# A Philadelphia ride-share story: An Investigation of ride-share's impact on transit

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16. Abstract
The inconclusive impact of ride-hail on transit hinders transit agencies' efforts to improve service. I examine how and where ride-hail has influenced transit ridership, and who uses ride-hail and why. I use time series analyses to examine transit ridership change in the Philadelphia region post-ride-hail. I then use multilevel analyses to investigate the relationship between post-ride-hailing ridership change at bus stops and neighborhood characteristics and bus services. Finally, I investigate ride-hailing user and trip characteristics using a survey among 600 ride-hailing customers. I use mixed logit to explore factors that predict ride-hailing users' willingness to choose ride-hail over transit based on choice experiments in the survey. My findings add evidence to ride-hail's substitution effect on transit; indicate busier buses are as prone to ridership loss as less busy buses post-ride-hail; suggest that shortening transit travel time could be more effective in attracting ride-hailing customers to transit than reducing transit fares alone; remind transit agencies to heed female and lower-income residents' travel needs amid rapid growth of ride-hail.

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# Table of Contents

# Executive Summary

The impact of ride-hailing services such as Uber and Lyft on transit has been inconclusive. This knowledge gap hinders cities' and transit agencies' efforts to improve transit service. I try to fill this knowledge gap by answering the question, what does ride-hailing services' growing popularity mean for transit use? To answer this overarching question, I address three interrelated sub-questions in the following chapters.

1. Have UberX and Lyft increased or lowered transit ridership in the Philadelphia region? What transit service factors and neighborhood characteristics are associated with the recent bus ridership decline?
2. Who uses UberX and Lyft in the Philadelphia region and more generally why?
3. What factors contribute to individuals' willingness to choose transit versus ride-hailing services in the Philadelphia region?

I find that ridership for all of SEPTA's four main transit modes in the study area declined after ride-hailing services' entry. Buses suffered the biggest ridership losses. The ridership declines for heavy rail and trolleys are less severe than the decline for buses, suggesting that higher speed, more frequent, and more reliable rail transit services might be less prone to ridership losses than traditional buses amid the increasing influence from ride-hailing services. Only Regional Rail showed signs of ridership rebounding since the entry of ride-hailing services, although as of mid-2019, ridership had not returned to the level in the two years prior to ride-hailing services' entry.

When it comes to ridership loss, not all buses and bus stops are equal. Buses and bus stops that serve more passengers had greater ridership declines than less busy buses and smaller stops. Bus stops in neighborhoods with characteristics that are traditionally associated with higher bus ridership might be as prone to ridership losses as other bus stops. Bus stops in urban neighborhoods are more likely to have gained riders in the post-ride-hailing period than those in suburban neighborhoods. Last, more frequent buses are more resilient to ridership decline than less frequent buses.

Like ride-hailing users in other regions in the U.S., users in the Philadelphia region use ride-hailing services to fill occasional rather than regular travel needs. Many ride-hailing trips are for short recreation and errand purposes in urban area. Younger and lower-income users tend to use ride-hailing services more frequently than older and higher-income users. Many replaced transit with ride-hailing services on their last ride-hailing trips, suggesting a substitution effect of ride-hail on transit. Additionally, ride-hailing users over 30 years old and those with higher income are more willing to choose ride-hailing services over transit, even though they use ride-hailing services less often than younger, lower-income users. While female customers use ride-hailing services as frequently as male customers, they have higher probabilities of choosing ride-hailing services over transit. More frequent transit users are more likely to choose transit over ride-hailing services than less frequent transit users.

High monetary cost, long travel time, and the presence of transfers are significant deterrents to travel. Ride-hailing users value the different time components in a trip differently, with time spent on walking to and from transit stops/stations being the most burdensome compared to in-vehicle travel time and wait time for transit and ride-hailing vehicles. While lower transit fares increase users' willingness to use transit over ride-hailing services, fare reductions alone may not be enough to generate a meaningful mode shift from ride-hailing services to transit without shortening overall travel time.

My findings have two major policy implications. First, there is a need to ensure that transit service is meeting the travel needs of lower-income residents adequately amid the popularity of ride-hailing services. Second, when improving the competitiveness of transit against ride-hailing services, shortening transit travel time and reducing transfer is more important than reducing transit fare. Although my study focuses on the Philadelphia region, findings offer insights for other large, multimodal American cities that are witnessing the rapid growth of ride-hailing services. Finally, ride-hailing services have become and likely will continue to be an integral part of megaregional travel by providing a convenient alternative transport mode to airports and train stations. Transit at airports and train stations might face challenges of recapturing passengers who have switched to ride-hailing services.

# Chapter 1. Chapters without Headings or Subheadings

## 1.1. Setting the Stage

Rarely has there been a shortage of words in describing how we access transportation services. Phrases such as “catch the bus”, “hail a taxi”, “dial a cab”, and “call a limo” have become so commonplace that we seldom ponder the subtlety behind the physical acts that they imply. Catch, for example, indicates that the user has to proactively “seek out” the service, as the latter’s spatial and temporal operation adheres to fixed routes and schedules, and does not respond to individual users’ impromptu requests. Hail and dial, on the other hand, indicate that the service comes to the customer upon request. The emergence of ride-hailing services such as Uber and Lyft pose a conundrum of describing how we access these services. Unlike taxis, ride-hailing services answer individual users’ requests mainly through a smartphone application-based platform, making the physical acts of hailing and dialing obsolete. Unlike public transit, the new services adhere to neither fixed routes nor schedules (TRB, 2015).

Unable to characterize the action of requesting ride-hailing services, many customers have resorted to the generic “take Uber/Lyft” when referring to using the services. The more creative minds even borrowed a page from the Google experience by simply referring to this process as “Uber it”. Ride-hailing services have experienced exponential growth shortly after their launch in U.S. cities in the late 2000s. High market demand for convenient travel alternatives, coupled with ride-hailing services’ relatively affordable fares that are partly subsidized by private investors, has enabled ride-hailing companies to increase their market share among travelers especially in urban areas. As of 2019, Uber operates in more than 200 cities in the U.S. (Uber, n.d.). The popular media have followed the rapid growth of ride-hailing services closely. According to a news report, between 2015 and 2017, Lyft rides increased from 163 million to 376 million in the U.S. and Toronto (Carson, 2018).

Despite ride-hailing services’ increasing presence, due to both their recentness and the proprietary operator data, planners and policy makers have not been able to fully grasp the services’ impact. Consensus is especially absent on two topics. First, although ride-hailing services’ recent growth coincides with transit ridership loss especially in big cities, the relationship between the new services and transit ridership has been murky. While some studies suggest that the services complement transit, others find a substitution effect of ride-hailing services on transit. Farebox revenue and funding for public transit are to a large extent predicated on ridership. Decrease in revenue and funding as a result of ridership loss limits transit agencies' ability to ensure adequate service and maintenance. Furthermore, a lack of understanding of how transit ridership has changed in the post-ride-hailing period could undermine transit agencies' ability to carry out service adjustment and improvement strategies effectively. Second, although researchers have started to examine who uses ride-hailing services and why, there are still many uncertainties about ride-hailing services' user characteristics and impact on travel behavior especially with respect to transit use. There is also a lack of understanding of how individual passengers weigh ride-hailing services against transit when making mode choice decisions. Together, the gaps in ride-hailing research pose a challenge for cities and transit agencies to design and implement measures to improve transit and manage the growth of ride-hailing services.

In this dissertation, I try to fill the knowledge gaps in the research on ride-hailing services by answering the question, what does ride-hailing services' growing popularity mean for transit use? To answer this overarching question, I address three interrelated sub-questions in the following chapters.

1. Have UberX and Lyft increased or lowered transit ridership in the Philadelphia region? What transit service factors and neighborhood characteristics are associated with the recent bus ridership decline?
2. Who uses UberX and Lyft in the Philadelphia region and more generally why?
3. What factors contribute to individuals' willingness to choose transit versus ride-hailing services in the Philadelphia region?

In Chapter 2, I examine the change in ridership trends after the entry of ride-hailing services using time series analyses with a regression discontinuity design. In Chapter 3, I use multilevel analyses to address the second question by investigating the relationship between stop-level bus ridership decline and bus service levels, neighborhood characteristics, and land use factors. In Chapter 4, I examine ride-hailing user and trip characteristics based on results from an online survey of more than 600 ride-hailing users in the Philadelphia region. I also discuss how ride-hailing users' travel behavior changed after adopting the services. Finally, in Chapter 5, I use logistic regression analyses to investigate factors that are related to individual ride-hailing users' willingness to choose ride-hailing services versus transit based on the stated preference choice experiments in the ride-hailing user survey. In the following paragraphs, I summarize the main findings from each chapter.

## 1.2. Summary of Chapter Findings

Chapter 2 Post-ride-hailing ridership trends

In Chapter 2, I explore the change in ridership trend after ride-hailing services entered the Philadelphia region for each of the four main transit modes operated by the Southeastern Pennsylvania Transportation Authority (SEPTA), Philadelphia region's primary transit operator. Using monthly ridership data from the National Transit Database, I conduct time series analyses with a regression discontinuity design and seemingly unrelated regression analyses to investigate the change in monthly ridership for buses, trolleys, heavy rail, and Regional Rail (Philadelphia region's commuter rail) between February 2011 and January 2019. I find that the post-ride-hailing ridership trends for all four modes are significantly different from the trends before ride-hailing services launched, controlling for macro-economic factors, service level, and the seasonal fluctuation in transit use. The findings suggest that, while transit service quality, seasonality, and the size of labor force play significant roles in explaining transit ridership trends in the post-ride-hailing period, ride-hailing services' presence contributes to the ridership losses for all four transit modes.

While ridership decreased for all four transit modes, the patterns and extents of the declines vary across modes. Buses experienced the most severe ridership decline after ride-hailing services' launch. Regional Rail ridership saw a slight rebound after an initial period of decline following the entry of ride-hailing services. Heavy rail and trolleys had the smallest ridership declines among the four modes in the post-ride-hailing period.

Chapter 3 Not all bus stops are equal

In Chapter 3, I conduct multilevel analyses with varying intercepts to investigate the associations between ridership and ridership change at bus stops and bus service level, neighborhood characteristics, and land use factors. Ridership at approximately 10,000 bus stops in the study region comes from SEPTA's passenger boarding data. I find that, between 2014 and 2018, buses and bus stops that serve more passengers correspond with bigger ridership declines. Ridership change also differs between urban and suburban neighborhoods. Not only did bus stops in urban neighborhoods have higher ridership than those in suburban neighborhoods, but they are also less likely to have had some of the biggest percentage ridership losses. Bus stops in neighborhoods with higher poverty rates are associated with higher ridership and bigger ridership declines, and are less likely to have gained riders in the post-ride-hailing period than bus stops in neighborhoods with lower poverty rates. Last, bus stops that serve buses with more frequent services are more likely to have gained riders and less likely to have had the most significant ridership losses.

My analysis also shows that in the post-ride-hailing era, some buses with higher ridership per operating hour and lower per passenger costs lost more riders than buses that carry fewer passengers with higher per passenger costs. This finding indicates that higher performance routes could be just as prone to ridership loss as lower performance routes.

Chapter 4 Who uses ride-hailing services in Philadelphia and why

In this chapter, I analyze results from an online survey among 611 adult ride-hailing users in the Philadelphia region to examine ride-hailing user and trip characteristics, as well as how the users' travel behavior changed after adopting ride-hailing services. Results suggest that younger and lower-income respondents use ride-hailing services more often than older and higher-income respondents. Conforming to existing findings, respondents across demographic groups use ride-hailing services to fill occasional rather than regular travel needs. Many ride-hailing trips are short and for recreation and errand purposes in urban area. Ride-hailing trips' purposes and temporal distribution reflect the activity patterns throughout the day on both weekdays and weekends.

In terms of travel behavior and mode substitution, more than a quarter of the respondents replaced transit with ride-hailing services on their last ride-hailing trips. This finding indicates that ride-hailing services are likely a substitute rather than a complement for transit. Ride-hailing services also replaced some driving, walking and biking trips, as well as trips that would not have been made had ride-hailing services not been available. As a result, ride-hailing services likely increased vehicle miles traveled (VMT) in the region. Meanwhile, ride-hailing services could enhance access by enabling users, including lower-income users, to take trips that they would not have taken otherwise, and/or by making their current trips easier. Last, most of the respondents did not change the overall number of trips they take or their vehicle ownership after adopting ride-hailing services.

Chapter 5 Trade Uber for the bus

In this chapter, I investigate ride-hailing users' willingness to choose ride-hailing services versus transit based on responses from the stated preference choice experiments in the ride-hailing user survey. I use mixed multinomial logistic regression (mixed logit) to estimate the relationship between respondents' socio-demographic characteristics and travel mode-specific factors, and their mode choice between ride-hailing services and transit. In the models, I allow the parameters for time spent walking to transit, waiting for transit or ride-hailing vehicles to arrive, and traveling in vehicle to vary across respondents to reflect individuals' different preferences for the various time components of a trip.

Results indicate that higher-income respondents and respondents over 30 years old are increasingly willing to choose ride-hailing services over transit, even though their reported usage of ride-hailing services is lower than that among lower-income and younger respondents. Female respondents are more willing to choose ride-hailing services over transit than male respondents and less frequent transit users are more likely to choose ride-hailing services than frequent transit users. Consistent with existing findings on mode choice studies, higher trip costs and longer trip duration are significant deterrents for travel by either mode. On average, respondents perceive the time spent on walking to and from transit to be more burdensome than in-vehicle travel time and wait time for transit and ride-hailing services, although not all respondents consider walking to and from transit a burden. Respondents consider waiting for ride-hailing services to be less burdensome than waiting for transit. Simulations indicate that reducing transit fares alone without shortening trip duration might not be enough to convince ride-hailing users to switch to transit.

Chapter 6 Implications and conclusion

In the last chapter, I recap the key findings and their implications for planning practice and future research. I highlight the need to include other types of ride-hailing services, such as shared Uber and Lyft, in the research of the relationship between ride-hailing services and transit. I also discuss the merits in examining how ride-hailing services might improve the access of disadvantaged residents and communities. Additionally, I argue that despite ride-hailing services have become an integral part of travel within megaregions by providing a convenient access mode to airports and train stations, high-quality transit links that connect the airport and train stations with the city and its public transit system could still play a crucial role amid ride-hail's popularity. Last, I advocate for more data sharing from ride-hailing companies to enable further research on their services' impact on the transport system.

## 1.3. Contributions

My study makes four principal contributions to the ride-hailing research. First, it adds further evidence to the association between the increasing presence of ride-hailing services and transit ridership decline. My findings indicate that ride-hailing services likely have substituted, rather than complemented transit services. Furthermore, findings corroborate the speculation that higher frequency, more reliable transit services might be more resilient to ridership loss in the post-ride-hailing period.

Second, my study investigates where and what type of transit services are more prone to ridership decline in the post-ride-hailing period. I find that busier bus stops and bus lines are just as prone to ridership loss as less busy bus stops and buses in the post-ride-hailing period. Currently, SEPTA identifies bus routes with low ridership and high cost per passenger for possible evaluation and intervention (Southeastern Pennsylvania Transportation Authority, 2019b). My findings suggest that the transit agency should also consider monitoring buses and neighborhoods that have traditionally had high ridership, as they might not be immune to post-ride-hailing ridership losses.

