites to gather information for shopping purposes, (II) online shoppers -- individuals who in the last 30 days prior to the survey made an online purchase, and (III) online browsers and/or shoppers -- individuals who either gathered information for shopping purposes (subsample I) and/or made an online purchase (subsample II) within the last 30 days prior to the survey.

It is important that we focus on these subsamples of shoppers because in the U.S. many transit users are not online shoppers, and vice versa. Poor and low-income individuals constitute the majority of the transit riders in the U.S. (Giuliano et al., 2001), and they tend to be the underbanked and have no access to a bank account or a credit card (Nielsen et al., 2016). Thus, online shopping is less common among them compared to individuals who are non-poor. By using the entire sample, we include groups of individuals who (i) have neither shopped online nor used public transit, (ii) have not shopped online but used public transit, (iii) have shopped online and used public transit, and (iv) who have shopped online but not used public transit. In Figure 4.2, Node 1 does not exist for individuals in Groups (i) and (ii), hence we cannot establish the connection between online shopping and mall visits, and Link 1 does not exist. However,

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[30] Giuliano (2007) distinguished "regular" transit users as those who reported to have used public transit at least once a week, and "occasional" transit users as those who reported to have used public transit at least once per month. The Simmons' survey only asks if the respondent had used public transit in the 30 days prior, and does not contain additional question on the frequency of use within the 30 days period. Hence, we are unable to distinguish between occasional and regular transit users based on the data we have.

Node 2 exists for all four groups, and the relationship between mall visits and transit use can be established by Link 2.

Since the objective of this study is examining how online shopping affects transit use, individuals in groups (iii) and (iv) are of interest. Specifically, to evaluate the two linkages depicted in Figure 4.1, we need to first identify individuals who may have made more or less physical store visits because of online shopping (Link 1), and if the change in physical store visits due to online shopping have altered their transit use (Link 2).

Most of the survey respondents in our data did not use public transit. I identified 21% of the respondents (or 21,335 individuals) in the full sample as those who gathered information online; 28% (28,469) respondents made an online purchase in the past 30 days prior to the survey. The combined sample (35,490) constitutes of 35% respondents who either gathered information online for shopping purposes or made an actual online purchase, or both gathered information and made purchases online. Table 4.3 displays the breakdowns of the 3 subsamples used in the analysis. For all three samples approximately 17.5% of the respondents are transit users.

Table 4.3. Sample breakdown

		Public Transit Users		
		0	1	Total
Online Browsers	0	67,377	12,494	79,871
	1	17,553	3,782	21,335
	Total	84,930	16,276	101,206
		Public Transit Users		
		0	1	Total
Online Shoppers	0	61,455	11,282	72,737
	1	23,475	4,884	28,469
	Total	84,930	16,276	101,206
		Public Transit Users		
		0	1	Total
Combined	0	55,473	10,243	65,716
	1	29,457	6,033	35,490
	Total	84,930	16,276	101,206

The summary statistics of the variables are displayed in Table 4.4 below. According to the Simmons survey data between 2012 and 2015, approximately 16% of the respondents reported to have used public transit in the past 30 days at the time of survey. In the sub-samples, approximately 33% individuals reported that they were increasingly doing more online shopping than before. Mall visits were comparatively higher for the sub-samples of online shoppers. Furthermore, male respondents in the sub-samples were ranging between 30-35%, compared to 43% in the full sample. Only a small percentage of the respondents in the sample data work from home. Sixty-two percent of the respondents in the full sample had an annual household income of $45,000 or more, while the sub-samples averaged around 76% for the respondents.

Table 4.4. Summary statistics

	Full Sample (N= 101,206)		Online Browsers (N=21335)		Online Shoppers (N=28469)		Combined (N=35490)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Public Transit	0.16	0.367	0.177	0.381	0.175	0.38	0.169	0.375
Online Shopping Behavior	0.157	0.364	0.329	0.47	0.338	0.473	0.307	0.461
Shopping Mall	0.515	0.499	0.62	0.485	0.61	0.487	0.609	0.487
Strip Mall	0.409	0.491	0.575	0.494	0.542	0.498	0.542	0.498
Driver's License	0.859	0.347	0.936	0.243	0.936	0.244	0.934	0.247
Auto Insurance	0.746	0.434	0.849	0.357	0.848	0.358	0.845	0.361
Gas Price	2.621	0.418	2.647	0.41	2.61	0.421	2.619	0.418
Employed	0.571	0.494	0.646	0.478	0.66	0.473	0.649	0.476
High School Grad	0.452	0.497	0.445	0.496	0.449	0.497	0.449	0.497
Some College	0.238	0.425	0.239	0.426	0.233	0.423	0.235	0.424
College Grad	0.308	0.462	0.345	0.499	0.342	0.498	0.331	0.497
Male	0.433	0.495	0.335	0.472	0.354	0.478	0.351	0.477
White	0.766	0.424	0.814	0.391	0.811	0.392	0.809	0.394
Asian	0.032	0.176	0.039	0.195	0.036	0.188	0.036	0.188
Black	0.084	0.278	0.063	0.243	0.063	0.243	0.065	0.246
Other (Races)	0.118	0.323	0.084	0.278	0.09	0.286	0.09	0.286
Work from home	0.021	0.146	0.035	0.185	0.033	0.18	0.031	0.174
HINC (≤ $25,000)	0.158	0.363	0.071	0.256	0.07	0.252	0.073	0.258
HINC ($25,000-$44,999)	0.221	0.415	0.159	0.366	0.159	0.366	0.165	0.371
HINC ($45,000-$74,999)	0.310	0.462	0.328	0.469	0.323	0.467	0.328	0.469
HINC (≥$75,000)	0.311	0.463	0.441	0.496	0.448	0.497	0.433	0.495
Age (18-21 years old)	0.044	0.202	0.039	0.191	0.039	0.187	0.040	0.187
Age (21-29 years old)	0.105	0.307	0.117	0.321	0.120	0.325	0.118	0.322
Age (30-44 years old)	0.231	0.421	0.282	0.450	0.282	0.450	0.277	0.447
Age (45-59 years old)	0.304	0.460	0.324	0.468	0.321	0.466	0.322	0.467
Age (≥60 years old)	0.316	0.465	0.238	0.425	0.238	0.426	0.243	0.429
Family (1-2 people)	0.406	0.306	0.416	0.392	0.413	0.392	0.403	0.390
Family (3-4 people)	0.376	0.484	0.403	0.490	0.399	0.489	0.399	0.489
Family (5-6 people)	0.171	0.377	0.151	0.358	0.156	0.363	0.155	0.362
Family (7 or more)	0.047	0.213	0.030	0.172	0.032	0.177	0.032	0.177
Children	0.555	0.496	0.599	0.489	0.595	0.490	0.597	0.490
Year 2012	0.244	0.430	0.264	0.441	0.224	0.417	0.236	0.425
Year 2013	0.237	0.425	0.260	0.439	0.232	0.422	0.239	0.426
Year 2014	0.233	0.423	0.209	0.407	0.240	0.427	0.232	0.422
Year 2015	0.285	0.451	0.268	0.442	0.304	0.460	0.293	0.455

4.6. Results and Discussion

For comparison purposes, in the first part of the analysis, I examine the relationship between shopping or strip mall visits and the use of public transit through a basic probit regression model using the full sample and 3 subsamples. Tables 4.5 and 4.6 present the results of the probit regression and its marginal effects, respectively. If an explanatory variable is binary, the marginal effect measures the discrete change of the values of the variable in question from 0 to 1, while for continuous variables, the marginal change measures the effect of an infinitesimally small change of the variable in question. Details on the marginal effects' calculation are discussed in the Appendix. The log likelihood Chi-square statistic clearly shows the composite effects of the independent variables to differ from zero. The Pseudo-R^2 values are 17.3% for the model using the full sample and average around 15.5% for the models used in the three sub-samples of online shoppers.