Third, my dissertation is one of the first studies that I know of to model mode choice between ride-hailing services and transit based on respondents' stated preferences. Through the analysis, I identify factors that affect individual's willingness to use one mode over the other under different trip cost and travel time scenarios. By investigating why residents might favor ride-hailing services over transit, my study could help transit agencies identify and evaluate the effectiveness of potential service improvement strategies. Transit agencies that aim to increase ridership might find my analyses relevant to their efforts to increase transit's attractiveness. Additionally, findings on individual's trade-off between ride-hailing services and transit provide a reference for future mode choice analyses that involve ride-hailing services and transit.

Last but not least, my study identifies potential unmet transit demand among lower-income residents and female passengers' concerns about using transit. Lower-income residents sometimes have to rely on ride-hailing services to meet certain travel needs, even though they might be reluctant to use such services. It is crucial for transit agencies to provide convenient transit service to lower-income neighborhoods so that the residents do not become captive to ride-hailing services, which are often less affordable than transit. The finding that female passengers are more concerned about their personal safety and whether they are traveling with small children when making mode choice decisions reminds transit agencies to accommodate female riders' travel needs when designing improvement measures.

Although my study focuses on the Philadelphia region, my findings offer insights for other large, multimodal American cities. Like Philadelphia, many big cities have seen declining transit ridership in recent years, coinciding with the growth of ride-hailing services. Local officials and transit planners in these cities might find my study relevant to their efforts to improve transit service and stem ridership loss.

# Chapter 2. Post-Ride-Hailing Ridership Trends

## 2.1. The Big Picture

Over the past two decades, the growth of public transit passenger miles (38%) has surpassed that of vehicle miles traveled (27%), while public transit ridership growth (31%) has outpaced the nation's population growth (20%) (American Public Transportation Association, 2018). Several cities have managed to promote transit through construction of new transit lines, system expansion, and/or transit network redesign. The federal government also increased financial commitments to support transit, with funding for the federal public transportation program increasing each year between 2011 and 2018 (Mallett, 2018). While transit remains an important travel mode especially in cities, the overall ridership has been in decline since its highest level in 2014. In 2017, transit ridership decreased in 31 of 35 major metropolitan areas in the U.S. (Siddiqui, 2018).

Figure 2.1 shows the total monthly transit ridership for each of the five largest bus, heavy rail, light rail, and commuter rail systems in the U.S. (excluding transit operated by the New York City Metropolitan Transportation Authority) between January 2002 and October 2019. With the exception of commuter rail, all of the major transit modes experienced ridership declines to various extents in recent year, coinciding with the increasing presence of ride-hailing services.

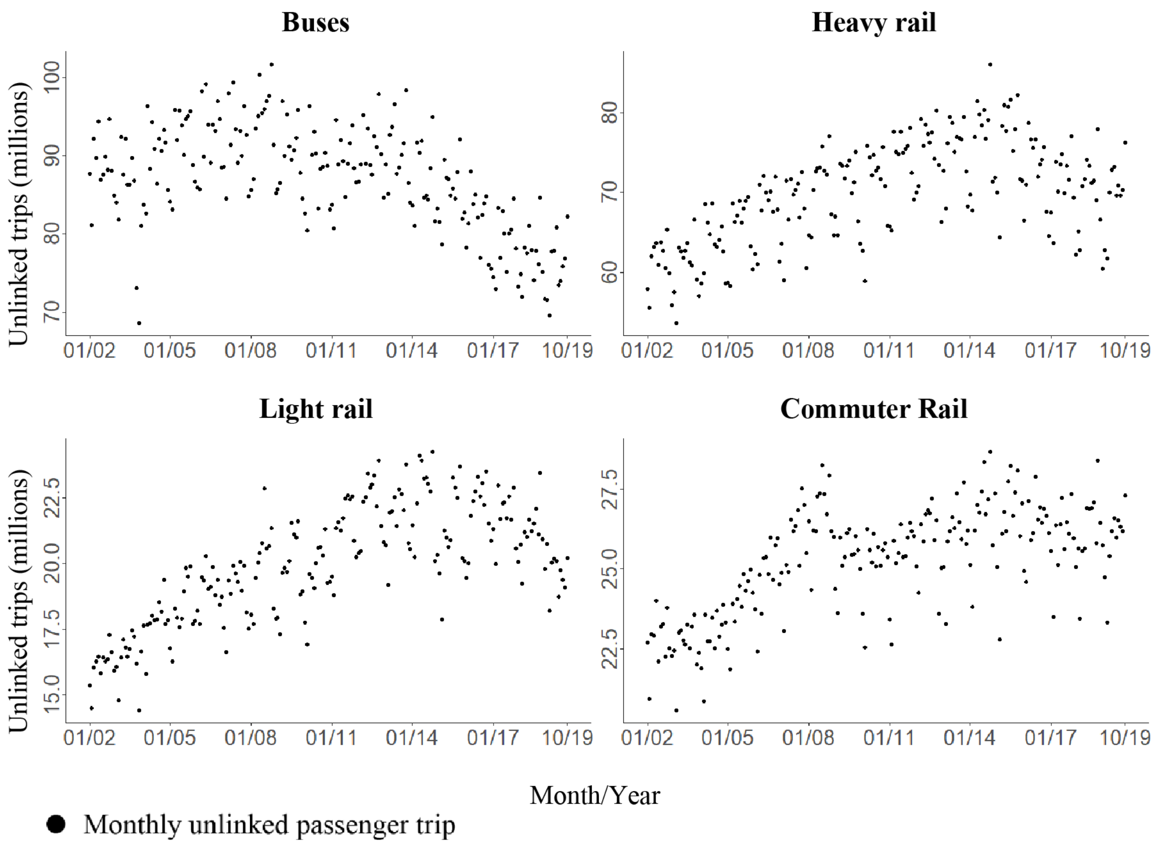


*Figure 2.1. Transit ridership for the five largest bus, heavy rail, light rail, and commuter rail systems in the U.S.*

Transit agencies for each mode
Bus (including bus, BRT, and trolleybus): CTA, LA Metro, MUNI, NJ Transit, SEPTA,
Heavy rail (excluding commuter rail): BART, CTA, MBTA, SEPTA, WMATA
Light rail (including cable car, light rail, and trolley): DART, LA Metro, MBTA, MUNI, TriMet
Commuter rail: MBTA, Metra Rail, Metro North, NJ Transit, SEPTA

In contrast to the recent transit ridership decline, ride-hailing services such as Uber and Lyft have seen trip growth and market expansion. So far, findings on ride-hailing services' impact on transit ridership have been inconclusive. The lack of understanding of the relationship between ride-hailing services' growing presence and the declining transit ridership could present a challenge for transit agencies' capital planning and operations. Transit farebox revenue, which is derived from ridership, enables transit agencies to maintain adequate service levels and carry out system maintenance and upgrade. Additionally, federal and state funding for public transit is, for a large part, predicated on ridership. In Pennsylvania, for example, one-quarter of transit agencies' allocated funds are determined by the number of passengers (SEPTA, 2019a). Declining ridership leads to shrinking revenue and funding, which in turn could force transit agencies to scale back or even cut services entirely, chasing away even more passengers (Cervero, 2017). Transit ridership is also a key factor in transit agencies' service management and resource allocation. A clear understanding of transit ridership amid the growing influence of ride-hailing services is therefore crucial to keep transit agencies afloat and maintain effective operation.

In the Philadelphia region, local transit and planning officials have suggested in various interviews that ride-hailing services might have contributed to the well-documented recent ridership decline (Saksa, 2017). However, there is still the need to go beyond speculation on the relationship between ride-hailing services and transit ridership. In this chapter and the next, I investigate the transit ridership decline in the post-ride-hailing period in the study area. In the current chapter, I use time series analysis with a regression discontinuity design and seemingly unrelated regression analysis to compare the ridership trends for SEPTA's buses, heavy rail, trolleys, and Regional Rail before and after ride-hailing services' entry in the study area. Seemingly unrelated regression accounts for potential cross-model error correlations among regression equations that might appear unrelated (Wooldridge, 2010). The models thus provide a more realistic representation of transit use in the study area. In the next chapter, I zoom in to examine how ridership has changed in the post-ride-hailing era for individual bus stops that serve buses with different catchment areas, service characteristics, and performance levels.

## 2.2. Factors Affecting Transit Ridership

Scholars have identified many factors that are associated with transit ridership. These factors can be placed into two broad categories: internal factors and external factors. Internal factors are ones that are subject to the discretion of the public transit operator (Kain & Liu, 1996). Some of the more well-studied internal factors include transit service levels and fares (Cervero, 1990; Chen et al., 2011; Chiang et al., 2011; Kain & Liu, 1996; Rose, 1986; Syed & Khan, 2003; Wang & Skinner, 1984). External factors are outside the control of the transit system (Taylor et al., 2009). Common external factors that have been examined in the transit ridership literature include socio-economic conditions such as vehicle ownership (Boisjoly et al., 2018; Kitamura, 1989), employment level

(Hendrickson, 1986), built environment characteristics such as population density, job density and the degree of sprawl (B. B. Brown et al., 2016; Guerra & Cervero, 2011; Morrall & Bolger, 1996; Taylor et al., 2009), gasoline prices (Agthe & Billings, 1978; Chao et al., 2015; Currie & Phung, 2007; Gomez-Ibanez, 1996; Lane, 2010, 2012; Nowak & Savage, 2013), and weather and seasonality (Arana et al., 2014; Kashfi et al., 2015; Li et al., 2018; Singhal et al., 2014; Stover & McCormack, 2012; Tao et al., 2018; Zhou et al., 2017). While factors such as inclement weather and high vehicle ownership were found to be significantly associated with lower transit ridership, the significance of variables such as transit fare level and gasoline prices are not consistent across studies.

## 2.3. Time Series Analysis in Transit Ridership Studies

A common method for studying transit ridership is time series analysis in a regression modeling framework. Since the 1970s, several scholars have analyzed ridership trends and performed ridership forecasts using multivariate regression time series analysis (Doi & Allen, 1986; Gaudry, 1975; Kyte et al., 1988; Lane, 2012; McLeod Jr et al., 1991; Rose, 1986). A few scholars also rely on time series analysis to examine transit ridership in the post-ride-hailing era in several recent studies (Boisjoly et al., 2018; Graehler Jr et al., 2019). Time series model offers several advantages for analyzing transit ridership, including easy access to data and its flexibility to allow for the study of time variation and delay effect in transit demand by incorporating these structural relationships in the models (Kyte et al., 1988).

## 2.4. Transit Ridership in the Philadelphia Region

Mirroring the national trend, transit ridership in Philadelphia has decreased in recent years. Figure 2.2 shows the monthly transit ridership by mode between January 2002 and October 2019. Among the four modes, buses have the highest ridership, followed by heavy rail, Regional Rail, and trolleys. For all four modes, ridership exhibits substantial seasonal fluctuation. Ridership exhibits different trends across the four modes. Before Lyft's entry, ridership for heavy rail and Regional Rail grew steadily. Bus ridership experienced a decline between 2005 and mid-2009, but then started to rebound in 2010. For buses, heavy rail, and Regional Rail, ridership reached its highest levels in 2013 and 2014. Trolley ridership peaked in 2010 and 2011, then started to decline until the early 2014. After Lyft's entry, buses, heavy rail, and Regional Rail saw gradual ridership declines. The decline is especially prominent for buses. By mid-2019, the overall bus ridership had dropped to its lowest level since 2002. Although the declines for heavy rail and Regional Rail are less severe, the two modes saw their ridership fall to the lowest levels since the Great Recession. In contrast, trolley ridership held steady since the early 2014, when the overall trolley ridership fell to the lowest level in almost a decade.

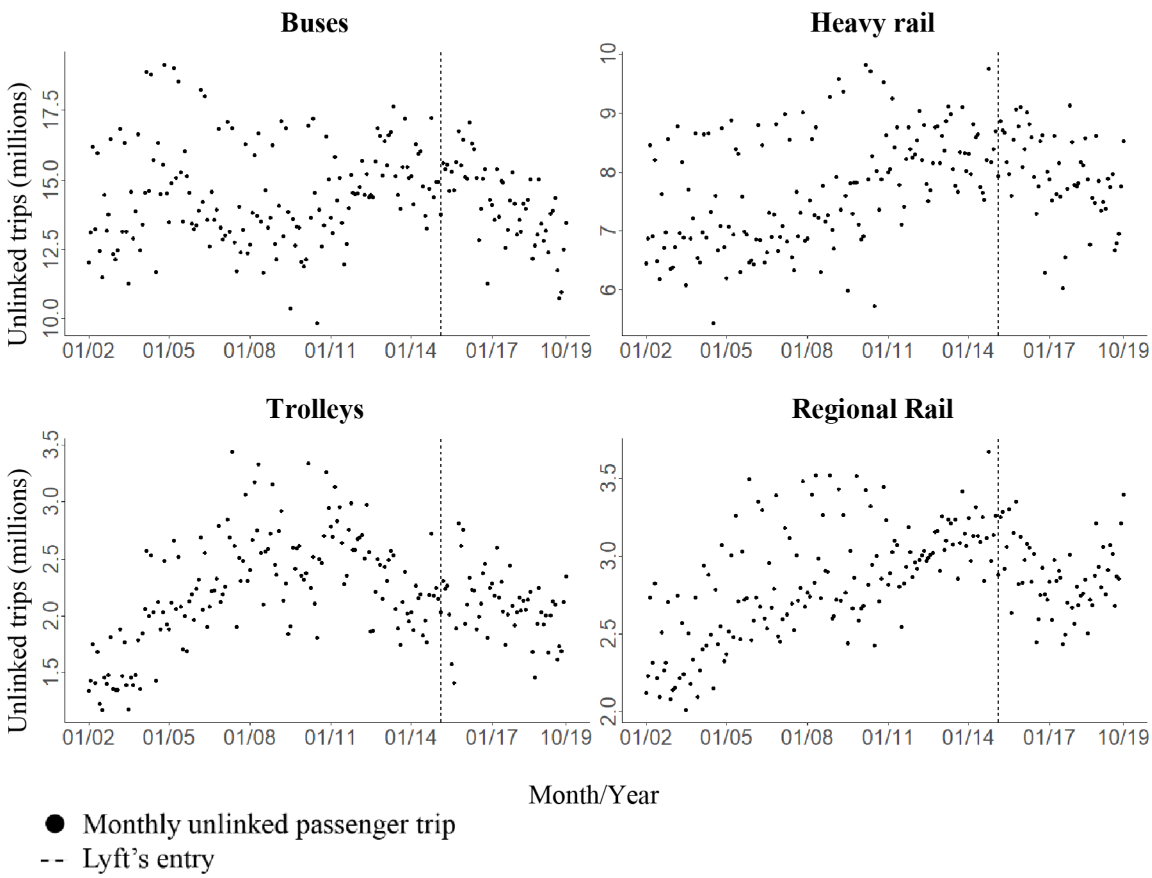


*Figure 2.2. Monthly SEPTA ridership by mode between January 2002 and October 2019*

## 2.5. Methods and Modeling Framework

### 2.5.1. Time Series Ridership Data

To understand whether the ridership trend for each transit mode changed after the entry of ride-hailing services, I zoom in to the period from February 2011 to January 2019, the 48 months on either side of Lyft' entry. Focusing on the selected 96-month period has two practical advantages.

First, having the same months before and after Lyft's entry ensures the symmetry of the monthly cycles. As shown in Figure 14, SEPTA's transit ridership is subject to seasonal fluctuation. The trend between the 12 months spanning from January to December, for example, is almost certainly different from the trend between June and May of the following year. The symmetry of the selected period allows the ridership trends on either side of Lyft's entry to follow the same monthly cycles and thus to be comparable. Since ridership for January 2020 was not available by the time this article was written, I was unable to extend beyond the selected months while keeping the symmetry of the data. Second, the selected period does not overlap the Great Recession from December 2007 to June 2009, thus ensuring the consistency of the macro-economic conditions before and after Lyft's entry. Previous studies suggest that transit ridership is correlated with economic factors such as gasoline prices and employment. As a result, ridership during a major economic recession may not reflect its trend under normal economic circumstances. Excluding the recession and the initial recovery period from the truncated time series allows the comparison of ridership trends to take place under normal economic circumstances.

In this analysis, I use Lyft's entry as the point of discontinuity. Lyft entered Philadelphia in February 2015, three months after UberX's entry in October 2014. Using Lyft as the intervention allows for the initial market adoption period for ride-hailing services in Philadelphia, thus enabling the model to capture both UberX and Lyft's potential effects on transit ridership.

## 2.5.2. Modeling Framework

I use times series analysis with a regression discontinuity design to examine the change in ridership trend for each of SEPTA's four main transit modes. The equation below shows the models' basic structure.

$$\overline{R}_a = \mu + \rho D_a + \gamma_1 a + \gamma_2 a^2 + \delta_1(a \cdot D_a) + \delta_2(a^2 \cdot D_a) + \beta X + e_a$$

Where $\overline{R}_a$ represents the ridership at time point $a$ (in this case, month $a$). The term μ represents the model's intercept. $D_a$ is the binary variable indicating Lyft's entry. It is assigned the value of 0 for months before Lyft's entry, and the value of 1 for months after Lyft's entry. The coefficient $\rho$ represents the ridership change at Lyft's entry. The variable $a$ is a running variable representing time points in the time series sequentially. In this analysis, this variable runs from 1 to 96, each representing a single month. I use the running variable to calculate the ridership trend. Polynomial functions of $a$ allows the ridership trend to be curvilinear rather than linear. The number of polynomial degrees is not limited. The terms $(a \cdot D_a)$ and $(a^2 \cdot D_a)$ are the interaction between the time running variable and Lyft's entry. As is the case with $a$, the number of polynomial degrees for the interaction terms is also unlimited. Nor do the polynomial degrees for the interaction terms have to match those for the time variables. The present model allows for different running variables coefficients before ($\gamma_1$ and $\gamma_2$) and after ($\delta_1$ and $\delta_2$) of Lyft's entry. This design enables the trend on either side of Lyft's entry to be different. The term $\beta$ represents the coefficients for the control factors, jointly denoted as $X$. I explain the control factors in detail in the next section. Finally, $e_a$ represents the error term for each month.

By allowing both the linear term (i.e., 1st degree polynomial term) and the higher degreed polynomial terms to change as ridership crosses the point of discontinuity (i.e., Lyft's entry), the model enables me to examine whether there is a significant change in the ridership trend before and after Lyft's entry. If the trends before and after Lyft's entry are similar, then the coefficients for the interaction terms should be statistically insignificant, because the interaction terms do not further what has already been accounted for by the time running variables alone, represented by the $\gamma_1 a + \gamma_2 a^2$ terms in the equation. In contrast, statistically significant coefficients for the interaction terms suggest that the time running variables alone could not adequately describe the post-Lyft ridership trends, and that the interaction terms make the post-Lyft trend fit the transit ridership data better. This in turn implies a significant change in ridership trend between the pre- and post-Lyft periods. By controlling for independent factors (i.e., the $X$ term in the equation) that are assumed to not have been affected by ride-hailing services, we gain confidence that ride-hailing services have contributed to the change in ridership trends.

I also estimate seemingly unrelated regression to investigate the change in ridership trends. A set of regression equations whose residuals, or error terms, are correlated is called a seemingly unrelated regression system (UCLA Statistical Consulting Group, n.d.). At first look, the regression equations might seem unrelated, but they are related through the correlation in the errors (UCLA Statistical Consulting Group, n.d.). In the current analysis, the four transit modes in the analysis do not operate in isolation. Rather, they are likely subject to the effect of some common factors, such as the macro-economic conditions and transit demand in the study area. As a result, the residuals in the four seemingly unrelated models could be correlated. When estimating ridership trends, seemingly unrelated regression considers the four modes as a system by accounting for the cross-model error correlations. Thus, the models offer a more realistic representation of transit use in the study region. Findings from the seemingly unrelated regression add further evidence to the behavior of ridership trends after the entry of ride-hailing services.

### 2.5.3. Model Building and Variable Selection

The dependent variables for the analysis are the monthly unlinked passenger trips for each mode. Unlinked trips are total boarding on an individual vehicle and are viewed as a measure of transit utilization (Bureau of Transportation Statistics, 2017). Unlinked trips consider transfers as separate trips. For example, a passenger traveling from Station A to Station B with a transfer from one line to another in between would register two unlinked passenger trips. I converted passenger trips to the logarithmic scale to reduce the changing variance. Unlinked passenger trip data come from the National Transit Database maintained by the Federal Transit Administration (Federal Transit Administration, 2018).

I place the independent variables into three categories- seasonality, trend, and control variables. Seasonality includes eleven month dummies, with January being the reference month. I also considered three trigonometry pairs (sine and cosine pairs 220, 348, and 432), but they were excluded from the final models due to statistical insignificance. Trend variables include the time running variables and the interaction terms between time and Lyft's entry. Control variables include transit service factors such as vehicle revenue miles for each mode and service disruptions; potential competing modes such as bike share trips; and economic factors such as labor force size and inflation adjusted gasoline price. Since monthly population statistics are not available, labor force size serves as an estimate for population in the study area, in addition to being an economic indicator. In transit ridership analyses, researchers have used gasoline prices as a surrogate for the cost of driving (Kyte et al., 1988). I use the weekly all grades reformulated retail gasoline price for the Energy Information Administration's Central Atlantic Region to calculate the inflation adjusted gasoline price for the study area. Table 2.1 summarizes the control variables' data sources and transformation.

*Table 2.1 Summary of the control variables' data sources and transformation*

| Variable | Data source | Transformation |
|---|---|---|
| **Vehicle revenue miles (for each of the four modes)** | National Transit Database | Transformed to the logarithmic scale |
| | | |
| **Transit service disruptions** | SEPTA | None |
| | | |
| **Labor force size (for Philadelphia County and the study area)** | Bureau of Labor Statistics | Transformed to millions |
| | | |
| **Gasoline price** | Energy Information Administration | Adjusted to 2017 inflation |
| | | |
| **Bike share trips** | Indego Blue Bike Share | None |

To account for the potential lagged effect of macro-economic factors on transit ridership, I include up to two-month lags for labor force size and adjusted gasoline prices in the initial models. Since buses and Regional Rail serve both the urban and suburban areas in the five-county region, I use the labor force size of the entire study area in their respective models. Heavy rail and trolleys primarily serve the City of Philadelphia and therefore include in their models the city's instead of the study area's labor force size.

I also considered the unemployment rates for both the study area and Philadelphia County, transit fare, and taxi trips as control variables. However, Pearson's correlation tests indicate that these variables are highly correlated with the trend variables or with other control variables. To avoid multicollinearity, I excluded these variables from the models. While taxis could serve as an alternative mode to transit, taxi trip data are not available prior to 2015. Total taxi trips after 2015 are not significantly associated with transit ridership and are therefore not included in the models.

For the trend variables, based on the shape of the ridership trend for each mode, I fit polynomial functions to the time running variables for the pre-Lyft period and the interaction variables for the post-Lyft period. In the same model, I also include control variables and seasonality. To ensure parsimony of the models, I remove insignificant control variables one by one using the backward stepwise variable selection method, until all the control variables in the models are significant. In cases where a trend variable becomes less significant than the control variables, I prioritize the trend variables by eliminating the insignificant control variables first. This process preserves the integrity of the trend by removing the control variables that could obscure the significance of the trend variables due to collinearity.

Once I settle on the control variables and seasonality, I proceed to determine which trend variables to include in the models. Among the initial trend variables, if the highest degree polynomial terms for the time and interaction variables are significant, I continue to add polynomial functions with increasing degrees one by one until they become insignificant. If the initial highest degree polynomial term for either the time variable or the interaction variable is insignificant, I remove the highest degree polynomial term until it becomes significant. The resulting time variables describe the ridership trends before and after Lyft's entry, while controlling for seasonality and other independent variables. For example, the ridership trends for buses before and after Lyft's entry appear to be concave, or in an upside-down U shape. To fit the patterns of the trends, I tentatively include in the initial model a time variable and a quadratic time variable (time variable squared) for the pre-Lyft period, and a first-degree polynomial (Lyft's entry interacting with the first-degree time variable) and a second-degree polynomial (Lyft's entry interacting with the second-degree time variable) for the interactions in the post-ride-hailing period. With significant seasonality and economic factors controlled, the second-degree polynomial time variable turns out to be significant, whereas the second-degree polynomial interaction term is not. Adding a third-degree polynomial to the time variable proved insignificant. Removing the insignificant second-degree polynomial for the interaction term results in the first-degree polynomial for the interaction becoming significant. The final model for bus ridership thus includes the first- and second-degree polynomial time variables and the first-degree interaction variable, in addition to seasonality and control variables. The equations below show the trend variables included in the initial models. Tables 8 and 9 in next section present the trend variables in the final models. Refer to the Modeling framework section for an explanation of the terms in the equations.

$$\overline{R}_{bus} = \mu_{bus} + \rho_{bus} D_a + \gamma_{bus\,1} a + \gamma_{bus\,2} a^2 + \delta_{bus\,1}(a \cdot D_a) + \delta_{bus\,2}(a^2 \cdot D_a) + \beta_{bus} X + e_{bus}$$
$$\overline{R}_{hr} = \mu_{hr} + \rho_{hr} D_a + \gamma_{hr\,1} a + \delta_{hr\,1}(a \cdot D_a) + \beta_{hr} X + e_{hr}$$
$$\overline{R}_{tr} = \mu_{tr} + \rho_{tr} D_a + \gamma_{tr\,1} a + \gamma_{tr\,2} a^2 + \delta_{tr\,1}(a \cdot D_a) + \delta_{tr\,2}(a^2 \cdot D_a) + \beta_{tr} X + e_{tr}$$

$\overline{R}_{rr} = \mu_{rr} + \rho_{rr} D_a + \gamma_{rr\,1} a + \delta_{rr\,1}(a \cdot D_a) + \delta_{rr\,2}(a^2 \cdot D_a) + \beta_{rr} X + e_{rr}$

*bus*: Bus
*hr*: Heavy rail
*tr*: Trolley
*rr*: Regional Rail

The seemingly unrelated regression models include the same variables as in the models that do not control for cross-model correlation. Table 2.2 shows the residual correlation among the four models. The residual correlation between the bus ridership and heavy rail ridership models, for example, is 0.5. The residual correlations among all the other models are weaker.

*Table 2.2 Residual correlation between each pair of ridership models*

| | **Bus** | **Heavy rail** | **Trolley** | **Regional Rail** |
|---|---|---|---|---|
| **Bus** | 1.00 | 0.50 | -0.03 | 0.22 |
| **Heavy rail** | 0.50 | 1.00 | 0.04 | 0.10 |
| **Trolley** | -0.03 | 0.04 | 1.00 | -0.05 |
| **Regional Rail** | 0.22 | 0.10 | -0.05 | 1.00 |

## 2.6. Results

### 2.6.1. Interpretation of Parameter Estimates

Tables 2.3 and 2.4 below show the parameter estimates from both the original models that do not account for cross-model correlation and the seemingly unrelated regression models for the four transit modes. Seasonality, labor force size, service disruption, and service levels are significantly correlated with one or more transit modes' ridership. As expected, service disruptions are associated with fewer riders, whereas higher transit service levels measured by vehicle revenue miles are associated with higher ridership. Seasonality and service level are the only variables that are consistently significant across transit modes. Labor force size is positively associated with trolley and heavy rail ridership. The parameter estimates from the seemingly unrelated regression models are not statistically different from the estimates from the original models. This finding indicates that taking into consideration the residual correlation across models does not alter the trend estimates significantly.

*Table 2.3 Parameter estimates from the original models for the four transit modes*

| | Bus | Heavy Rail | Trolley | Regional Rail |
|---|---|---|---|---|
| | *Original* Coefficient (S.E.) | *Original* Coefficient (S.E.) | *Original* Coefficient (S.E.) | *Original* Coefficient (S.E.) |
| **(Intercept)** | 6.654* (2.953) | -5.185** (1.840) | 9.629*** (2.045) | 5.147* (2.329) |
| **Time** | 0.011*** (0.001) | 0.0003 (0.0003) | -0.018*** (0.005) | 0.001 (0.001) |
| **Time$^2$** | 0.0002*** (0.00003) | | 0. (0.0001) | |
| **Lyft's entry** | -0.491*** (0.121) | 0.166*** (0.029) | -1.150** (0.339) | 0.920*** (0.176) |
| **Lyft * Time** | 0.011*** (0.002) | -0.003*** (0.001) | 0.043*** (0.010) | -0.026*** (0.005) |
| **Lyft * Time$^2$** | | | 0.0004*** (0.0001) | 0.0001*** (0.00003) |
| **February** | 0.021 (0.028) | 0.093*** (0.018) | -0.026 (0.040) | -0.009 (0.023) |
| **March** | 0.060** (0.022) | 0.063*** (0.015) | 0.108* (0.045) | -0.013 (0.021) |
| **April** | 0.036 (0.021) | 0.066*** (0.016) | 0.038 (0.040) | 0.024 (0.020) |
| **May** | 0.052* (0.021) | 0.049** (0.015) | 0.065 (0.040) | -0.018 (0.020) |
| **June** | 0.022 (0.022) | -0.007 (0.016) | -0.042 (0.039) | -0.018 (0.021) |
| **July** | -0.078*** (0.022) | -0.120*** (0.016) | -0.211*** (0.045) | -0.054** (0.020) |
| **August** | -0.090*** (0.021) | -0.132*** (0.016) | -0.093 (0.057) | -0.114*** (0.020) |
| **September** | 0.021 (0.022) | 0.045** (0.016) | 0.014 (0.040) | 0.011 (0.022) |
| **October** | 0.078*** (0.021) | 0.084*** (0.015) | 0.101* (0.040) | 0.062** (0.020) |
| **November** | 0.031 (0.022) | 0.078*** (0.017) | 0.053 (0.045) | -0.006 (0.021) |
| **December** | -0.008 (0.021) | 0.016 (0.015) | 0.079 (0.048) | -0.040 (0.020) |
| **Labor force (in millions for Philadelphia County)** | | 1.820* (0.694) | 12.100** (3.923) | |
| **1-month lag labor force (in millions for Philadelphia County)** | | | -8.827* (4.176) | |
| **Bus vehicle revenue mile (log)** | 0.647** (0.196) | | | |
| **Heavy rail vehicle revenue mile (log)** | | 1.400*** (0.121) | | |
| **Trolley vehicle revenue mile (log)** | | | 0.241* (0.107) | |
| **Regional rail vehicle revenue mile (log)** | | | | 0.686*** (0.164) |
| **Transit strike 2016 (bus, trolley, and heavy)** | -0.191*** (0.054) | | -0.218* (0.083) | |
| **Adjusted $R^2$** | 0.83 | 0.86 | 0.74 | 0.74 |
| **Significance levels: < 0.001 ***, < 0.01 **, < 0.05 *** | | | | |