The marginal effects of Shopping Mall in the full sample is 0.022, and it is significant at 1% level. Similarly, for the 3 sub-samples, the marginal effects of Shopping Mall are significant at 1% level and are 0.025, 0.018 and 0.020 respectively for online browsers, online shoppers and the combined sub-samples. On average, this suggests that, an increase in visits to shopping malls increases the predicted probability of using public transit between 1.8% and 2.5%.Strip mall visits significantly increases public transit use for the full sample, but for the sub-samples, the result is insignificant.

Driver's license and auto insurance are used as proxies for vehicle ownership, since having a driver's license or auto insurance may imply vehicle ownership, and automobile usage has a negative effect on public transit ridership in the U.S. (Paulley et al., 2006; Manville et al. 2018). Both license and insurance variables have the expected negative significant coefficients suggesting that vehicle ownership reduces the probability of public transit. The marginal effects in Table 4.6 suggest that, for the full sample, driver's license and auto insurance possessions reduce the probability of transit use by 12% and 11%, respectively. For online browsers and/or shoppers, the probability of transit use is reduced by 15-16% among those who have a driver's license. Based on the results, car ownership, as proxied by driver's license and auto insurance, is the largest deterrence of transit use.

In addition, socio-economic characteristics are among some of the factors affecting transit use as well. Employment raises the probability of transit use by 2% in the full sample, but its effect is even larger (3.5-4.1%) for the sub-samples. Relatively to non-Hispanic Caucasians, respondents of Asian, Black and other ethnic backgrounds are more likely to use public transit. This result holds for the full and sub-samples. Similarly, individuals who hold a college or higher degree are more likely to use public transit compared to individuals who have high school or less educational attainments in all the samples considered.

Furthermore, our results indicate that the higher the household income, and when the number of family members increases, the tendency to use public transit is less. This finding falls in line with Zhao and Gustafson (2013) where they suggest that low-income working families more likely to rely on public transit. Both age and having dependent children also have a negative effect on transit use.

Table 4.5. Results from the Standard Probit Regression. Dependent Variable: Public Transit.

	(1) Full sample	(2) Online browsers	(3) Online shoppers	(4) Combined
Shopping Mall	0.111***	0.108***	0.081***	0.089***
	(0.012)	(0.024)	(0.021)	(0.019)
Strip Mall	0.074***	-0.025	0.040*	0.030
	(0.012)	(0.024)	(0.021)	(0.019)
Driver's License	-0.585***	-0.671***	-0.702***	-0.695***
	(0.015)	(0.044)	(0.038)	(0.034)
Auto Insurance	-0.542***	-0.519***	-0.519***	-0.516***
	(0.013)	(0.032)	(0.028)	(0.024)
Gas Price	0.013	-0.004	0.016	0.022
	(0.009)	(0.019)	(0.016)	(0.015)
Employed	0.100***	0.179***	0.157***	0.164***
	(0.012)	(0.026)	(0.023)	(0.021)
Some college	0.026**	0.035	0.053**	0.049**
	(0.012)	(0.025)	(0.022)	(0.020)
Graduated college	0.322***	0.304***	0.349***	0.333***
	(0.012)	(0.024)	(0.021)	(0.019)
Male	0.047***	0.126***	0.122***	0.112***
	(0.011)	(0.023)	(0.020)	(0.018)
Asian	0.189***	0.247***	0.205***	0.200***
	(0.027)	(0.051)	(0.046)	(0.041)
Black	0.372***	0.371***	0.340***	0.347***
	(0.017)	(0.041)	(0.037)	(0.032)
Other	0.148***	0.172***	0.148***	0.148***
	(0.016)	(0.039)	(0.034)	(0.030)
Work from home	0.128***	0.077	0.106**	0.102**
	(0.034)	(0.057)	(0.051)	(0.047)
HINC (\$25,000-\$44,999)	-0.192***	-0.220***	-0.177***	-0.183***
	(0.017)	(0.049)	(0.043)	(0.038)
HINC (\$45,000-\$74,999)	-0.231***	-0.229***	-0.226***	-0.225***
	(0.017)	(0.045)	(0.040)	(0.035)
HINC (≥\$75,000)	-0.107***	-0.091**	-0.078*	-0.083**
	(0.018)	(0.046)	(0.040)	(0.036)
Age (21-29 years old)	-0.119***	-0.113*	-0.088	-0.105**
	(0.027)	(0.062)	(0.055)	(0.048)
Age (30-44 years old)	-0.184***	-0.237***	-0.214***	-0.228***
	(0.027)	(0.062)	(0.055)	(0.048)
Age (45-59 years old)	-0.184***	-0.229***	-0.228***	-0.233***
	(0.027)	(0.063)	(0.056)	(0.049)
Age (≥60 years old)	-0.344***	-0.310***	-0.321***	-0.316***
	(0.027)	(0.067)	(0.059)	(0.052)

Table 4.5. Results from the Standard Probit Regression. Dependent Variable: Public Transit (continued)

	(1) Full sample	(2) Online browsers	(3) Online shoppers	(4) Combined
Family (3-4 people)	-0.112***	-0.115***	-0.140***	-0.122***
	(0.014)	(0.029)	(0.025)	(0.023)
Family (5-6 people)	-0.187***	-0.187***	-0.210***	-0.194***
	(0.017)	(0.038)	(0.033)	(0.030)
Family (≥7 people)	-0.195***	-0.190***	-0.220***	-0.224***
	(0.026)	(0.068)	(0.058)	(0.052)
Children	-0.107***	-0.148***	-0.122***	-0.135***
	(0.012)	(0.025)	(0.022)	(0.020)
2013	-0.021	-0.005	-0.024	0.002
	(0.017)	(0.034)	(0.031)	(0.028)
2014	-0.010	-0.050	-0.026	-0.003
	(0.023)	(0.049)	(0.042)	(0.038)
2015	0.082	-0.004	0.097	0.177
	(0.085)	(0.180)	(0.151)	(0.137)
Constant	-1.283***	-0.361	-1.129**	-1.238***
	(0.280)	(0.585)	(0.507)	(0.455)
Wald X^2 (76)	13006.860	2668.080	3539.590	4329.340
Prob > X^2	0.000	0.000	0.000	0.000
Pseudo R^2	0.173	0.153	0.158	0.156
#Observations	101,130	21,201	28,326	35,303

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1, State fixed effects are not reported.

Table 4.6. Marginal effects of the Standard Probit Regression Model

	(1) Full sample	(2) Online browsers	(3) Online shoppers	(4) Combined
Shopping Mall	0.023***	0.025***	0.018***	0.020***
	(0.002)	(0.006)	(0.005)	(0.004)
Strip Mall	0.015***	-0.006	0.009*	0.007
	(0.002)	(0.005)	(0.005)	(0.004)
Driver's License	-0.120***	-0.153***	-0.157***	-0.152***
	(0.003)	(0.010)	(0.009)	(0.007)
Auto Insurance	-0.111***	-0.118***	-0.116***	-0.113***
	(0.003)	(0.007)	(0.006)	(0.005)
Gas Price	0.003	-0.001	0.004	0.005
	(0.002)	(0.004)	(0.004)	(0.003)
Employed	0.020***	0.041***	0.035***	0.036***
	(0.003)	(0.006)	(0.005)	(0.005)
Some college	0.005**	0.008	0.012**	0.011**
	(0.002)	(0.006)	(0.005)	(0.004)
Graduated college	0.066***	0.069***	0.078***	0.073***
	(0.002)	(0.005)	(0.005)	(0.004)
Male	0.010***	0.029***	0.027***	0.025***
	(0.002)	(0.005)	(0.004)	(0.004)
Asian	0.039***	0.056***	0.046***	0.044***
	(0.006)	(0.012)	(0.010)	(0.009)
Black	0.076***	0.085***	0.076***	0.076***
	(0.004)	(0.009)	(0.008)	(0.007)
Other	0.030***	0.039***	0.033***	0.033***
	(0.003)	(0.009)	(0.008)	(0.007)
Work from home	0.026***	0.018	0.024**	0.022**
	(0.007)	(0.013)	(0.011)	(0.010)
HINC ($25,000-$44,999)	-0.039***	-0.050***	-0.040***	-0.040***
	(0.003)	(0.011)	(0.010)	(0.008)
HINC ($45,000-$74,999)	-0.047***	-0.052***	-0.051***	-0.049***
	(0.003)	(0.010)	(0.009)	(0.008)
HINC (≥$75,000)	-0.022***	-0.021**	-0.018*	-0.018**
	(0.004)	(0.010)	(0.009)	(0.008)
Age (21-29 years old)	-0.024***	-0.026*	-0.020	-0.023**
	(0.006)	(0.014)	(0.012)	(0.011)
Age (30-44 years old)	-0.038***	-0.054***	-0.048***	-0.050***
	(0.005)	(0.014)	(0.012)	(0.011)
Age (45-59 years old)	-0.038***	-0.052***	-0.051***	-0.051***
	(0.005)	(0.014)	(0.012)	(0.011)
Age (≥60 years old)	-0.070***	-0.071***	-0.072***	-0.069***
	(0.006)	(0.015)	(0.013)	(0.011)
Family (3-4 people)	-0.023***	-0.026***	-0.031***	-0.027***
	(0.003)	(0.007)	(0.006)	(0.005)

Table 4.6. Marginal effects of the Standard Probit Regression Model (continued)

	(1) Full sample	(2) Online browsers	(3) Online shoppers	(4) Combined
Family (5-6 people)	-0.038***	-0.043***	-0.047***	-0.043***
	(0.004)	(0.009)	(0.007)	(0.007)
Family (≥7 people)	-0.040***	-0.043***	-0.049***	-0.049***
	(0.005)	(0.016)	(0.013)	(0.011)
Children	-0.022***	-0.034***	-0.027***	-0.030***
	(0.002)	(0.006)	(0.005)	(0.004)
2013	-0.004	-0.001	-0.005	0.000
	(0.003)	(0.008)	(0.007)	(0.006)
2014	-0.002	-0.011	-0.006	-0.001
	(0.005)	(0.011)	(0.009)	(0.008)
2015	0.017	-0.001	0.023	0.040
	(0.018)	(0.041)	(0.035)	(0.032)
#Observations	101,130	21,201	28,326	35,303

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1, State fixed effects are not reported.

The results of the probit model in Table 4.5 establish the positive relationship between mall visits and transit use, but the linkage between online shopping behavior and mall visits, and the way the outcome of this linkage affects transit use are yet to be examined. Next a bivariate probit model is used to identify the impact of online shopping on mall trips, and how mall trips affect transit use. The analysis was performed only using the sub-samples to analyze how the behavioral changes of online shoppers affects the probability of mall visits, which in turn affects public transit use. In other words, the full sample was not considered since the data contain a large number of consumers who neither shopped online nor used public transit, and transit users who did not shop online. That is the linkage between Node 1 and Node 2 in Figure 4.2 does not exist for the full sample. The bivariate probit model seeks to capture the linkage between Node 1 and Node 2 and how Node 2 affects Node 3.

The dependent variable (Y_1) in equation (4.3) indicates consumer making visits to brick-and-mortar shopping malls or strip malls in the last 30 days, and the dependent variable (Y_2) in equation (4.4) indicates consumer taking public transit in the same period. Table 4.7 displays the results of the bivariate probit model and Table 4.8 displays marginal effects for the bivariate probit model. For all 3 sub-samples, the correlation coefficient between ε_1 and ε_2 (ρ= -0.07) is significant at 1%, indicating that a bivariate probit model rather than two separate univariate probit models is more appropriate for the analysis.

The equation (4.3) results in Table 4.7 also suggest that, for the online browsers and the combined subsamples, we see a significant negative impact of increased online shopping on mall visits. In other words, if consumers increasingly shopped online, the probability of them going to a brick-and-mortar shopping mall or a strip mall would be lower. In addition, for all the sub-samples, the positive significant coefficient on shopping mall in equation (4.4) means that consumer's shopping mall visits would increase the probability of transit use. The effect of strip mall visit is positive and significant for online shoppers and combined samples, but it is insignificant for online browsers. In summary, I observe that public transit usage is indirectly and negatively impacted by increased online shopping because the latter led to reduced consumers' visits to shopping malls and strip malls.

Among the observations in all 3 sub-samples, female shoppers tend to visit shopping malls more compared to their male counterparts, and male shoppers are more likely to use public transit. Furthermore, we find that the tendency to visit shopping malls and strip malls is not statistically different between non-Hispanic Caucasian and ethnic minority consumers, except Asians. The positive significant coefficients on HINC levels indicate that, higher household income consumers tend to visit shopping malls more frequently than lower household income consumers. Similarly, families with one or more dependent children tend to visit shopping malls compared to families without children in our sample.

Interestingly, the year effects on mall visits have a positive significant coefficient in equation (3). While this suggests that the probability of mall visits was higher relative to 2012, these increased mall visits may not imply consumer spending more or making purchases during their visits.

The coefficient estimates of equation (4.4) in Table 4.7 display similar results to that of the previously estimated single probit model on public transit usage. Since the bivariate probit model for online browsers and shoppers suggest that the reduction in mall visits would reduce transit ridership, I infer that the emergence of online shopping behavior triggers a loss of transit ridership among consumers who are increasingly engaged in online shopping-related activities.

Table 4.7. Bivariate Recursive Probit Regression Results

Variables	Online browsers		Online shoppers		Combined	
	Equation (3) Mall Visits	Equation (4) Public Transit	Equation (3) Mall Visits	Equation (4) Public Transit	Equation (3) Mall Visits	Equation (4) Public Transit
Online Shopping	-0.061***		-0.020		-0.032**	
	(0.021)		(0.017)		(0.016)	
Shopping Mall		0.168***		0.153***		0.150***
		(0.036)		(0.032)		(0.029)
Strip Mall		0.017		0.088***		0.071***
		(0.030)		(0.026)		(0.023)
Driver's License		-0.670***		-0.700***		-0.694***
		(0.044)		(0.038)		(0.034)
Auto Insurance		-0.516***		-0.516***		-0.514***
		(0.032)		(0.028)		(0.024)
Gas Price		-0.038		0.163		0.222
		(0.195)		(0.163)		(0.149)
Employed	-0.007	0.179***	0.014	0.157***	0.008	0.163***
	(0.022)	(0.026)	(0.019)	(0.023)	(0.017)	(0.021)
Some college	-0.011	0.035	0.000	0.053**	0.003	0.049**
	(0.022)	(0.025)	(0.019)	(0.022)	(0.017)	(0.020)
Graduated college	0.179***	0.299***	0.163***	0.342***	0.161***	0.328***
	(0.021)	(0.024)	(0.018)	(0.021)	(0.016)	(0.019)
Male	-0.307***	0.136***	-0.303***	0.133***	-0.303***	0.121***
	(0.020)	(0.023)	(0.017)	(0.020)	(0.015)	(0.018)
Asian	0.108**	0.245***	0.120**	0.203***	0.127***	0.198***
	(0.052)	(0.051)	(0.046)	(0.046)	(0.042)	(0.041)
Black	-0.071*	0.374***	-0.021	0.339***	-0.026	0.347***
	(0.039)	(0.041)	(0.034)	(0.037)	(0.030)	(0.032)
Other	-0.014	0.172***	0.029	0.145***	0.021	0.147***
	(0.035)	(0.039)	(0.030)	(0.034)	(0.026)	(0.030)
Work from home		0.078		0.108**		0.103**
		(0.057)		(0.050)		(0.047)
HINC ($25,000-$44,999)	0.186***	-0.227***	0.181***	-0.185***	0.172***	-0.189***
	(0.041)	(0.049)	(0.035)	(0.043)	(0.031)	(0.038)
HINC ($45,000-$74,999)	0.328***	-0.241***	0.324***	-0.239***	0.317***	-0.236***
	(0.038)	(0.045)	(0.033)	(0.040)	(0.029)	(0.036)
HINC (≥$75,000)	0.448***	-0.108**	0.446***	-0.097**	0.434***	-0.099***
	(0.039)	(0.046)	(0.034)	(0.041)	(0.030)	(0.036)
Age (21-29 years old)	-0.210***	-0.108*	-0.224***	-0.080	-0.223***	-0.099**
	(0.057)	(0.062)	(0.049)	(0.055)	(0.043)	(0.048)