*Table 2.4 Parameter estimates from seemingly unrelated regression models for the four modes*

| | Bus | Heavy Rail | Trolley | Regional Rail |
|---|---|---|---|---|
| | *SUR* Coefficient (S.E.) | *SUR* Coefficient (S.E.) | *SUR* Coefficient (S.E.) | *SUR* Coefficient (S.E.) |
| **(Intercept)** | 6.266* (2.676) | -3.801* (1.773) | 9.281*** (2.041) | 5.805* (2.284) |
| **Time** | 0.011*** (0.001) | 0.0003 (0.0003) | -0.018*** (0.005) | 0.001 (0.001) |
| **Time$^2$** | 0.0002*** (0.00002) | | 0.0002* (0.0001) | |
| **Lyft's entry** | -0.477*** (0.109) | 0.163*** (0.028) | -1.150** (0.339) | 0.935*** (0.173) |
| **Lyft * Time** | 0.011*** (0.002) | -0.003*** (0.001) | 0.043*** (0.010) | -0.026*** (0.005) |
| **Lyft * Time$^2$** | | | 0.0004*** (0.0001) | 0.0001*** (0.00003) |
| **February** | 0.024 (0.027) | 0.086*** (0.018) | -0.026 (0.040) | -0.012 (0.023) |
| **March** | 0.059** (0.021) | 0.063*** (0.015) | 0.105* (0.045) | -0.012 (0.021) |
| **April** | 0.037 (0.021) | 0.064*** (0.016) | 0.037 (0.040) | 0.023 (0.020) |
| **May** | 0.052* (0.021) | 0.049** (0.015) | 0.064 (0.040) | -0.017 (0.020) |
| **June** | 0.023 (0.022) | -0.009 (0.016) | -0.042 (0.039) | -0.019 (0.021) |
| **July** | -0.076*** (0.022) | -0.119*** (0.016) | -0.209*** (0.045) | -0.055** (0.020) |
| **August** | -0.090*** (0.021) | -0.130*** (0.016) | -0.093 (0.057) | -0.113*** (0.020) |
| **September** | 0.022 (0.022) | 0.042* (0.016) | 0.013 (0.040) | 0.008 (0.022) |
| **October** | 0.077*** (0.021) | 0.085*** (0.015) | 0.099* (0.040) | 0.062** (0.020) |
| **November** | 0.028 (0.022) | 0.072*** (0.017) | 0.051 (0.045) | -0.008 (0.021) |
| **December** | -0.008 (0.021) | 0.014 (0.015) | 0.077 (0.048) | -0.040* (0.020) |
| **Labor force (in millions for Philadelphia County)** | | 1.626* (0.630) | 11.939** (3.916) | |
| **1-month lag labor force (in millions for Philadelphia County)** | | | -8.543* (4.168) | |
| **Bus vehicle revenue mile (log)** | 0.673*** (0.178) | | | |
| **Heavy rail vehicle revenue mile (log)** | | 1.312*** (0.117) | | |
| **Trolley vehicle revenue mile (log)** | | | 0.261* (0.107) | |
| **Regional rail vehicle revenue mile (log)** | | | | 0.640*** (0.161) |
| **Transit strike 2016 (bus, trolley, and heavy)** | -0.157** (0.047) | | -0.212* (0.083) | |
| **Adjusted R$^2$** | 0.83 | 0.86 | 0.74 | 0.74 |
| **Significance levels: < 0.001 ***, < 0.01 **, < 0.05 *** | | | | |

Seasonality, as indicated by the month dummies, has mostly consistent direction of association with ridership across transit modes. The seasonal indices presented in Figure 2.3 indicate that summer months have lower ridership for all four modes. In contrast, ridership peaks in the fall.

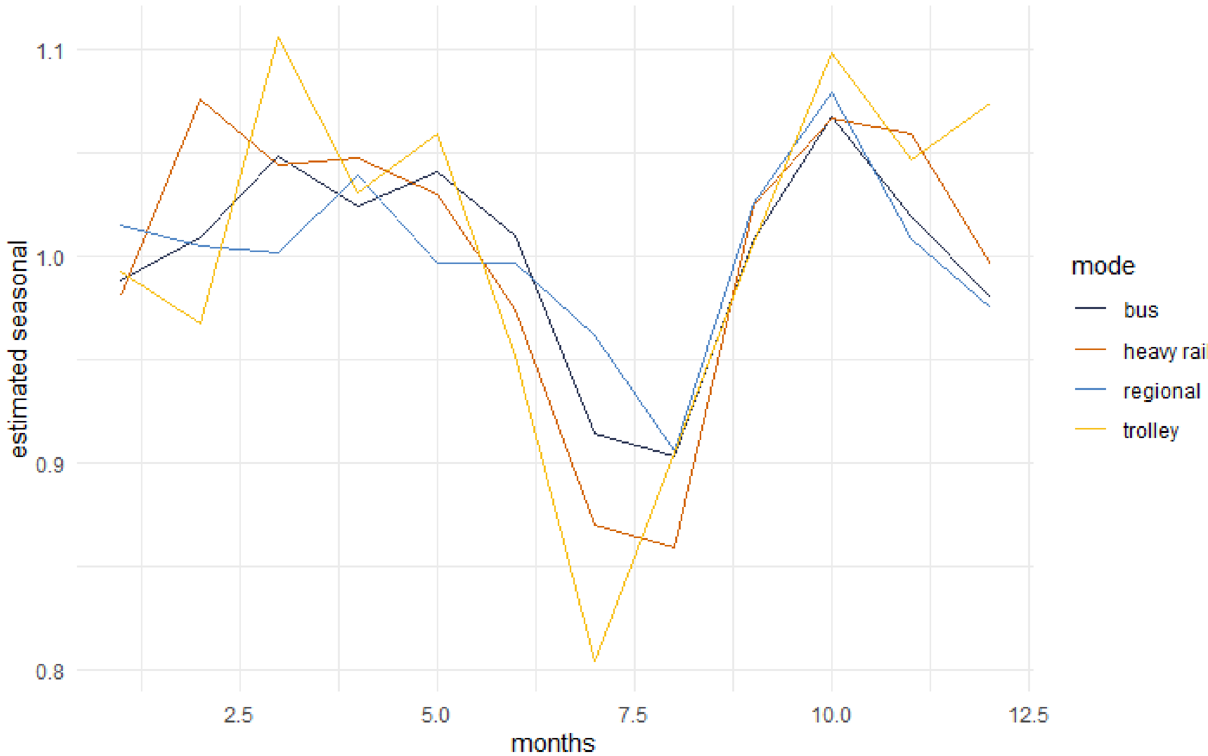


*Figure 2.3. Seasonal indices for each transit mode*

The month of Lyft's entry saw significantly lower bus and trolley ridership, but significantly higher heavy rail and Regional Rail ridership. The increases and drops at Lyft's entry, however, likely reflect seasonal ridership fluctuation and might not have been direct responses to the launch of Lyft. For each model, all control variables have variance inflation factors below 5, suggesting limited multicollinearity.

## 2.6.2. Trend Significance Test

I carry out partial F tests to examine the significance of the interaction terms (i.e., the terms that describe the post-Lyft ridership trends) by comparing models with and without the terms. Results in Table 2.5 suggest that the interaction terms in each model are statistically significant at the 95% level, indicating that adding the interactions significantly improves the model fit. In other words, ridership trends for all four modes are significantly different between the pre- and post-ride-hailing periods, and the interaction terms could help explain the fluctuation in the post-ride-hailing ridership trends. The results imply that, while transit service, macro-economic factors, and seasonality are significantly related to transit ridership, ride-hailing services' presence contributes to the change in ridership trends.

*Table 2.5 Partial F test on the significance of post-ride-hailing ridership trends*

| Transit mode | Change in degree of freedom | Change in residual sum of square | F statistic and significance |
|---|---|---|---|
| **Bus** | 1 | 0.03 | 19.16*** |
| **Heavy Rail** | 1 | 0.03 | 37.62*** |
| **Trolley** | 2 | 0.10 | 8.83*** |
| **Regional Rail** | 2 | 0.12 | 37.16*** |
| **Significance levels: < 0.001 ***, < 0.01 **, < 0.05 *** | | | |

## 2.7. Discussion of Findings

### 2.7.1. Change in Ridership Trends

To illustrate the ridership trends before (February 2011 to January 2015) and after (February 2015 to January 2019) Lyft's entry, I construct the trend lines for each transit mode using the time variables, Lyft's entry, and the interaction terms from the original models (Figure 2.4). The different shapes of the trend lines in the plots indicate Lyft's relationship with ridership varies across transit modes.

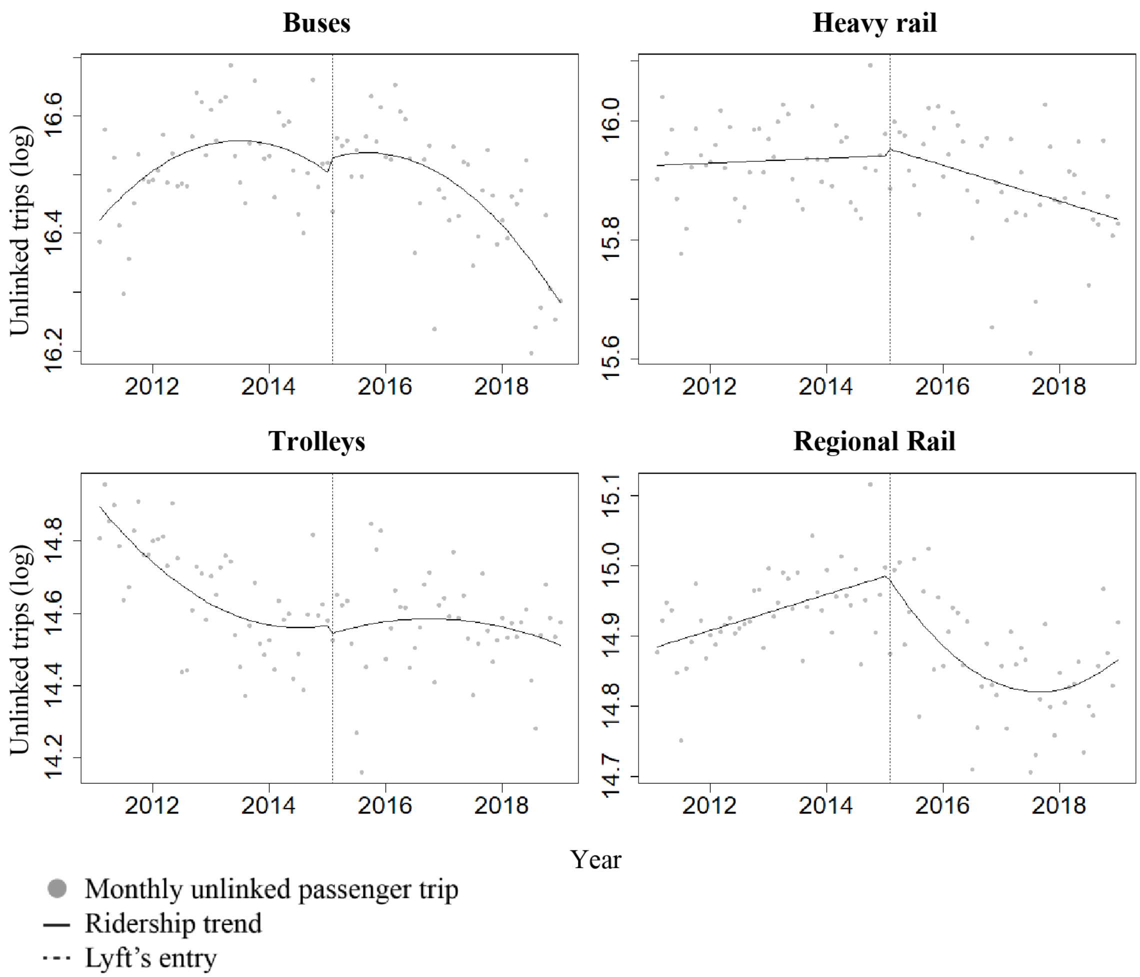


*Figure 2.4. Change in ridership trends for the four modes before and after Lyft's entry*

For buses, both the trends before and after Lyft's entry started to decline after an initial period of increase, giving the trends a concave pattern. However, the decline in the post-Lyft period appears to be steeper and lasted longer than the brief decline between late 2013 and early 2015. Compared to other modes, the post-ride-hailing decline in bus ridership appears to be the steepest and did not shown signs of rebounding. The plot also suggests that bus ridership decline had begun before ride-hailing services' entry. This observation indicates that ride-hailing services could have exacerbated or at least contributed to a declining trend that preceded the services' arrival.

Heavy rail's ridership follows linear trends both before and after Lyft's entry. Prior to Lyft, heavy rail's ridership generally held steady with a gentle increase that extends beyond the 48-month analysis period into the early 2000s (Figure 14). The time variable's coefficients for both the original and seemingly unrelated regressions suggest that the pre-Lyft ridership increase is insignificant, as indicated by the relatively flat trend line. After Lyft's entry, the upward trend turned downward and continued into 2019. While the transit strike in November 2016 and the sudden ridership drop in July 2017 appear to be outliers, the absolute values for the Difference in Fits (DFFITS) statistics for both months are below 2, indicating that the influence of those abrupt ridership drops on the trend estimation is likely limited.

Trolley's ridership trend changed from a convex pattern before Lyft to a concave pattern after Lyft's entry. After an initial period of decline between 2011 and 2014, trolley's ridership mostly held steady with a slight increase. The increasing trend turned into a mild decline in early 2017. As shown in Figure 14, the declining trend continued into late 2019.

Unlike the other three modes, Regional Rail's ridership rebounded after an initial period of noticeable decline after Lyft's entry. In the 48 months before Lyft's arrival, Regional Rail saw its ridership increase steadily, continuing a growing trend that started in the early 2000s. Almost immediately after Lyft's entry, ridership started a decline that lasted a year and a half, before rebounding toward the end of 2017. In contrast to the upward, linear trend prior to Lyft's entry, the post-ride-hailing ridership follows a convex pattern. Despite the recent growth, Regional Rail's ridership has not recovered to its pre-ride-hailing level. Additionally, due to the lack of ride-hailing trip information, it is unclear whether Regional Rail's recent ridership increase was the result of decreasing mode shift from Regional Rail to ride-hailing services or new transit trips that were able to compensate for the ridership lost to ride-hailing services.

The less severe ridership declines for trolleys and heavy rail than buses and Regional Rail seem to support the speculation that higher speed, more reliable, and higher frequency transit services might be less prone to ridership decline amid the increasing influence from ride-hailing services. In the study area, all three heavy rail lines and some portions of the trolley line operate on dedicated right-of-way. Separate from street traffic, trolleys and heavy rail are not as susceptible to delays due to traffic congestion as are SEPTA buses. Trolleys and heavy rail also operate at higher frequency than Regional Rail. Previous surveys suggest that many passengers favor ride-hailing services over transit for the former's faster service and better reliability. Trolleys and heavy rail's faster service, higher on-time rates, and higher frequency might help explain why they have been able to retain riders more effectively than buses and Regional Rail in the post-ride-hailing period.

### 2.7.2. Magnitude of Trip Substitution

So far, we have seen that the ridership trends for all four modes changed after ride-hailing services' entry. While it might be tempting to quantify ride-hailing services' impact on ridership declines, it should be noted that ridership estimates away from the discontinuity (i.e., Lyft's entry) constitute a bold extrapolation, because there are no data on counterfactual ridership in a world where ride-hailing services had not entered Philadelphia (Angrist & Pischke, 2014). Luckily, since ridership exhibits seasonal patterns, monthly ridership in the years just before ride-hailing services' entry serves as a reference for what post-ride-hailing ridership could have been without ride-hailing services. Figure 2.5 compares the monthly average ridership 48 months before (from February 2011 to January 2015) and after (from February 2015 to January 2019) Lyft's entry. With a few exceptions, post-ride-hailing average monthly ridership decreased from its pre-ride-hailing level for all four modes.