Table 4.7. Bivariate Recursive Probit Regression Results (continued)

	Online browsers		Online shoppers		Combined	
Variables	Equation (3) Mall Visits	Equation (4) Public Transit	Equation (3) Mall Visits	Equation (4) Public Transit	Equation (3) Mall Visits	Equation (4) Public Transit
Age (30-44 years old)	-0.113**	-0.235***	-0.159***	-0.210***	-0.161***	-0.224***
	(0.055)	(0.062)	(0.048)	(0.055)	(0.042)	(0.048)
Age (45-59 years old)	-0.127**	-0.227***	-0.170***	-0.223***	-0.184***	-0.228***
	(0.054)	(0.063)	(0.047)	(0.056)	(0.041)	(0.049)
Age (≥60 years old)	-0.069	-0.310***	-0.119**	-0.318***	-0.114***	-0.315***
	(0.055)	(0.067)	(0.048)	(0.059)	(0.042)	(0.052)
Family (3-4 people)		-0.115***		-0.141***		-0.123***
		(0.029)		(0.025)		(0.023)
Family (5-6 people)		-0.188***		-0.210***		-0.195***
		(0.038)		(0.033)		(0.030)
Family (≥7 people)		-0.191***		-0.221***		-0.225***
		(0.068)		(0.058)		(0.052)
Children	0.041*	-0.149***	0.081***	-0.125***	0.070***	-0.137***
	(0.021)	(0.025)	(0.018)	(0.022)	(0.016)	(0.020)
2013	0.171***	-0.009	0.139***	-0.027	0.148***	-0.002
	(0.026)	(0.034)	(0.024)	(0.031)	(0.021)	(0.028)
2014	0.163***	-0.053	0.103***	-0.028	0.121***	-0.005
	(0.028)	(0.049)	(0.024)	(0.042)	(0.021)	(0.038)
2015	0.155***	-0.006	0.096***	0.096	0.120***	0.176
	(0.026)	(0.179)	(0.023)	(0.151)	(0.020)	(0.137)
Constant	0.451***	-0.413	0.470***	-1.187**	0.422***	-1.288***
	(0.140)	(0.585)	(0.127)	(0.507)	(0.108)	(0.455)
ρ	-0.068**		-0.079***		-0.066***	
	(0.029)		(0.025)		(0.023)	
Observations	21,335	21,335	28,469	28,469	35,490	35,490

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The estimated marginal effects of the variables of Equation (4.3) and (4.4) are displayed in Table 4.8. For continuous variables, the marginal effects are calculated at the mean of the variable in question. That is, the marginal effect of a given *z* explanatory variable on the conditional expectation of transit use is $\frac{\partial E(Y_2|\mathbf{X}, \mathbf{Z})}{\partial z}$ which is evaluated at the mean of z. However, since the variables in the model are mostly discrete, the marginal effects for discrete variables are calculated based on the a change in the values of the discrete variable from 0 to 1, i.e. $E(Y_2|\mathbf{X}, \mathbf{Z}, z = 1) - E(Y_2|\mathbf{X}, \mathbf{Z}, z = 0)$, holding all other variables fixed at their means. The details of the marginal effects are discussed in Appendix C.

Based on the results in Table 4.8, we can see that for consumers who report to have done more online browsing, the probability of them visiting local shopping malls is about 2% lower. When considering the sample of the combination of online browsers and shoppers, the probability of them visiting local shopping malls is about 1% lower. Similarly, shopping mall visits increase the probability of using public transit by 3.1- 3.6%. The marginal effect of strip mall visits on transit use probability is insignificant for online browsers but it is positive and significant for the other two sub-samples considered.

The largest deterrent of transit use is car ownership which is proxied by driver's license and auto insurance in the model. Having a driver's license reduces the probability of transit use by 19-20% on average, and having auto insurance reduces the probability of transit use by roughly 13% on average for the 3 sub-samples. Jointly, car ownership, measured by the marginal effects of driver's license and auto insurance possessions, reduces the predicted probability of transit use by approximately 33% among the subsamples of online browsers and shoppers. Gas price is not a significant factor for transit use. Among the ethnic minorities, African Americans are more likely to use public transit relative to non-Hispanic Caucasians, and the probability is 9.7% higher after controlling for income, employment and all other factors.

Table 4.8. Estimated marginal effects for the Bivariate Recursive Probit Regression

	Online browsers		Online shoppers		Combined	
Variables	Equation (3) Mall Visits	Equation (4) Public Transit	Equation (3) Mall Visits	Equation (4) Public Transit	Equation (3) Mall Visits	Equation (4) Public Transit
Online Shopping	-0.019***		-0.006		-0.010**	
	(0.006)		(0.006)		(0.005)	
Shopping Mall		0.036***		0.033***		0.031***
		(0.008)		(0.007)		(0.006)
Strip Mall		0.004		0.019***		0.015***
		(0.007)		(0.006)		(0.005)
Driver's License		-0.193***		-0.202***		-0.196***
		(0.015)		(0.013)		(0.012)
Auto Insurance		-0.135***		-0.134***		-0.131***
		(0.010)		(0.008)		(0.007)
Gas Price		-0.008		0.035		0.047
		(0.043)		(0.035)		(0.031)
Employed	-0.002	0.038***	0.005	0.033***	0.003	0.034***
	(0.007)	(0.005)	(0.006)	(0.005)	(0.005)	(0.004)
Some college	-0.003	0.008	0.000	0.012**	0.001	0.010**
	(0.007)	(0.006)	(0.006)	(0.005)	(0.006)	(0.004)
Graduated college	0.055***	0.066***	0.052***	0.075***	0.051***	0.071***
	(0.006)	(0.005)	(0.006)	(0.005)	(0.005)	(0.004)
Male	-0.097***	0.030***	-0.099***	0.030***	-0.100***	0.026***
	(0.007)	(0.005)	(0.006)	(0.005)	(0.005)	(0.004)
Asian	0.032**	0.060***	0.037***	0.049***	0.039***	0.046***
	(0.015)	(0.014)	(0.014)	(0.012)	(0.012)	(0.011)
Black	-0.022*	0.097***	-0.007	0.086***	-0.008	0.086***
	(0.013)	(0.012)	(0.011)	(0.011)	(0.010)	(0.009)
Other	-0.004	0.041***	0.009	0.034***	0.007	0.033***
	(0.011)	(0.010)	(0.009)	(0.008)	(0.008)	(0.007)
Work from home		0.018		0.025**		0.023**
		(0.013)		(0.012)		(0.011)
HINC ($25,000-$44,999)	0.054***	-0.046***	0.055***	-0.038***	0.053***	-0.037***
	(0.011)	(0.009)	(0.010)	(0.008)	(0.009)	(0.007)
HINC ($45,000-$74,999)	0.096***	-0.051***	0.099***	-0.050***	0.098***	-0.048***
	(0.011)	(0.009)	(0.010)	(0.008)	(0.009)	(0.007)
HINC (≥$75,000)	0.134***	-0.024**	0.140***	-0.021**	0.136***	-0.021***
	(0.011)	(0.010)	(0.010)	(0.009)	(0.009)	(0.008)
Age (21-29 years old)	-0.068***	-0.023*	-0.075***	-0.017	-0.075***	-0.020**
	(0.019)	(0.012)	(0.017)	(0.011)	(0.015)	(0.009)

Table 4.8. Estimated marginal effects for the Bivariate Recursive Probit Regression (continued)

	Online browsers		Online shoppers		Combined	
Variables	Equation (3) Mall Visits	Equation (4) Public Transit	Equation (3) Mall Visits	Equation (4) Public Transit	Equation (3) Mall Visits	Equation (4) Public Transit
Age (30-44 years old)	-0.035**	-0.049***	-0.052***	-0.043***	-0.053***	-0.045***
	(0.017)	(0.012)	(0.016)	(0.011)	(0.014)	(0.009)
Age (45-59 years old)	-0.040**	-0.048***	-0.055***	-0.046***	-0.060***	-0.046***
	(0.017)	(0.013)	(0.016)	(0.011)	(0.014)	(0.009)
Age (≥60 years old)	-0.021	-0.062***	-0.039**	-0.063***	-0.037***	-0.061***
	(0.017)	(0.012)	(0.016)	(0.011)	(0.014)	(0.009)
Family (3-4 people)		-0.025***		-0.030***		-0.026***
		(0.006)		(0.005)		(0.005)
Family (5-6 people)		-0.038***		-0.042***		-0.038***
		(0.007)		(0.006)		(0.005)
Family (≥7 people)		-0.038***		-0.043***		-0.042***
		(0.012)		(0.010)		(0.009)
Children	0.013*	-0.033***	0.026***	-0.028***	0.023***	-0.029***
	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.004)
2013	0.054***	-0.002	0.045***	-0.006	0.048***	-0.000
	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)	(0.006)
2014	0.051***	-0.012	0.034***	-0.006	0.040***	-0.001
	(0.009)	(0.011)	(0.008)	(0.009)	(0.007)	(0.008)
2015	0.049***	-0.001	0.032***	0.022	0.039***	0.039
	(0.008)	(0.040)	(0.007)	(0.034)	(0.007)	(0.031)
Observations	21,335	21,335	28,469	28,469	35,490	35,490

4.7. Conclusions

This research was carried out to determine if public transit usage is impacted by the reduction in shopping mall visits which may be directly associated with increased online shopping activities in the U.S. The first part of the analysis involves predicting the relationship between mall visits and transit use using the full sample of survey respondents and 3 subsamples of online browsers and shoppers. The next part of my research involves estimating a bivariate recursive probit regression model to determine if the number of mall visits is affected by online shopping activities of consumers and to observe if the outcome of this relationship affects public transit use in the U.S. For this purpose, I restricted the dataset to consumers who either gathered shopping information online or who made purchases online, and I analyzed how their online shopping behaviors affect their transit use.

First, I find that there is a positive significant relationship between shopping mall visits and public transit use. In other words, the more people visit shopping malls, the more public transit will be utilized by these consumers. This means that, if the number of shopping mall visits is reduced, public transit use is lowered as well. This result holds for the full sample of consumers as well as the 3 subsample groups considered.

However, the effect of mall visits on transit use is small relative to the effects of driver's license and auto insurance possessions which are proxy variables of consumer's car ownership. Taken together, the marginal effects of driver's license and auto insurance possessions contribute to a total of 33% lower probability of transit use in the bivariate probit model for the subsamples; this effect is 9 times larger than the effect of mall visits.

In addition, socio-demographic characteristics matter as well. We observe that minorities were significantly more likely to take public transit compared to non-Hispanic Caucasians after controlling for income, family size and other factors.

Public transit agencies in the U.S. has been facing heavy ridership declines in recent years. Transit agencies have not been able to pinpoint reasons for these ridership declines. Thus, this study emphasizes importance of understanding indirect effects of consumer activities, such as online shopping, as well as the direct effects of socio-demographic characteristics, which transit agencies and city planners should consider when addressing the issue of transit ridership decline in the U.S. I conclude that online shopping likely plays a rather minimal role in causing the ridership decline in recent years.

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CHAPTER 5. CONCLUSIONS

With economic development and urbanization, public transportation has become an essential component of urbanization. Public transportation has also become a key player in promoting sustainable development and improving the quality of life of urban communities. In recent years, the inception of ride-hailing services, such as Lyft, Uber, Juno, Uber Pool and Google bus, which can be collectively referred to as transportation network services (TNCs), have transformed urban transportation. The availability of TNCs have given consumers more transportation options. However, the implications of TNC on public transit ridership and transit operations are unknown. Additionally, consumer behavior has also been changing over the years, with many consumers leaning towards online shopping due to its convenience. Such aspects of consumer behavior can also impact public transit use. But in which direction?

It is also important to determine the relationship between TNC use and transit ridership. If TNC services and public transit are complementary, then it makes good practical and economic sense for transit agencies to partner with TNCs to facilitate consumer transportation. If TNC services and public transit are substitutes, then transit operators must evaluate any potential factors that stir consumers away from public transit, and city planners should approach any long-term financial commitments and transportation projects with a futuristic vision. In this context, the objectives of this dissertation were to examine how public transit services are impacted by the rise of TNCs, transit outsourcing, transit partnership, and the change in consumer shopping behavior.

In the study focused on public transit services and TNCs (Chapter 2), the results showed that transit effectiveness of both bus and rail decreased during the years 2014 through 2017, while the availability of TNCs helped increase rail ridership only in 2015. The results also showed that transit effectiveness was highly associated with ridership, and that TNCs neither complement nor substitute bus transit.

The results in Chapter 3 indicate that for bus transit agencies, outsourcing led to negative efficiency change. Outsourcing led to a positive technological change for bus transit, the effect is not significant. The results suggest that transit agencies that seek to partner with shared-mobility service providers or to integrate shared-mobility with transit service must address challenges that hinder transit efficiency, and that transit technology has yet to keep up with technological progress in urban mobility.

In Chapter 4, I investigated the effect of online shopping on public transit use. The results showed that in general, consumers who visit shopping malls use public transit. This holds true for the entire sample as well as the subsamples of online shoppers. Among the online shoppers, I find that increased online shopping reduced visits to traditional malls, which in turn results in declined in public transit ridership. However, this effect on public transit use is rather small compared to the effect of car ownership on transit use.

Overall, the findings of these studies show that public transit ridership declines are associated with different factors such as transit (in)effectiveness, car ownership, and to a lesser extent, online shopping. Car ownership and consumer’s shopping trend are both driven by consumer income and current internet technology; they are beyond the control of transit operators. However, transit operators can and should focus on internal operational performance in both short and long terms. Any partnership with TNCs and micromobility service providers should involve meticulous planning and information sharing to ensure maximum benefits for the two parties as well as the society as a whole.

APPENDIX A. DETERMINANTS ON TRANSIT DEMAND

The linear demand function yields independent effects of the determinants on transit demand. Consider the following linear transit demand function, where R is the number of passenger trips, F is fare, and X is a demand determinant

$$R = \beta_0 + \beta_1 F + \beta_2 X, \qquad \text{(A1)}$$

and where β_0, β_1 and β_2 constant parameters. The effect of transit fare, F, on the number of trips can be measured by

$$\frac{\partial R}{\partial F} = \beta_1 \qquad \text{(A2)}$$

which is independent of X. The sensitivity of transit demand with respect to any changes in transit fare is measured by the price elasticity of demand, defined as the percentage change in the quantity of transit demanded to a percentage change in transit fare,

$$\varepsilon_F = \frac{\partial R}{\partial F} \cdot \frac{F}{R} = \beta_1 \cdot \frac{F}{R}, \qquad \text{(A3)}$$

which is invariant with respect to the units of measurements of R and F (Marshall, 1890; Kraft and Wohl, 1967), and clearly, ε_F depends on the values of F and R. It can also be shown that the elasticity of demand with respect to X is $\varepsilon_X = \frac{\partial R}{\partial X} \cdot \frac{X}{R} = \beta_2 \cdot \frac{X}{R}$.

A multiplicative or hyperbolic demand function such as

$$R = \beta_0 F^{\beta_1} X^{\beta_2} \qquad \text{(A4)}$$

allows the effect of F on R to be dependent on X since

$$\frac{\partial R}{\partial F} = \beta_0 \beta_1 F^{(\beta_1 - 1)} X^{\beta_2}, \qquad \text{(A5)}$$

and the price elasticity of demand associated with (A4) is

$$\varepsilon_F = \frac{\partial R}{\partial F} \cdot \frac{F}{R} = \beta_1, \qquad \text{(A6)}$$

which is a constant and does not depend on F and R. In a similar fashion, the elasticity of demand with respect to X is $\varepsilon_X = \beta_X$. Equation (A4) can be log-transformed such that

$$\ln R = \ln\beta_0 + \beta_1 \ln F + \beta_2 \ln X. \tag{A7}$$

Equation (A4') is a log-log model that specifies the logarithm of transit demand as a linear function of the logarithms of explanatory variables (Kraft and Wohl, 1967; Oum, 1989), and the parameter β_1 yields the exact price elasticity measure in (A8):

$$\frac{\partial \ln R}{\partial \ln F} = \beta_1. \tag{A8}$$

Econometric estimation of demand models like (A1) and (A4') are commonly found in the literature due to the ease of estimation and parameter interpretation, but they are also restrictive (Oum, 1989).