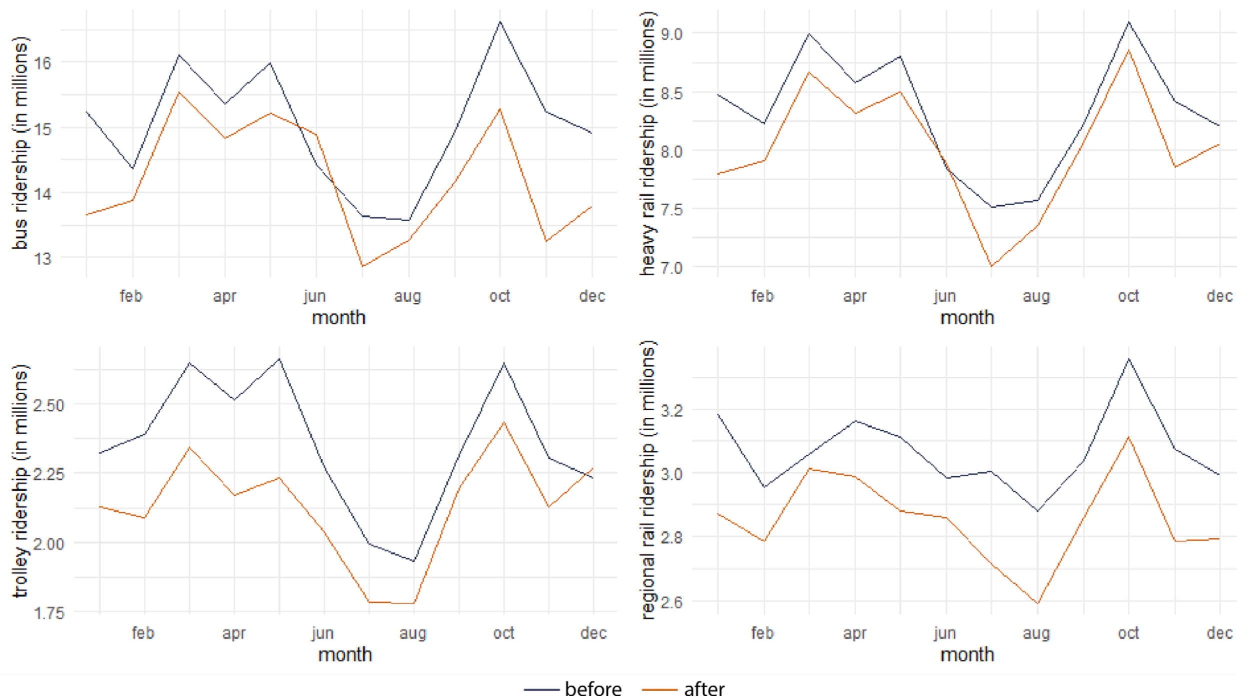


*Figure 2.5. Average monthly ridership for the four modes before and after Lyft's entry*

To better illustrate the ridership losses between the pre- and post-ride-hailing periods, I compare ridership by mode in fiscal year 2018 (between July 2017 and June 2018) to ridership in fiscal year 2014 (between July 2013 and June 2014). Using fiscal year 2018 instead of earlier post-ride-hailing periods allows the initial market penetration of ride-hailing services. Furthermore, it avoids the transit service disruptions and ridership inflation due to special events in 2016. Table 2.6 presents the average monthly ridership change, monthly ridership change as a percent of pre-ride-hailing average monthly ridership, and the share of total ridership change by mode. Between the two periods, only trolleys experienced a ridership increase. The increase, however, is modest and constitutes only 2% of the ridership for fiscal year 2014. Buses lost the most trips, accounting for more than 60% of SEPTA's total ridership loss. Regional Rail had the biggest ridership loss as a percentage of its pre-ride-hailing ridership. Heavy rail had the smallest ridership loss as a percentage of pre-ride-hailing ridership. The finding that heavy rail suffered the smallest ridership loss while trolleys gained riders provide further evidence that frequent and reliable transit services might be more resilient to ridership losses in the post-ride-hailing period.

*Table 2.6 Ridership comparison between fiscal year 2014 and fiscal year 2018*

| Mode | Average monthly ridership loss/gain | Ridership losses as a percentage of pre-ride-hailing ridership | Share of total ridership losses |
|---|---|---|---|
| **Buses** | -1,445,052 | -9.4% | 61.8% |
| **Heavy rail** | -440,308 | -5.3% | 18.8% |
| **Trolleys** | +45,102 | 2.2% | |
| **Regional Rail** | -453,701 | -14.4% | 19.4% |

A comparison of transit ridership loss and the total trips completed by ride-hailing services suggest that ride-hailing services absorbed at least some of the transit ridership decline. In fiscal year 2018, the four transit modes had combined 27.5 million fewer trips than they did in fiscal year 2014, and 35 million fewer trips than in fiscal year 2016. Meanwhile, in fiscal year 2018, Uber and Lyft completed approximately 36 million trips that originated in Philadelphia (Laughlin, 2018b), more than offsetting the transit ridership losses. This finding indicates that ride-hailing services almost certainly accounted for some of the losses in transit ridership.

## 2.7.3. Robustness Check

I conduct robustness checks to the period before the entry of Lyft to detect significant changes in ridership trends that are unrelated to ride-hailing services. A declining ridership trend that started before and continued after ride-hailing services' entry could confound the services' impact on ridership. In contrast, steady, upward ridership trends before ride-hailing services' entry add confidence to the statistical finding that ridership has trended downward since the entry of ride-hailing services.

I apply the modeling and variable selection method that was explained in the Model building and variable selection section to the 48-month period before Lyft's entry (from February 2011 to January 2015) to construct trend for each of the four modes. To ensure sufficient data points for constructing meaningful trends, I use February 2013, the mid-point of the data series, as the point of discontinuity. Figure 2.6 shows the trend lines constructed based on parameter estimates from the robustness check models. Ridership for heavy rail and Regional Rail had sustained upward trends and did not experience significant change before Lyft's entry. In contrast, ridership for buses and trolleys experienced declines and had significant change during the pre-Lyft period. Their trends, however, started to go up a few months before Lyft's entry. Results from the robustness checks confirm the findings that post-ride-hailing ridership for all four modes departed from the pre-ride-hailing trends.

Figure 2.6 shows

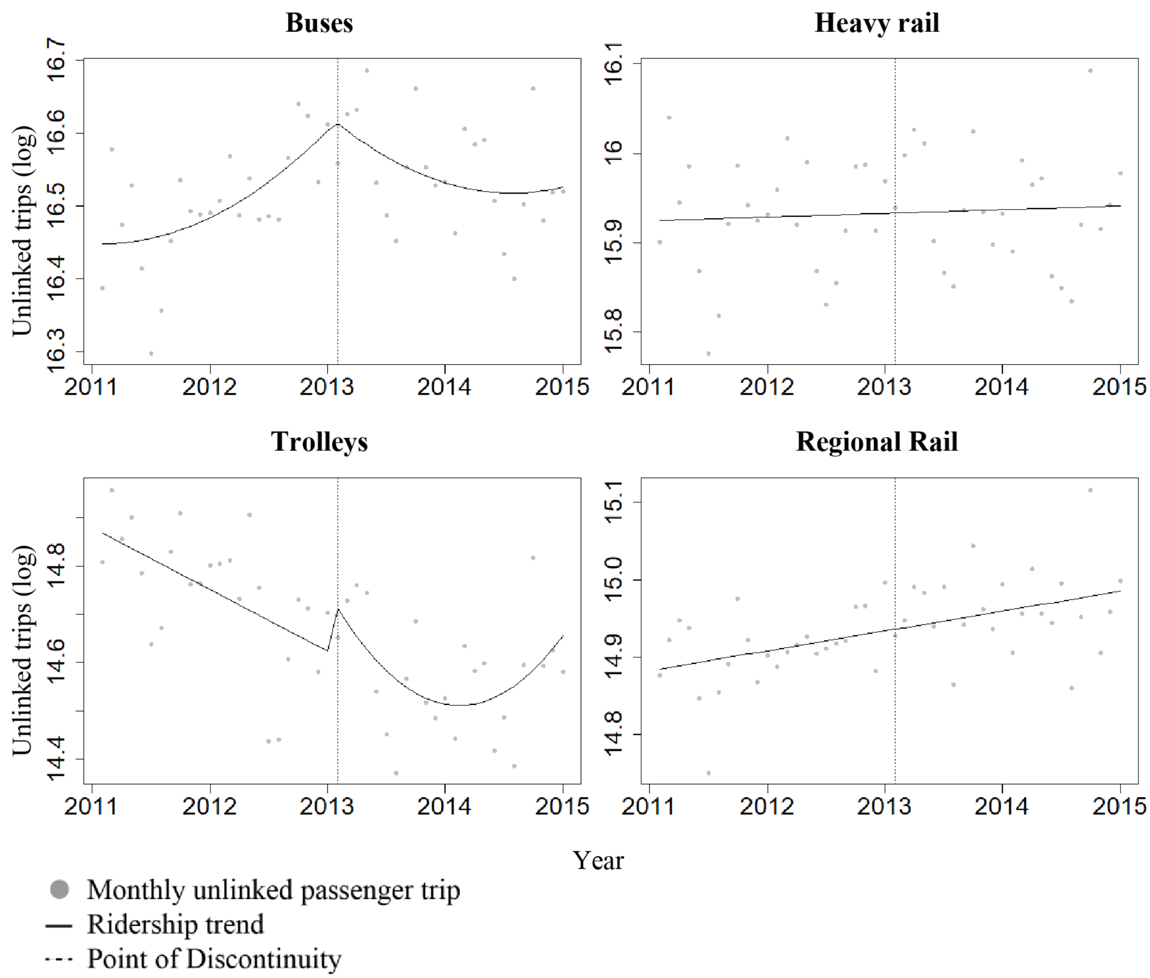


*Figure 2.6. Change in ridership trends for the four modes between February 2011 and January 2015*

## 2.8. Limitations

As with any time series analysis that extrapolates the long-term trend, the current study has a few limitations. The unique socio-economic and transportation context of the Philadelphia region poses a challenge to finding a comparable market as a control group that has not seen ride-hailing services' influence. Since there are no data on the counterfactual transit ridership, it is impossible to know what the ridership would have been had ride-hailing services not been available. Thus, the extrapolation of the ridership trends should be interpreted with caution. Additionally, the decision on how many polynomial functions to include in the initial models is, above all, a judgement call. Indeed, settling on the suitable model has been a challenge to scholars and statisticians. When confronted with choosing between a fancier or a simpler model, Angrist and Pischke suggest that there are no general rules, and no substitute for a thoughtful look at the data (Angrist & Pischke, 2014). To ensure that the models are suitable for the data, when choosing variables, I considered the observed ridership patterns and carefully weighed the tradeoffs between model parsimony and the overall fit of the trends. I also tested several other variable combinations in the initial models. While some of these models ended up with different variables from the ones presented in this chapter, they nonetheless support the conclusion that ride-hailing services contributed to change in the ridership trends.

## 2.9. Conclusion

Mirroring a national trend, ridership for SEPTA's four transit modes in the study area declined after ride-hailing services' entry. While Regional Rail ridership rebounded after an initial decline in the post-ride-hailing period, ridership for the other three modes did not show signs of recovery. Findings suggest that transit ridership trends for all four modes changed significantly after the entry of ride-hailing services, and that ride-hailing services likely have contributed to the change in ridership trends.

Among all modes in the SEPTA transit system, buses carry the most passengers, cover the largest service area, and had the most severe ridership decline after ride-hailing services' entry. The recent bus ridership decline poses a challenge for the City of Philadelphia and SEPTA to achieve their goal of increasing bus ridership in the next 5 years. An understanding of the factors that might be associated with ridership declines for different bus routes and neighborhoods could inform strategies to retain riders and cope with the increasing influence of ride-hailing services. In the next chapter, I zoom in to investigate where and what type of buses are more prone to ridership declines in the post-ride-hailing period.

# Chapter 3. Not All Bus Stops Are Equal[1]

## 3.1. Unanswered Questions

Despite serving the largest geographic area and carrying the most riders in the SEPTA system, buses experienced the most severe ridership decline in the post-ride-hailing period. While the system-wide analysis in Chapter 2 provides insights into the bus's overall ridership decline, it leaves several crucial questions unanswered. For example, are the ridership changes comparable among transit routes with similar service characteristics and performance levels? Where are buses more likely to have gained riders? What factors are associated with buses that saw the biggest ridership declines? Answers to these questions will provide critical information on bus ridership decline across different operating contexts and service levels. This knowledge could in turn help transit agencies adjust services to better serve the market needs amid the increasing influence from ride-hailing services.

In this chapter, I first explore bus ridership declines by performance level within each bus route service category. I then zoom in on individual bus stops to examine the association between bus ridership and neighborhood demographics, the built environment, and service factors using multilevel analyses. In the multilevel analyses, I model factors that correspond to passenger boarding at each bus stop in the study area between 2014 and 2018. I then predict ridership change at each bus stop between 2014 and 2018. Last, I conduct two multilevel binomial logistic regression analyses to investigate the factors that are associated with bus stops that had the biggest ridership losses and those that gained riders between 2014 and 2018. Findings suggest that buses and bus stops that serve more passengers and neighborhoods with higher poverty and higher job density correspond with bigger ridership declines between 2014 and 2018. Bus stops in urban neighborhoods are less likely to have had some of the biggest percentage ridership losses. Last, buses with higher service frequency are more likely to have gained riders and less likely to have had the most severe ridership drops.

[1] A modified version of this chapter is under review with *Transportation Research Part A: Policy and Practice*.

## 3.2. Bus Ridership Decline by Performance

SEPTA places its buses into five categories based on their service and route characteristics. Table 3.1 explains the classification of the bus routes (Southeastern Pennsylvania Transportation Authority, 2019). In 2018, City routes made up almost 60% of SEPTA's bus lines and carried more than 80% of SEPTA's entire bus system's riders (excluding Special Purpose buses). Within each route category, the performance of buses varies due to the different operating contexts. Certain routes serve more passengers at a lower per passenger cost while others carry fewer passengers at a higher cost. In this exploratory analysis, I examine the ridership change between the pre- and post-ride-hailing periods to see if buses with different performance within each route service category experienced different levels of ridership loss.

*Table 3.1 SEPTA bus route category, operating context, and ridership statistics*

| Route service category | Operating context | Number of routes | 2018 average annual ridership per route (in millions) |
|---|---|---|---|
| **City** | Routes operate primarily on local city streets, serving a variety of different functions from local trips, to connections to high speed services. | 64 | 1.8 |
| | | | |
| **Suburban** | Suburban routes operate in lower-density areas, providing access to specific destinations such as malls, shopping centers, office parks, and industrial parks. | 24 | 0.24 |
| | | | |
| **Arterial** | Routes that travel (for the most part) on heavily-trafficked city or suburban arterials with multiple destinations and often a strong reverse-commute constituency, usually terminating at a major transportation center. | 14 | 1.1 |
| | | | |
| **Expressway** | Routes that travel on an interstate for portions of their routing. | 6 | 0.8 |
| | | | |
| **Special Purpose** | Routes administered by SEPTA but operated by outside vendors or routes specifically defined to provide last mile connections from Regional Rail stations and limited service city routes that are designed to meet specific markets. | 11 | 0.1 |

SEPTA uses passengers per revenue hour and cost per passenger to measure the performance of individual bus routes. Passengers per revenue hour is a productivity measure that indicates the average number of passengers who board a bus for every hour of service that a bus is operating (Southeastern Pennsylvania Transportation Authority, 2019). Routes with higher passenger per revenue hour are more productive. Due to data availability, I calculate passengers per revenue hour using buses' vehicle hours. Vehicle hours include both the hours that the buses are in service (i.e., revenue hours) and deadhead hours (i.e., time spent in pull-in and out operations that are not part of passenger revenue service). In fiscal year 2018, the correlation between vehicle hours and revenue hours is 0.998. Cost per passenger is a cost effectiveness measure that indicates the difference between the per-passenger cost and passenger revenue of operating a route (Southeastern Pennsylvania Transportation Authority, 2019d). Routes with lower per-passenger costs are able to recover a larger portion of costs via fares, and are therefore more cost-effective (Southeastern Pennsylvania Transportation Authority, 2019d).

I place buses within each route category into performance quartiles based on the route's passenger per revenue hour and cost per passenger. In each route category, the stronger performing routes carry more passengers per hour of operation at a lower per passenger cost than the weaker performers. The top performing bus routes include those whose passengers per revenue hour are in the 4th quartile (i.e., the 75th percentile) and cost per passenger in the first quartile (i.e., the 25th percentile) of the category. Figure 3.1 shows the performance classification for bus routes in each category. The strongest performing routes appear in the top right in each plot. The weakest performers carry the fewest passenger (with passengers per revenue hour in the 1st quartile) at the highest cost per passenger (with cost per passenger in the 4th quartile), and appear in the bottom left in each plot. To avoid ride-hailing services' potential effect on buses' productivity and cost-effectiveness, I use the pre-ride-hailing average passengers per revenue (i.e., operating) hour and per passenger cost between 2010 and 2014 when classifying the bus routes. Among the four route categories, City routes have the highest average passenger per hour and the lowest average cost per passenger. Suburban routes carry the fewest passengers on average while suffering the biggest per passenger revenue loss. SEPTA identifies bus routes that fall in the bottom 15th percentile for both productivity and cost-effectiveness within each route category as candidates for possible evaluation and intervention (Southeastern Pennsylvania Transportation Authority, 2019b).

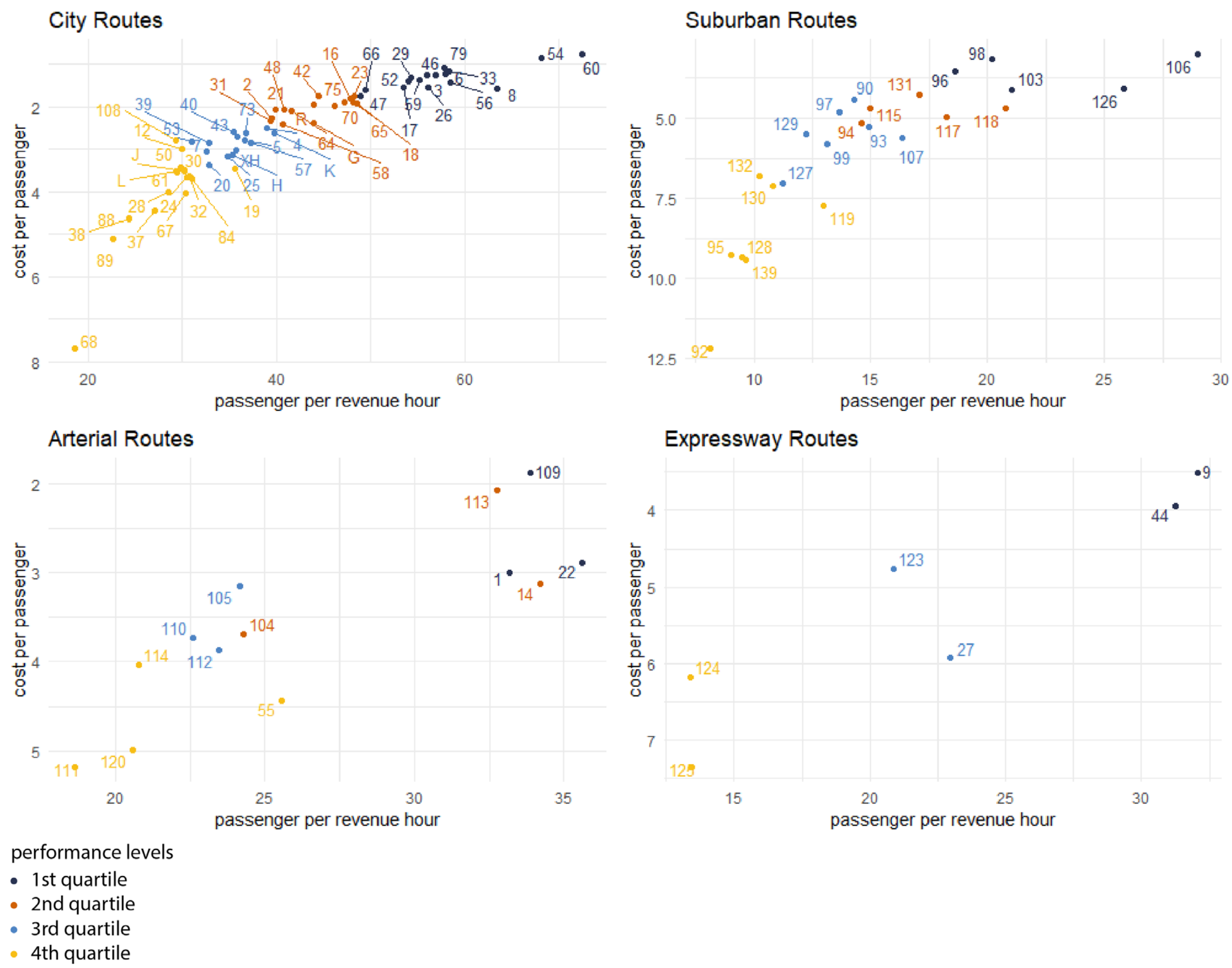


*Figure 3.1. Performance classification for each bus route by route category based on passenger per hour and cost per passenger*

After ride-hailing services' entry, while the overall bus ridership dropped significantly from its pre-ride-hailing level, the decline varies across performance levels and does not exhibit clear patterns. Table 3.2 presents the average annual ridership for the pre- (from 2010 to 2014) and the post-ride-hailing periods (from 2015 to 2018) for each bus route category and performance class. City routes, for example, saw across-the-board ridership declines, with buses in the top and second performance tiers suffering bigger percentage ridership declines than buses in the third and bottom performing tiers. In contrast, the top performers among the Suburban routes had the biggest percentage increase (5.6%), even though the actual ridership increase (200,000 trips) is modest compared to the ridership losses (8.2 million) suffered by buses in the other categories. The lack of clear pattern in ridership declines across performance levels and route categories highlights the need to explore factors that might correspond with ridership declines in the post-ride-hailing period.

*Table 3.2 Pre- and post-ride-hailing bus ridership and ridership change by performance classification*

| **Route category and performance level** | **Number of routes** | **Pre-ride-hailing total average annual ridership (in millions)** | **Post-ride-hailing total average annual ridership (in millions)** | **Percent change in ridership** |
|---|---|---|---|---|
| City Routes | 63 | 132.7 | 125.3 | -5.6% |
| *Top tier* | 16 | 48.6 | 44.7 | -8.1% |
| *2nd tier* | 15 | 44.1 | 41.3 | -6.4% |
| *3rd tier* | 14 | 22 | 21.9 | -0.4% |
| *Bottom tier* | 18 | 17.9 | 17.3 | -3.1% |
| | | | | |
| Suburban Routes | 24 | 5.8 | 6 | 3.5% |
| *Top tier* | 5 | 1.6 | 1.6 | 5.6 % |
| *2nd tier* | 5 | 1.4 | 1.4 | -0.4% |
| *3rd tier* | 7 | 1.8 | 1.8 | 4.4% |
| *Bottom tier* | 7 | 1 | 1 | 4.6% |
| | | | | |
| Arterial Routes | 13 | 14.9 | 14.6 | -2.1% |
| *Top tier* | 3 | 4 | 3.8 | -6.6% |
| *2nd tier* | 3 | 6.6 | 6.5 | -1.9% |
| *3rd tier* | 3 | 1.5 | 1.4 | -5.7% |
| *Bottom tier* | 4 | 2.8 | 2.9 | 6.1% |
| | | | | |
| Expressway Routes | 6 | 5.6 | 5.2 | -8.0% |
| *Top tier* | 2 | 2.8 | 2.6 | -8.3% |
| *3rd tier* | 2 | 1.8 | 1.6 | -12.2% |
| *Bottom tier* | 2 | 1 | 1 | 0.4% |

## 3.3. Data and Methods for Multilevel Analyses

In this analysis, I explore the relationship between ridership at bus stops and neighborhood characteristic, land use, and bus service factors using the number of boarding passengers at each bus-stop for each bus route between 2014 and 2018. SEPTA records weekday passenger boarding counts during the fall period of each year using automated passenger counters (APC) installed on buses. Bus stops that serve more than one bus route have ridership record for each route. As a result, the same bus stop might have multiple ridership records.

### 3.3.1. Outcome Measures

The reported models include four outcome measures: bus stop-level ridership for each year from 2014 to 2018, ridership change between 2014 and 2018, whether a bus stop had one of the biggest ridership declines among all bus stops between 2014 and 2018, and whether a bus stop experienced ridership increases between 2014 and 2018. In the first outcome measure, each bus stop has one ridership record for each bus route it serves for each year from 2014 to 2018. The longitudinal nature of the records gives the data a panel structure. I convert ridership to logarithmic scale to mitigate the skewness of the data. The second outcome measure is the difference in ridership between 2014 and 2018 and has one record for each bus stop for each route. Since a negative percentage change cannot be larger in magnitude than -1 (or -100%), while a positive percentage change is unbounded, using percentage change as the dependent variable might violate the assumption for linear regression. Thus, I estimate the actual ridership change instead of the percent change in the model. The third and fourth outcome measures are binary variables that categorize the change in ridership at each bus stop for each route between 2014 and 2018. For the third outcome, I classify bus stops whose percent ridership change between 2014 and 2018 falls in the first quartile (i.e., the quartile with the biggest percentage declines) among all bus stops as the category of interest. The other bus stops are classified as the baseline category. For the last outcome measure, I classify bus stops based on whether they experienced ridership increases between 2014 and 2018, with bus stops that had ridership declines being the baseline category. For each analysis, I only consider bus stops that existed in both 2014 and 2018.

### 3.3.2. Data Summary

Table 3.3 presents the summary statistics for the variables in the multilevel analyses. I place the variables under three categories: bus service levels, neighborhood characteristics, and land use factors. I assign bus route service levels to bus stops that serve those routes. I use Census tracts as a proxy for neighborhoods. Bus stops are matched to Census tracts based on their XY coordinates provided by SEPTA. I exclude three regular bus routes from the analyses due to incomplete data, as well as the 11 Special Purpose Routes that are operated by outside vendors to meet specific markets.

*Table 3.3 Summary of the weighted average, standard deviation, maximum, and minimum values for variables in the multilevel analyses**

| | Mean | Standard deviation | Maximum | Minimum |
|---|---|---|---|---|
| **Outcome measures** | | | | |
| ***Annual ridership***** | 34.02 | | 4,015.7 | 0 |
| ***Ridership change*** | -5.33 | | 1,021.89 | -783 |
| ***Biggest declines (binary)*** | 0.25 | | | |
| ***Ridership increase (binary)*** | 0.26 | | | |
| **Service factors***** | | | | |
| ***2014 ridership (in millions)*** | 1.61 | | 6.54 | 0.11 |
| ***One-way route mile*** | 13.86 | | 31.3 | 3 |
| ***Peak frequency*** | 20.76 | | 70 | 3 |
| ***2019 on-time rate*** | 79.25 | | 95.53 | 63.91 |
| ***Change in average on-time rate*** | 2.43 | | 9.64 | -6.84 |
| **Neighborhood characteristics** | | | | |
| ***Population density*** | 19.81 | | 131.52 | 0.07 |
| ***Job density*** | 16.73 | | 838.86 | 0.03 |
| ***Median age*** | 37.52 | | 65.1 | 19.9 |
| ***Percent of residents in poverty*** | 19.57 | | 67.96 | 0.5 |
| ***Percent of residents with college degree or higher*** | 33.58 | | 92.95 | 0.96 |
| ***Percent of transit commuters*** | 19.03 | | 62.16 | 0 |
| ***Percent of renters*** | 43.45 | | 100 | 0.95 |
| **Land use characteristics** | | | | |
| ***Residential land use share*** | 58.55 | | 99.67 | 0.44 |
| ***Commercial land use share*** | 13.01 | | 70.3 | 0 |
| ***Urban area dummy*** | 0.61 | | | |

***n = 74,454 for annual ridership analysis; n = 14,932 for ridership change, biggest declines, and ridership increase analyses.**
****Summary statistics for annual ridership reflect the five-year (from 2014 to 2018) ridership.**
*****Summary statistics for service, neighborhood, and land use characteristics reflect the statistics for a single year.**

Bus service levels

The route-level bus service factors measure the service quality and coverage of SEPTA buses. These factors include annual bus ridership for fiscal year 2014 (from July 2013 to June 2014), one-way route length, peak frequency, average monthly on-time rates for fiscal year 2019, and change in on-time rates between the periods before and after ride-hailing services' entry. Annual bus ridership comes from SEPTA's Annual Service Plan for 2016 (Southeastern Pennsylvania Transportation Authority, 2015). I use one-way route length as a proxy for service coverage. Both one-way route length and peak frequency come from SEPTA's 2018 Route Statistics (Southeastern Pennsylvania Transportation Authority, n.d.).

Buses' monthly on-time rates were provided by SEPTA's Service Planning Department. I calculate the annual on-time rates by averaging the monthly on-time rates for each bus route. The change in on-time rates is calculated as the difference between the average on-time rates from fiscal years 2010 to 2014 and the average on-time rates from fiscal years 2015 to 2018. On-time performance measures the percent of trips that arrive within a given window around the scheduled arrival time. SEPTA defines a bus as being on time if it is between 0 and 5 minutes late (Jarrett Walker + Associates, 2018). A bus that arrives early is considered not on time (Jarrett Walker + Associates, 2018). So a bus that arrives 6 minutes behind schedule and a bus that arrives one minute ahead of schedule will both be considered not on time according to SEPTA's metrics. Contrary to the popular belief that buses' on-time performance worsened over time due to deteriorating traffic condition in Philadelphia, the average on-time rates improved, albeit insignificantly, between the pre- and post-ride-hailing periods.

Neighborhood characteristics

Population density and job density are calculated respectively as residents per acre and jobs per acre of each Census tract's land area. Total resident population comes from the U.S. Census's 2017 5-year ACS (U. S. Census Bureau, n.d.-a). Total jobs data come from the 2015 Longitudinal Employer-Household Dynamics published by the U.S. Census Bureau (U. S. Census Bureau, n.d.-b). I convert both variables to the logarithmic scale to mitigate their skewed distributions.

Socio-demographic characteristics for each Census tract come from the 2017 5-year ACS. The models include median age, percent of residents living in poverty, percent of residents above 25 years old with college degrees or higher, percent of transit commuters among workers 16 years old and above, and percent of renters.

Land use characteristics

I use the shares of land for residential and commercial purposes within each Census tract to describe the neighborhood's land use characteristics. The calculation of land use share excludes non-urban land uses, such as wooded area, area for military use, and agriculture area. Land use data come from the DVRPC's land use shape files.

I use a binary variable to indicate whether a census tract is in Philadelphia or the four surrounding counties. This variable captures the differences in typologies between the urban and suburban counties in the study area.