To address the shortcoming, an exponential demand function combines features of (A1) and (A4) and is given by

$$R = \exp(\beta_0 + \beta_1 F + \beta_2 X), \tag{A9}$$

and the partial derivative with respect to F is

$$\frac{\partial R}{\partial F} = \beta_1 \cdot \exp(\beta_0 + \beta_1 F + \beta_2 X). \tag{A10}$$

The specification in (A7) provides greater flexibility by (i) allowing for interaction between the effects of F and X as shown in (A8) where the effect of F on R depends on the values of both F and X, and (ii) by permitting the elasticity of demand to vary:

$$\varepsilon_F = \beta_1 \cdot \exp(\beta_0 + \beta_1 F + \beta_2 X) \cdot \frac{F}{R} = \beta_1 F, \tag{A11}$$

where ε_F clearly depends on the value of F. The same can be said of the other variable X as well, $\varepsilon_X = \beta_2 X$ (Kanafani, 1983). Equation (A7) can be log-transformed into a semi-log equation for estimation:

$$\ln R = \beta_0 + \beta_1 F + \beta_2 X, \tag{A12}$$

which yields semi-elasticity measures, $\frac{\partial \ln R}{\partial F} = \beta_1$ and $\frac{\partial \ln R}{\partial X} = \beta_2$. That is, β_1 measures the percentage change in transit demand with respect to a unit change in F, and β_2 measures the same semi-elasticity with respect to a unit change in X (Wooldridge, 2018).

The demand equation is more commonly represented by the combined multiplicative and exponential functional form:

$$R = \beta_0 \exp(\beta_1 X) \, F^{\beta_2}, \tag{A13}$$

which allows the elasticity of demand with respect to X to vary, while the elasticity of demand with respect to F to be constant (Kanafani, 1983). Equation (A10) can be log-transformed for econometric estimation:

$$\ln R = \beta_0 + \beta_1 X + \beta_2 \ln F, \tag{A14}$$

where β_1 is a semi-elasticity of demand with respect to X and β_2 is the elasticity of demand with respect to F.

APPENDIX B. SUPPLEMENTAL TABLES

Table B1. Top 45 bus transit agencies

Urban Areas	Agencies
Oakland, CA	Alameda-Contra Costa Transit District (AC Transit)
St. Louis, MO	Bi-State Development Agency (METRO)
Plantation, FL	Broward County Transportation Department (BCT)
Austin, TX	Capital Metropolitan Transportation Authority (CMTA)
Orlando, FL	Central Florida Regional Transportation Authority (LYNX)
Seattle, WA	Central Puget Sound Regional Transit Authority (ST)
Charlotte, NC	Charlotte Area Transit System (CATS)
Chicago, IL	Chicago Transit Authority (CTA)
Honolulu, HI	City and County of Honolulu Department of Transportation Services (DTS)
Detroit, MI	City of Detroit Department of Transportation (DDOT)
Los Angeles, CA	City of Los Angeles Department of Transportation (LADOT)
Phoenix, AZ	City of Phoenix Public Transit Department dba Valley Metro (Valley Metro)
Dallas, TX	Dallas Area Rapid Transit (DART)
Denver, CO	Denver Regional Transportation District (RTD)
Seattle, WA	King County Department of Transportation - Metro Transit Division (King County Metro)
Long Beach, CA	Long Beach Transit (LBT)
Los Angeles, CA	Los Angeles County Metropolitan Transportation Authority (LACMTA)
New York, NY	MTA Bus Company (MTABUS)
New York, NY	MTA New York City Transit (NYCT)
Baltimore, MD	Maryland Transit Administration (MTA)
Boston, MA	Massachusetts Bay Transportation Authority (MBTA)
Minneapolis, MN	Metro Transit
New York, NY	Metro-North Commuter Railroad Company (MTA-MNCR)
Atlanta, GA	Metropolitan Atlanta Rapid Transit Authority (MARTA)
Houston, TX	Metropolitan Transit Authority of Harris County, Texas (Metro)
Miami, FL	Miami-Dade Transit (MDT)
Milwaukee, MI	Milwaukee County Transit System (MCTS)
Garden City, NY	Nassau Inter County Express (NICE)
Jersey City, NJ	New Jersey Transit Corporation (NJ TRANSIT)
Buffalo, NY	Niagara Frontier Transportation Authority (NFT Metro)
Orange, CA	Orange County Transportation Authority (OCTA)
Arlington Heights, IL	Pace - Suburban Bus Division (PACE)
Pittsburgh, PA	Port Authority of Allegheny County (Port Authority)
Las Vegas, NV	Regional Transportation Commission of Southern Nevada (RTC)
Sacramento, CA	Sacramento Regional Transit District (Sacramento RT)
San Diego, CA	San Diego Metropolitan Transit System (MTS)
San Francisco, CA	San Francisco Municipal Railway (MUNI)
Santa Clara, CA	Santa Clara Valley Transportation Authority (VTA)
Philadelphia, PA	Southeastern Pennsylvania Transportation Authority (SEPTA)
Cleveland, OH	The Greater Cleveland Regional Transit Authority (GCRTA)
Portland, OR	Tri-County Metropolitan Transportation District of Oregon (TriMet)
Salt Lake City, UT	Utah Transit Authority (UTA)
San Antonio, TX	VIA Metropolitan Transit (VIA)
Washington, DC	Washington Metropolitan Area Transit Authority (WMATA)
Mount Vernon, NY	Westchester County Bee-Line System (The Bee-Line System)

Table B2. Top 32 rail transit agencies

Urban Areas	Agencies
St. Louis, MO	Bi-State Development Agency (METRO)
Seattle, WA	Central Puget Sound Regional Transit Authority (ST)
Charlotte, NC	Charlotte Area Transit System (CATS)
Chicago, IL	Chicago Transit Authority (CTA)
Dallas, TX	Dallas Area Rapid Transit (DART)
Denver, CO	Denver Regional Transportation District (RTD)
Seattle, WA	King County Department of Transportation - Metro Transit Division (King County Metro)
Los Angeles, CA	Los Angeles County Metropolitan Transportation Authority (LACMTA)
Baltimore, MD	Maryland Transit Administration (MTA)
Boston, MA	Massachusetts Bay Transportation Authority (MBTA)
Minneapolis, MN	Metro Transit
New York, NY	Metro-North Commuter Railroad Company (MTA-MNCR)
Atlanta, GA	Metropolitan Atlanta Rapid Transit Authority (MARTA)
Houston, TX	Metropolitan Transit Authority of Harris County, Texas (Metro)
Miami, FL	Miami-Dade Transit (MDT)
New York, NY	MTA Long Island Rail Road (MTA LIRR)
New York, NY	MTA New York City Transit (NYCT)
New York, NY	New Jersey Transit Corporation (NJ TRANSIT)
Buffalo, NY	Niagara Frontier Transportation Authority (NFT Metro)
Chicago, IL	Northeast Illinois Regional Commuter Railroad Corporation (Metra)
Pittsburgh, PA	Port Authority of Allegheny County (Port Authority)
Jersey City, NJ	Port Authority Trans-Hudson Corporation (PATH)
Sacramento, CA	Sacramento Regional Transit District (Sacramento RT)
San Diego, CA	San Diego Metropolitan Transit System (MTS)
San Francisco, CA	San Francisco Bay Area Rapid Transit District (BART)
San Francisco, CA	San Francisco Municipal Railway (MUNI)
Santa Clara, CA	Santa Clara Valley Transportation Authority (VTA)
Philadelphia, PA	Southeastern Pennsylvania Transportation Authority (SEPTA)
Cleveland, OH	The Greater Cleveland Regional Transit Authority (GCRTA)
Portland, OR	Tri-County Metropolitan Transportation District of Oregon (TriMet)
Salt Lake City, UT	Utah Transit Authority (UTA)
Washington, DC	Washington Metropolitan Area Transit Authority (WMATA)

Table B3. Equation (7) Random effects regression results§

	(1) Bus	(2) Bus	(3) Rail	(4) Rail
Constant	12.01***	12.33***	12.27***	12.43***
	(1.142)	(1.051)	(1.411)	(1.398)
TNC	0.00122	-0.001	-0.0137	-0.0161
	(0.0185)	(0.0186)	(0.0162)	(0.0165)
leffi	0.0963**		0.493***	
	(0.0400)		(0.0854)	
leffo		0.0987***		0.485***
		(0.0341)		(0.0789)
lfare	-0.0948*	-0.0967**	-0.561***	-0.571***
	(0.0513)	(0.0488)	(0.0914)	(0.0922)
lvhours	0.187***	0.177***	0.420***	0.417***
	(0.0645)	(0.0658)	(0.105)	(0.104)
lempcnt	0.434***	0.412***	0.0840**	0.0704**
	(0.0922)	(0.0962)	(0.0376)	(0.0317)
2008	0.0323***	0.0368***	0.0431***	0.0420***
	(0.00992)	(0.00894)	(0.0110)	(0.0109)
2009	0.0174	0.0220	0.0871***	0.0879***
	(0.0177)	(0.0172)	(0.0198)	(0.0204)
2010	-0.0228	-0.0136	0.0954***	0.0995***
	(0.0215)	(0.0218)	(0.0217)	(0.0222)
2011	-0.00139	0.00438	0.165***	0.168***
	(0.0316)	(0.0316)	(0.0335)	(0.0330)
2012	0.00963	0.0168	0.179***	0.181***
	(0.0322)	(0.0324)	(0.0310)	(0.0307)
2013	-0.00127	0.00307	0.226***	0.233***
	(0.0332)	(0.0330)	(0.0423)	(0.0425)
2014	-0.0109	0.00255	0.232***	0.235***
	(0.0338)	(0.0332)	(0.0401)	(0.0397)
2015	-0.0401	-0.0268	0.230***	0.235***
	(0.0328)	(0.0319)	(0.0423)	(0.0419)
2016	-0.0563	-0.0460	0.238***	0.243***
	(0.0357)	(0.0364)	(0.0438)	(0.0433)
2017	-0.108***	-0.0961**	0.210***	0.220***
	(0.0369)	(0.0376)	(0.0485)	(0.0477)
Observations	495	495	352	352
#Agencies	45	45	32	32
Year Effects (X^2)	114.45***	113.07***	65.39***	70.95***

§ Values in parentheses are clustered standard errors. ***, **, * denote 1%, 5% and 10% significance levels, respectively.

Table B4. Equation (8) Random effects regression results§

	(1) Bus	(2) Bus	(3) Rail	(4) Rail
Constant	11.97***	12.30***	12.22***	12.39***
	(1.157)	(1.061)	(1.394)	(1.368)
TNC*2010	0.00377	0.00277	0.00421	0.00358
	(0.0203)	(0.0211)	(0.0425)	(0.0432)
TNC*2011	0.0208	0.0158	0.00968	0.00933
	(0.0257)	(0.0255)	(0.0299)	(0.0292)
TNC*2012	-0.0127	-0.0140	-0.0323	-0.0279
	(0.0204)	(0.0212)	(0.0198)	(0.0198)
TNC*2013	-0.0148	-0.0166	-0.0375	-0.0416
	(0.0188)	(0.0184)	(0.0302)	(0.0325)
TNC*2014	0.0549	0.0567	-0.00542	-0.0311
	(0.0521)	(0.0476)	(0.0353)	(0.0476)
TNC*2015	-0.0144	-0.0106	0.0694**	0.0303
	(0.0194)	(0.0205)	(0.0341)	(0.0379)
TNC*2016	-0.0548	-0.0466	0.222***	0.225***
	(0.0408)	(0.0410)	(0.0430)	(0.0425)
TNC*2017	-0.107**	-0.0966**	0.195***	0.202***
	(0.0419)	(0.0421)	(0.0477)	(0.0470)
leffi	0.0981**		0.492***	
	(0.0412)		(0.0860)	
leffo		0.0995***		0.484***
		(0.0347)		(0.0805)
lfare	-0.0950*	-0.0970**	-0.550***	-0.564***
	(0.0510)	(0.0486)	(0.0932)	(0.0927)
lvhours	0.188***	0.177***	0.423***	0.419***
	(0.0647)	(0.0660)	(0.104)	(0.102)
lempcnt	0.437***	0.414***	0.0844**	0.0707**
	(0.0931)	(0.0968)	(0.0380)	(0.0321)
2008	0.0324***	0.0368***	0.0426***	0.0417***
	(0.0100)	(0.00898)	(0.0109)	(0.0108)
2009	0.0175	0.0221	0.0861***	0.0873***
	(0.0178)	(0.0173)	(0.0197)	(0.0202)
2010	-0.0227	-0.0135	0.0930***	0.0974***
	(0.0215)	(0.0217)	(0.0215)	(0.0219)
2011	-0.00718	-0.000594	0.154***	0.156***
	(0.0312)	(0.0312)	(0.0323)	(0.0315)
2012	0.0173	0.0240	0.189***	0.187***
	(0.0324)	(0.0331)	(0.0321)	(0.0313)
2013	0.0100	0.0141	0.241***	0.251***
	(0.0350)	(0.0340)	(0.0491)	(0.0517)
2014	-0.0608	-0.0509	0.222***	0.248***
	(0.0605)	(0.0573)	(0.0588)	(0.0662)
2015	-0.0249	-0.0172	0.148**	0.188***
	(0.0288)	(0.0297)	(0.0638)	(0.0657)
Observations	495	495	352	352
#Agencies	45	45	32	32
Year Effects (X^2)	44.31***	58.75***	72.75***	55.72***

§ Values in parentheses are clustered standard errors. ***, **, * denote 1%, 5% and 10% significance levels, respectively.