### 3.3.3. Model Specification

I use multilevel models to estimate ridership from 2014 to 2018 and ridership change between 2014 and 2018 (outcome measures 1 and 2), and multilevel binomial logistic regression models to predict bus stops that experienced the biggest declines (outcome measure 3) and those that had ridership increases (outcome measure 4) between 2014 and 2018.

Two attributes of multilevel model make the method suitable for the current analyses. First, multilevel models estimate the variation between groups (Gelman & Hill, 2006). As shown in Table 3.1, different types of bus routes serve different purposes and operate in different contexts in the study area. For example, Route 125 runs primarily on an expressway and connects Center City Philadelphia with a large shopping mall in the suburbs. In contrast, Route 21 transports passengers between downtown Philadelphia and a major transit hub in West Philadelphia, making frequent stops in dense commercial districts and residential neighborhoods along the way. The different operating contexts across bus routes and the repeated observations for the same bus route across bus stops give the data a multilevel structure. Second, multilevel models use all the data to perform inferences for groups with small sample size (Gelman & Hill, 2006). In the current data set, the number of observations for each bus route varies from as few as 10 to as many as 273. Multilevel models give proper weights to observations in each group and ensures that the model estimates are not skewed by small sample sizes for certain groups.

For each outcome, I estimate a model with bus service levels, neighborhood characteristics, and land use variables. I allow the reported models' intercepts for neighborhoods, bus stops, and bus routes to vary. Variables that are highly correlated with other independent variables are excluded from the models. Neighborhood characteristics such as household vehicle ownership and percent of commuters who drove to work, and service level factors such as base frequency and bus operating ratio were excluded due to high multicollinearity with other independent variables. In the reported models, all of the variables have variance inflation factors below 4, suggesting limited multicollinearity.

## 3.4. Interpretation of Parameter Estimates

Table 3.4 shows the parameter estimates from the multilevel models and multilevel binomial logistic models with varying intercepts. In Model 1, for independent variables on the original scale, the exponentiated coefficients minus one indicate the percent change in bus ridership associated with a one unit increase in the independent variables. For example, a one percentage point increase in a neighborhood's share of transit commuters corresponds to an average 1.7% increase in ridership at the bus stop, all else being equal. For log transformed variables, the percentage increases raised to the power of the coefficients have the interpretation as the expected ratios in ridership. For example, a 10% increase in neighborhood job density is associated with an average 0.7% increase (110% raised to the power of 0.078 minus one) in ridership, while holding other variables constant. In Model 2, parameter estimates for untransformed variables have direct interpretations as the average increase or decrease in the change in ridership between 2014 and 2018 that is associated with each unit change in the independent variable, all else being equal. For variables on the logarithmic scale, the natural logs of the percentage increase in the independent variables multiply by the coefficients computes the expected difference in the change in ridership between 2014 and 2018. For example, a doubling of neighborhood job density is associated with an average 1 fewer passenger (the natural log of 2 times -1.52) at the bus stop in 2018 than in 2014, all else being equal. In Models 3 and 4, the exponentiated parameter estimates have interpretation as odds ratios for untransformed variables. For variables on the logarithmic scale, the odds ratios are the percentage increase in the independent variables raised to the power of the coefficients. For example, in Model 3, each 50% increase in neighborhood population density corresponds to an average 12% decrease (1.5 raised to the power of -0.32 minus 1) in the odds of the bus stop having had some of the biggest ridership declines, while controlling for all other factors.

*Table 3.4 Parameter estimates from multilevel models and multilevel binomial logistic models with varying intercepts for annual ridership, ridership change, biggest ridership losses, and biggest ridership increase*

| | **Annual ridership** *(1)* **Coefficient (S.E.)** | **Ridership change** *(2)* **Coefficient (S.E.)** | **Biggest loss** *(3)* **Coefficient (S.E.)** | **Ridership gain** *(4)* **Coefficient (S.E.)** |
|---|---|---|---|---|
| **Intercept** | 0.867 (0.635) | 34.544* (13.689) | 0.114 (1.19) | -0.031 (1.246) |
| **Service factors** | | | | |
| ***2014 ridership (in millions)*** | 0.239*** (0.04) | -3.548*** (0.836) | -0.079 (0.07) | -0.106 (0.078) |
| ***One-way route mile*** | -0.006 (0.008) | 0.003 (0.18) | -0.001 (0.015) | 0.009 (0.017) |
| ***Peak headway**** | -0.011** (0.003) | -0.106 (0.073) | 0.013* (0.006) | -0.015* (0.007) |
| ***2019 on-time rate*** | 0.007 (0.007) | -0.309* (0.147) | -0.007 (0.013) | -0.003 (0.014) |
| ***Change in avg. on-time rates*** | 0.001 (0.014) | 0.27 (0.291) | 0.001 (0.024) | 0.008 (0.027) |
| **Neighborhood characteristics** | | | | |
| ***Population density (log)*** | | 0.641 (0.705) | -0.321*** (0.071) | 0.061 (0.057) |
| ***Job density (log)*** | 0.078** (0.027) | -1.516** (0.504) | -0.008 (0.052) | 0.038 (0.041) |
| ***Median age*** | -0.012*** (0.004) | 0.028 (0.061) | 0.007 (0.006) | -0.003 (0.005) |
| ***Percent of residents in poverty*** | 0.007** (0.003) | -0.085* (0.041) | 0.001 (0.004) | -0.011*** (0.003) |
| ***Percent of residents with college degree or higher*** | -0.002 (0.001) | 0.014 (0.025) | 0.005 (0.003) | -0.003 (0.002) |
| ***Percent of transit commuters*** | 0.017*** (0.002) | -0.067 (0.044) | -0.023*** (0.005) | 0.002 (0.004) |
| ***Percent of renters*** | -0.0005 (0.002) | -0.01 (0.025) | -0.001 (0.002) | 0.002 (0.002) |
| **Neighborhood land use characteristics** | | | | |
| ***Residential land use share*** | 0.005*** (0.001) | -0.059* (0.029) | 0.003 (0.003) | -0.007** (0.002) |
| ***Commercial land use share*** | 0.012*** (0.003) | -0.109* (0.043) | -0.008 (0.005) | -0.003 (0.003) |
| ***Urban area*** | 0.659*** (0.065) | -1.998 (1.457) | -0.445** (0.141) | 0.143 (0.119) |
| **Year** | | | | |
| ***2015*** | 0.037*** (0.006) | | | |
| ***2016*** | -0.212*** (0.006) | | | |

| | | | | |
|---|---|---|---|---|
| ***2017*** | -0.063*** (0.006) | | | |
| ***2018*** | -0.051*** (0.006) | | | |
| **Observations** | 74,454 | 14,932 | 14,932 | 14,932 |
| **Log likelihood** | -71,378.58 | -72,345.93 | -7,053.65 | -7,918.74 |
| **AIC** | 142,803.20 | 144,731.90 | 14,145.30 | 15,875.48 |
| **BIC** | 143,015.20 | 144,884.10 | 14,289.92 | 16,020.09 |
| **Significance levels: < 0.001 ***, < 0.01 **, < 0.05 *** | | | | |
| ***Peak headway indicates the interval between bus arrivals. Higher values for headway indicate less frequent service.** | | | | |

## 3.5. Findings

### 3.5.1. Annual Ridership

Between 2014 and 2018, while controlling for the route-level ridership for 2014, bus stops that serve urban neighborhoods with higher job density and higher percent of residents living in poverty saw higher ridership. As indicated by parameter estimates in Model 1, on average, each 10% increase in jobs per acre in a neighborhood corresponds to an average 0.7% increase in bus stop ridership, all else being equal. A one percentage point increase in a neighborhood's share of residents living in poverty is associated with an average 0.7% increase in bus ridership, while holding other variables constant. Bus stops that serve neighborhoods in Philadelphia are associated with more passengers than those that are in the suburban neighborhoods.

In terms of service quality, higher peak frequency (i.e., shorter headway) is associated with higher ridership. Each one-minute increase in headway corresponds to an average 1.1% fewer passengers, all else being equal.

Last, on average, ridership at each bus stop is significantly lower in 2016, 2017, and 2018 than in 2014 and 2015. This finding provides further statistical evidence to the ridership loss after the entry of ride-hailing services in late 2014 and early 2015.

### 3.5.2. Ridership Change

Parameter estimates from Model 2 show that on average, bus stops in neighborhoods with higher job density and higher poverty experienced bigger ridership declines between 2014 and 2018. As mentioned above, a doubling of neighborhood job density is associated with an average 1 fewer passenger at the bus stops in 2018 than in 2014, all else being equal. A ten percentage point increase in the share of residents in poverty corresponds with an average one fewer passenger at the bus stops in 2018 than in 2014.

In terms of land use, bus stops that serve neighborhoods with a higher share of commercial and residential land had greater ridership declines between 2014 and 2018, even though higher share of either type of land use corresponds to higher bus ridership. The model detects no significant differences in ridership change between neighborhoods in Philadelphia and those in the surrounding suburban counties.

Last, buses' ridership change is significantly associated with on-time rates. Bus stops that serve more punctual buses had greater ridership declines between 2014 and 2018. On average, each three percentage point increase in on-time rates corresponds with one fewer passenger at the bus stops. Additionally, bus stops that serve buses with higher route-level ridership in 2014 saw bigger ridership declines between 2014 and 2018. On average, each additional million passengers for the bus route in 2014 corresponds with almost 4 fewer passengers in 2018 than in 2014 at the bus stops that serves the route, all else being equal.

### 3.5.3. Biggest Ridership Losses

Bus stops in denser neighborhoods and neighborhoods with higher shares of transit users are less likely to have had some of the biggest ridership declines between 2014 and 2018. As shown in Model 3, each 10% increase in residents per acre corresponds to an average 3% decrease in the odds of the bus stops having had some of the biggest ridership declines, while controlling for all other factors. For each percentage point increase in the share of transit commuters in a neighborhood, the odds of the bus stops that serve the neighborhood having had some of the biggest declines decrease by 2%, all else being equal.

Bus stops in urban neighborhoods are less likely to have had some of the biggest ridership declines. Compared to bus stops in the suburbs, those in urban neighborhoods have 11% lower probabilities (or 36% lower odds) of having had the biggest declines, all else being equal.

As bus services become less frequent, the likelihood of a bus stop having some of the biggest ridership declines increases. Each one-minute decrease in peak service frequency is associated with an average 1.3% higher odds, or roughly 0.3% higher probability, of the bus stops having had some of the biggest ridership declines.

### 3.5.4. Ridership Gains

Bus stops serving neighborhoods with higher poverty rates and those with higher shares of residential land are less likely to have had ridership increases between 2014 and 2018. Each percentage point increase in a neighborhood's share of residents living in poverty is associated with the bus stops having an average 1% lower odds of having gained riders, all else being equal. On average, a one percentage point increase in the share of residential land corresponds with 0.7% lower odds of the bus stops having had ridership increases, while holding other factors constant.

Bus stops in the urban area are more likely to have had ridership increases than those in the suburbs. However, this association is not statistically significant.

## 3.6. Discussion of Findings

Four themes emerge from the findings of the multilevel analyses. First, buses and bus stops that serve more passengers had greater ridership declines than less busy routes and smaller bus stops. For an explanation of this finding, consider the following example. A 10% ridership drop at a bus stop with hundreds of riders has a larger decrease in the actual number of passengers than a 10% ridership decrease at a bus stop that only serves a few passengers. Despite the larger decrease, however, the ridership at the busier bus stop could still be significantly higher than that at the less used stop. As a result, a bus stop could have both high ridership and large ridership change. Thus, certain factors could be associated with both higher ridership and bigger ridership loss. Findings indicate that bus stops in neighborhoods with higher job density and higher poverty rates, and serve buses with better on-time performance, factors that are associated with higher bus ridership, might be as prone to ridership loss as other bus stops. These findings, along with the observation that high performing City routes had greater average ridership declines than lower performing routes, suggest that SEPTA should monitor buses with high ridership and high performance, as they might not be immune to ridership decline in the post-ride-hailing period.

Second, not only do bus stops in urban neighborhoods have higher ridership than those in suburban neighborhoods, but they are also less likely to have had some of the biggest percentage ridership losses. Philadelphia is the population and employment center of the study region. It has more transit service, more transit users, and higher share of transit commuters than the surrounding suburban counties. The fact that bus stops in Philadelphia are less likely to have had some of the most severe declines suggests that post-ride-hailing ridership might be more resilient in urban area than in suburban area.

Third, higher neighborhood poverty rates are associated with both higher ridership and bigger ridership declines. Bus stops in neighborhoods with higher poverty rates also are less likely to have gained riders than bus stops in more affluent neighborhoods. While ridership declines in low-income neighborhoods could come from reduced travel demand, it could also be the result of residents replacing transit with other, more convenient travel modes. If the new modes are less affordable than transit, then the mode shift could add to the financial burden of travel facing lower-income residents. The bigger ridership losses in neighborhoods with higher poverty therefore reminds local authorities to investigate whether bus services are meeting the travel needs of lower-income residents.

Last, bus stops that serve more frequent buses are more likely to have gained riders and less likely to have had the biggest ridership losses than other bus stops. Buses with high service frequency are often those that serve neighborhoods with high transit demand. Those bus routes therefore might be more resilient to ridership declines than buses with less frequent services, which often serve areas with lower transit demand. Transit wait time has proven a deterrent for passengers (Yoh et al., 2011). Long wait time could be especially burdensome for bus passengers, who often have to wait for their buses at bus stops in the street, sometimes exposed to the elements. The transit literature estimates that the cost of waiting at a bus stop to be \$11 per hour, or \$0.18 per minute (Iseki & Taylor, 2009). Higher bus frequency means shorter wait time, and subsequently shorter overall travel time for passengers. The lower travel burden on passengers as a result of higher bus service frequency might help explain why more frequent buses are more effective at retaining passengers than buses with longer headway in the post-ride-hailing period.

## 3.7. Conclusion

In this chapter, I investigated the associations between bus stop ridership and neighborhood characteristics, bus service levels, and land use factors. Results show that factors such as job density, poverty level, and bus service frequency correspond with bus ridership and ridership change before and after ride-hailing services entered Philadelphia. Findings remind SEPTA to pay close attention to the travel demand of lower-income residents, especially those who replaced transit with more convenient but less affordable modes of travel. Currently, SEPTA identifies bus routes that fall in the bottom 15th percentile for both productivity and cost-effectiveness within each route category as candidates for possible evaluation and intervention (Southeastern Pennsylvania Transportation Authority, 2019b). The finding that higher performing, higher ridership bus routes could be as prone to ridership loss as lower performing routes in the post-ride-hailing era suggests that SEPTA should consider monitoring ridership of not only the less cost-effective routes, but also the high performing buses.

In chapters 2 and 3, I examined ridership change between the pre- and post-ride-hailing periods at both the system and bus stop levels. Whether to use transit is, above all, an individual choice. The increasingly popular ride-hailing services have added an alternative to the array of transport options in the Philadelphia region. What remains to be studied is the factors that could affect individual travelers' decisions when choosing between ride-hailing services and other modes. In the next two chapters, I answer the question, who uses ride-hailing services and why, through an investigation of ride-hailing user and trip characteristics based on an online survey. I also examine the trade-off between ride-hailing services and transit for individuals ride-hailing users to gain an understanding of what people value when choosing ride-hailing services versus transit.