Table B5. Equation (9) Random effects regression results§

	(1) Bus (Input-oriented)	(2) Bus (Output-oriented)	(3) Rail (Input-oriented)	(4) Rail (Output-oriented)
Constant	14.913***	14.84***	13.21***	13.36***
	1.297	(1.123)	(1.011)	(1.011)
leff*2008	-0.0513	-0.209	0.182***	0.178***
	(0.0764)	(0.173)	(0.0384)	(0.0345)
leff*2009	-0.0436	-0.263	0.204***	0.192***
	(0.0870)	(0.190)	(0.0500)	(0.0470)
leff*2010	-0.0166	-0.328	0.206***	0.193***
	(0.0559)	(0.255)	(0.0500)	(0.0478)
leff*2011	-0.671	-0.713	0.413***	0.373***
	(0.695)	(0.706)	(0.0901)	(0.0789)
leff*2012	0.0333	-0.0608	0.271***	0.255***
	(0.0762)	(0.0685)	(0.0619)	(0.0590)
leff*2013	0.110	-0.0357	0.241***	0.221***
	(0.0850)	(0.0690)	(0.0619)	(0.0556)
leff*2014	0.0113	-0.168	0.280***	0.255***
	(0.0892)	(0.231)	(0.0680)	(0.0589)
leff*2015	0.0727	-0.106	0.331***	0.301***
	(0.0849)	(0.206)	(0.0769)	(0.0673)
leff*2016	-0.149	-0.181	0.409***	0.369***
	(0.223)	(0.250)	(0.0949)	(0.0843)
leff*2017	-0.125	-0.141	0.444***	0.408***
	(0.214)	(0.244)	(0.0955)	(0.0840)
TNC	-0.141	-0.112	-0.0226	-0.0267
	(0.136)	(0.103)	(0.0196)	(0.0206)
lfare	-0.202*	-0.171**	-0.658***	-0.670***
	(0.107)	(0.0797)	(0.0696)	(0.0712)
lemp	0.381**	0.391**		
	-0.183	(0.160)		
lvhours			0.384***	0.373***
			(0.0750)	(0.0753)
2008	0.00656	-0.0786	0.135***	0.137***
	(0.0311)	(0.0942)	(0.0230)	(0.0218)
2009	-0.000597	-0.118	0.176***	0.175***
	(0.0322)	(0.105)	(0.0339)	(0.0329)
2010	-0.0221	-0.218	0.191***	0.191***
	(0.0305)	(0.150)	(0.0337)	(0.0345)
2011	-0.452	-0.528	0.368***	0.357***
	(0.445)	(0.512)	(0.0701)	(0.0657)
2012	0.102	0.0273	0.307***	0.307***
	(0.120)	(0.0651)	(0.0475)	(0.0480)
2013	0.154	0.0478	0.328***	0.325***
	(0.143)	(0.0757)	(0.0570)	(0.0549)
2014	0.136	-0.00996	0.360***	0.353***
	(0.144)	(0.0804)	(0.0583)	(0.0547)
2015	0.147	-0.00109	0.394***	0.385***
	(0.147)	(0.0743)	(0.0625)	(0.0590)
2016	0.00485	-0.0678	0.458***	0.443***
	(0.0779)	(0.0798)	(0.0752)	(0.0706)
2017	-0.0406	-0.104	0.453***	0.445***
	(0.0790)	(0.0868)	(0.0812)	(0.0774)
Observations	495	495	352	352
#Agencies	45	45	32	32
Year Effects (X^2)	31.31***	23.42***	77.37***	88.50***

§ Values in parentheses are clustered standard errors. ***, **, * denote 1%, 5% and 10% significance levels, respectively.

APPENDIX C. MARGINAL EFFECTS

C.1. Univariate Probit Model

According to Greene (1998), for a standard binary probit model, the conditional expectation of the binary dependent variable y_1, given its explanatory variables, represented by $\boldsymbol{x}$, is

$$E(y_1|\boldsymbol{x}) = \Phi_1(\boldsymbol{x}'\boldsymbol{\beta}) = P(y_1 = 1), \tag{C1}$$

where Φ_1 is the cumulative distribution function (CDF) of the standard normal distribution. Thus, for a continuous explanatory variable, z,

$$\frac{\partial E(y_1|\boldsymbol{x})}{\partial z} = \frac{\partial \Phi_1(x'\beta)}{\partial z} = \phi_1(\boldsymbol{x}'\boldsymbol{\beta})\beta_z, \tag{C2}$$

where $\phi_1(\cdot)$ is the probability density function (PDF) of the standard normal distribution, and β_z is the coefficient on z. If z is a binary variable, then the marginal effect can be the effect due to a discrete change of the values of z from 0 to 1. That is:

$$E(y_1|\boldsymbol{x}, z = 1) - E(y_1|\boldsymbol{x}, z = 0). \tag{C3}$$

C.2. Bivariate Probit Model

For bivariate model, the joint probabilities of Y_1 and Y_2 are:

$$P(Y_1 = 1, Y_2 = 0) = P(Y_1 = 1|\ Y_2 = 0)P(Y = 0),$$

$$P(Y_1 = 1, Y_2 = 1) = P(Y_1 = 1|\ Y_2 = 1)P(Y = 1),$$

$$P(Y_1 = 0, Y_2 = 0) = P(Y_1 = 0|\ Y_2 = 0)P(Y = 0), \text{ and}$$

$$P(Y_1 = 0, Y_2 = 1) = P(Y_1 = 0|\ Y_2 = 1)P(Y = 1).$$

Let **X** be the vector of regressors $(Online, X_1, \dots, X_k)$ in equation (3) and **Z** be the vector of regressors $(Z_1, \dots, Z_j)$ in equation (4). For the recursive bivariate model, the joint probabilities of Y_1 and Y_2 are thus:

$$P(Y_1 = 1, Y_2 = 0) = \Phi(\mathbf{Z}'\boldsymbol{\beta}, -\mathbf{X}'\boldsymbol{\alpha}, -\rho),$$

$$P(Y_1 = 1, Y_2 = 1) = \Phi(\mathbf{Z}'\boldsymbol{\beta} + \eta, \mathbf{X}'\boldsymbol{\alpha}, \rho),$$

$$P(Y_1 = 0, Y_2 = 0) = \Phi(-\mathbf{Z}'\boldsymbol{\beta}, -\mathbf{X}'\boldsymbol{\alpha}, \rho), \text{ and}$$

$$P(Y_1 = 0, Y_2 = 1) = \Phi(-\mathbf{Z}'\boldsymbol{\beta} - \eta, \mathbf{X}'\boldsymbol{\alpha}, -\rho),$$

where $\Phi(\cdot)$ is the bivariate normal CDF. The recursive bivariate model for the public transit use and mall visits is

$$P(Y_1 = 1, Y_2 = 1|\mathbf{X}, \mathbf{Z}) = \Phi(\mathbf{Z}'\boldsymbol{\beta} + \eta, \mathbf{X}'\boldsymbol{\alpha}, \rho).$$

The conditional mean of Y_2 (transit use) is

$$E(Y_2|\mathbf{X}, \mathbf{Z}) = \mathrm{P}(Y_1 = 1)E(Y_2|Y_1 = 1, \mathbf{X}, \mathbf{Z}) + \mathrm{P}(Y_1 = 0)E(Y_2|Y_1 = 0, \mathbf{X}, \mathbf{Z})$$

$$= \Phi(\mathbf{Z}'\boldsymbol{\beta} + \eta, \mathbf{X}'\boldsymbol{\alpha}, \rho) + \Phi(-\mathbf{Z}'\boldsymbol{\beta} - \eta, \mathbf{X}'\boldsymbol{\alpha}, -\rho). \quad \text{(C4)}$$

According to Greene (1998), for a continuous explanatory variable, z, in either equation (3) or (4) or in both equations, the marginal effect on transit use is

$$\frac{\partial E(Y_2|\mathbf{X}, \mathbf{Z})}{\partial z} = [\Phi(\mathbf{X}'\boldsymbol{\alpha})\phi(\mathbf{Z}'\boldsymbol{\beta} + \eta) + \Phi(-\mathbf{X}'\boldsymbol{\alpha})\phi(\mathbf{Z}'\boldsymbol{\beta})]\beta_{\boldsymbol{z}}$$

$$+ [\phi(\mathbf{X}'\boldsymbol{\alpha})\Phi(\mathbf{Z}'\boldsymbol{\beta} + \eta) + \phi(-\mathbf{X}'\boldsymbol{\alpha})\Phi(\mathbf{Z}'\boldsymbol{\beta})]\alpha_{\boldsymbol{z}}, \quad \text{(C5)}$$

where $\beta_{\boldsymbol{z}}$ and $\alpha_{\boldsymbol{z}}$ are the coefficients on z in the two equations of the bivariate probit model. If z is a binary variable, then the calculation of the marginal effect is analogous to equation (C3) where we measure the difference in the conditional expectations when the values of z changes from 0 to 1:

$$E(Y_2|\mathbf{X}, \mathbf{Z}, z = 1) - E(Y_2|\mathbf{X}, \mathbf{Z}, z = 0) = [\Phi(\mathbf{X}'\boldsymbol{\alpha})\phi(\mathbf{Z}'\boldsymbol{\beta} + \eta) + \Phi(-\mathbf{X}'\boldsymbol{\alpha})\phi(\mathbf{Z}'\boldsymbol{\beta})]|z = 1$$

$$-[\phi(\mathbf{X}'\boldsymbol{\alpha})\Phi(\mathbf{Z}'\boldsymbol{\beta} + \eta) + \phi(-\mathbf{X}'\boldsymbol{\alpha})\Phi(\mathbf{Z}'\boldsymbol{\beta})]|z = 0. \quad \text{(C6)}$$