# Chapter 4. Who Uses Ride-Hailing Services in Philadelphia and Why[2]

## 4.1. Shifting Focus

In the previous two chapters, I examined how transit ridership has changed in the post-ride-hailing era. In chapters 4 and 5, I shift focus to ride-hailing services and individual ride-hailing users in the five-county study area. Through an investigation of ride-hailing customers based on an online survey, I intend to answer the questions, who uses ride-hailing services and more generally why, and what are ride-hailing users' preferences between ride-hailing services and transit? In the current chapter, I examine ride-hailing user characteristics, trip purposes, and possible impact on travel behavior. In the next chapter, I explore ride-hailing users' willingness to choose ride-hailing services versus transit, and more specifically how their willingness varies by socio-demographic backgrounds and travel mode specific factors. A better understanding of who the ride-hailing users are, as well as how and why they use the services in the Philadelphia region can help local planning organizations and SEPTA identify and accommodate residents' travel needs amid the growing influence of ride-hailing services.

## 4.2. Ride-Hailing Survey

### 4.2.1. Survey Design and Distribution

To examine ride-hailing users' characteristics, as well as their willingness to choose ride-hailing services versus transit, I surveyed 611 UberX and Lyft users ages 19 and above living in the five-county study area. Similar to previous survey studies on ride-hailing users, the online survey includes both stated and revealed preference questions. These questions were divided into demographic and socio-economic characteristics, travel behavior, ride-hailing usage, and choice experiment sections. Most questions were presented to the respondents as multiple choices. A few questions, such as the origins and destinations of the respondents' last ride-hailing trips, either require respondents to write in the answers or provide options for text responses. The demographic and socio-economic characteristics section asks the respondents' year of birth, gender, race and

[2] A modified version of this chapter was published in the *Journal of American Planning Association* (Dong, 2020).

ethnicity, household income, vehicle ownership, etc. The travel behavior section includes questions on how the respondents' trip-making and mode choice changed after adopting ride-hailing services, as well as factors that affect their mode choice decisions. The ride-hailing usage section asks for information about the respondents' last ride-hailing trips, such as the time and day, monetary cost, and duration of the trips. The section also asks why the respondents favored ride-hailing services over other modes and what mode they would have chosen had ride-hailing services not been available. Lastly, the choice experiment section asks the respondents to choose between transit and ride-hailing services under different trip conditions in a series of choice games. I explain the choice experiment section in detail in the next chapter. In this chapter, I analyze ride-hailing user and trip characteristics, possible impact on trip making, and substitution effect on other modes based on the first three sections of the survey.

The survey company Qualtrics recruited the respondents and distributed the online surveys in four waves between March 18 and April 19, 2019. Qualtrics builds samples from multiple sources to form blended panels, and each sample from the panel base is proportioned to the general population (Qualtrics, 2014). Respondents were given compensation in various forms (such as a dollar amount or points to use toward gift cards and other rewards) in a range of worth of $1 to $8.75 to answer the survey. The survey was approved by the University of Pennsylvania's Institutional Review Board (IRB). The Kleinman Center for Energy Policy at the University of Pennsylvania provided funding for the survey.

Table 4.1 shows each of the five counties' share of respondents in the survey sample relative to the county's share of resident population in the study area according to the 2017 5-year ACS. The survey oversamples residents in Philadelphia and under-samples residents in the suburban counties. Since the ACS uses age 20 as an age category threshold, each county's share of population in the table is calculated as the county's resident population at or above 20 years old as a percentage of the 20-and-above population in the study area.

*Table 4.1 Comparison of the share of population for each county in the study area and in the survey sample*

| County | Population | Population Share | Sample size | Sample share |
|---|---|---|---|---|
| **Bucks** | 479,781 | 16% | 81 | 13% |
| **Chester** | 379,692 | 12% | 49 | 8% |
| **Delaware** | 420,154 | 14% | 72 | 12% |
| **Montgomery** | 620,136 | 20% | 114 | 19% |
| **Philadelphia** | 1,177,738 | 38% | 295 | 48% |
| **Total** | 3,077,501 | | 611 | |

# 4.3. Survey Findings

## 4.3.1. Ride-Hailing User Characteristics

Table 4.2 compares the demographic characteristics between the survey sample and the Census Bureau's 2017 5-year ACS for the study area (US Census Bureau, 2017), as well as the weighted demographic characteristics for ride-hailing users in the Philadelphia metropolitan area according to the 2017 National Household Travel Survey (NHTS) (Federal Highway Administration, 2017). The NHTS only records ride-hailing usage in the past 30 days. The Philadelphia metropolitan area encompasses the 5-county study area and 6 counties outside of the study area. Thus, ride-hailing user characteristics in the Philadelphia metropolitan area as described by the NHTS might not be representative of the study area's user characteristics. In the travel survey, 88 observations in the Philadelphia metropolitan area meet the criteria used in my survey study (i.e., ages 19 and above and have used ride-hailing services).

*Table 4.2 Comparison of ride-hailing user characteristics and average weekly ride-hailing usage among survey respondents*

| | **Comparison of Demographics** | | | **Ride-hailing usage** |
|---|---|---|---|---|
| | Survey | Census | NHTS | Survey |
| **Age (20 and above for Census)** | 38 (mean) | 48 (mean) | 41 (mean) | |
| ***19 to 29*** | 32% | 19% | 43% | 1.9 |
| ***30 to 34*** | 16% | 9% | 19% | 1.6 |
| ***35 to 54*** | 37% | 34% | 19% | 1.5 |
| ***55 to 64*** | 10% | 17% | 14% | 1.3 |
| ***65 and older*** | 6% | 20% | 4% | 0.8 |
| **Gender (20 and above for Census)** | | | | |
| ***Female*** | 76% | 53% | 45% | 1.6 |
| ***Male*** | 24% | 47% | 55% | 1.8 |

| | | | | |
|---|---|---|---|---|
| **Household income** | | | | |
| ***Less than $10,000*** | 8% | 8% | 3% | 2.0 |
| ***$10,000 to $49,999*** | 37% | 33% | 16% | 1.8 |
| ***$50,000 to $99,999*** | 33% | 27% | 23% | 1.6 |
| ***$100,000 to $149,999*** | 16% | 15% | 24% | 1.2 |
| ***$150,000 or more*** | 6% | 17% | 34% | 1.3 |
| **Race (20 and above for Census)** | | | | |
| ***White*** | 69% | 68% | 84% | 1.5 |
| ***African American*** | 20% | 21% | 7% | 1.6 |
| ***Asian*** | 4% | 6% | 5% | 2.4 |
| ***Other (including prefer not to answer)*** | 7% | 4% | 4% | 2.3 |
| **Education attainment (18 and above for Census)** | | | | |
| ***High school graduate or less*** | 19% | 40% | 6% | 2.1 |
| ***Some college*** | 27% | 25% | 12% | 1.6 |
| ***Bachelor's degree or higher*** | 54% | 35% | 82% | 1.5 |
| **Household vehicle** | | | | |
| ***0*** | 17% | 16% | 8% | 1.9 |
| ***1*** | 42% | 36% | 42% | 1.8 |
| ***2*** | 31% | 33% | 27% | 1.4 |
| ***3 or more*** | 10% | 15% | 23% | 1.3 |

My survey respondents have lower incomes, lower education attainment, and own fewer vehicles than the Philadelphia metropolitan area's ride-hailing users from the NHTS. Compared to the Census estimates, my survey oversamples women and residents with college degrees or higher and under-samples residents whose highest education attainment is high school or less. The average age of the respondents is much lower than that of the population in the study area, and comparable to that of ride-hailing users in the Philadelphia metropolitan area from the NHTS.

In the sample, 78% of the respondents have driver's licenses. Fifty-four percent of the respondents have full-time employment; 8% are unemployed, including those who are looking for jobs; and 7% are full-time students.

## 4.3.2. Ride-Hailing Service Usage

Among the respondents, driving alone is the most common mode of travel, with almost one-third of the respondents traveling by that mode more than 10 times per week (in the survey, round trips are considered to be two trips in the survey. For example, if the respondent drove alone to and from work once a week, it would count as using "driving alone" mode 2 times). In contrast, nearly two-thirds of the respondents use ride-hailing services once per week or less, while only 5% use it more than 6 times per week. The low frequency of ride-hailing use indicates that, consistent with existing findings, customers likely use ride-hailing services to fill occasional rather than regular travel needs. About 31% of the respondents take transit more than twice per week, with 8% use transit more than 10 times per week.

Ride-hailing usage varies by both demographics and geography. The ride-hailing usage column in Table 16 compares respondents' average weekly ride-hailing use across demographic subgroups. The inverse relationship between age and ride-hailing use in the sample conforms to previous findings (Conway et al., 2018; Corey, Canapary & Galanis Research, 2017; Smith, 2016). T tests show that ride-hailing usage rates are comparable across income groups. However, lower-income respondents tend to make shorter, cheaper ride-hailing trips than higher-income respondents. The average cost per ride-hailing trip is $10.4 among respondents making $50,000 or less, compared to an average $12.3 per ride among those making $50,000 or more. Somewhat contrary to intuition, ride-hailing usage rate among respondents who consider daily travel a financial burden (1.9 rides per week), 58% of whom are in the two lowest income brackets in Table 16, is slightly higher than the usage rate among those who are not burdened by daily travel (1.5 rides per week), although this difference is not statistically different. Differing from existing findings that ride-hailing adoption and usage rates increase with education attainment (Alemi et al., 2018; Clewlow & Mishra, 2017; Smith, 2016), respondents without college degrees use ride-hailing services more often than those with college degrees or higher. I did not find significant differences in ride-hailing usage rates between genders.

Respondents living in Philadelphia use ride-hailing services more often (1.8 rides per week) than residents of the four suburban counties (1.5 rides per week), echoing previous findings that denser urban area has higher ride-hailing usage (Conway et al., 2018; Feigon & Murphy, 2018). This is despite the fact that suburban respondents have a 46% higher average household income than residents of Philadelphia, and therefore might be less financially constrained when making mode choice decisions.

### 4.3.3. Ride-hailing trip characteristics

Echoing findings from previous studies, ride-hailing trips in the study area tend to be short and concentrate in urban area. Customers often use ride-hailing services to fill occasional recreation, shopping, and errand purposes rather than meet regular travel needs. Ride-hailing trips' temporal distribution reflects the activity patterns throughout the day on both weekdays and weekends.

Where are ride-hailing trips

Table 4.3 aggregates the surveyed ride-hailing trips by their origin and destination counties. Origin and destination counties were collected based on the origin and destination addresses provided by the respondents. A total of 203 observations were excluded from the trip table due to either missing data or the trip destinations being outside of the study region.

*Table 4.3 Summary of ride-hailing trip origin and destination counties*

| | | Destination county | | | | | |
|---|---|---|---|---|---|---|---|
| | | Bucks | Chester | Delaware | Montgomery | Philadelphia | Total |
| Origin county | Bucks | 32 | 0 | 0 | 2 | 9 | 43 |
| | Chester | 0 | 7 | 1 | 5 | 4 | 17 |
| | Delaware | 0 | 2 | 21 | 0 | 19 | 42 |
| | Montgomery | 5 | 1 | 2 | 32 | 24 | 64 |
| | Philadelphia | 7 | 2 | 3 | 7 | 223 | 242 |
| | Total | 44 | 12 | 27 | 46 | 279 | 408 |

The geographic distribution for Philadelphia's ride-hailing trips is different from the trip distribution for the suburban counties. Over 90% of trips originated in Philadelphia also ended in Philadelphia. In the suburbs, only Bucks county has more than half of its ride-hailing trips both started and ended within its limits. Three-quarters of the inter-county trips that originated in Bucks, Delaware, and Montgomery counties ended in Philadelphia. Excluding the airport trips, among trips that originated in the suburban counties and ended in Philadelphia, 64% were for recreation or errand purposes. The trip patterns suggest that Philadelphia's large number of business and recreational establishments likely attract ride-hailing trips from the suburban counties.

Why do people use ride-hailing services

Figure 4.1 shows ride-hailing usage by activity. For each type of activity, at least 70% of the respondents use ride-hailing services less than twice per week, once again indicating that ride-hailing services likely fills occasional rather than regular travel needs. Recreation and errand trips are the most common trips, with approximately 25% of the respondents using ride-hailing services for such trips more than twice per week. Despite some previous studies claiming that ride-hailing services complements transit by providing a first/last mile connection, less than 17% of the respondents use ride-hailing services for transit connection more than twice a week, whereas almost two-thirds use ride-hailing services less than once per week on average to connect to transit.

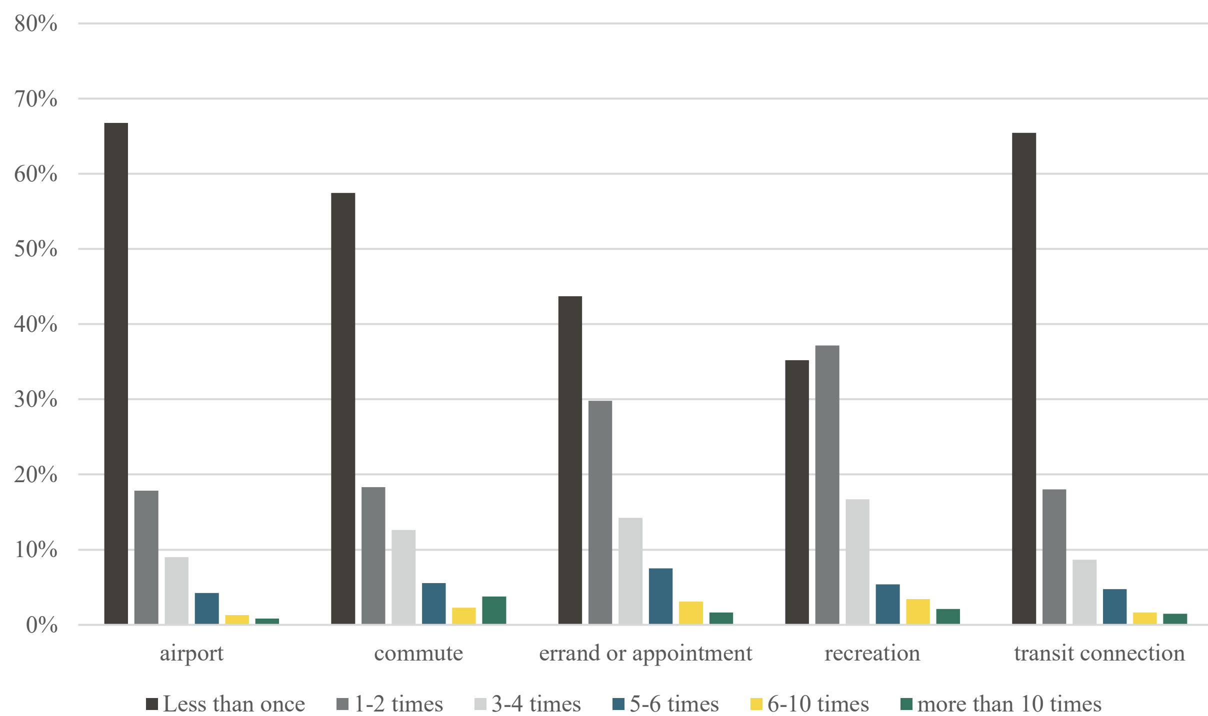


*Figure 4.1. Ride-hailing trip purpose by average weekly usage rate*

As illustrated by Figure 4.2, the purposes for respondents' last ride-hailing trips are consistent with the overall ride-hailing trip purposes, with recreation and social activities being the most common trips, followed by commute and errand trips. Less than 7% of the respondents travel to or from transit stations on their last ride-hailing trips, providing further evidence that ride-hailing services' complementary effect on transit might be limited. Of all the reported trips, 65% either began or ended at the respondents' homes.

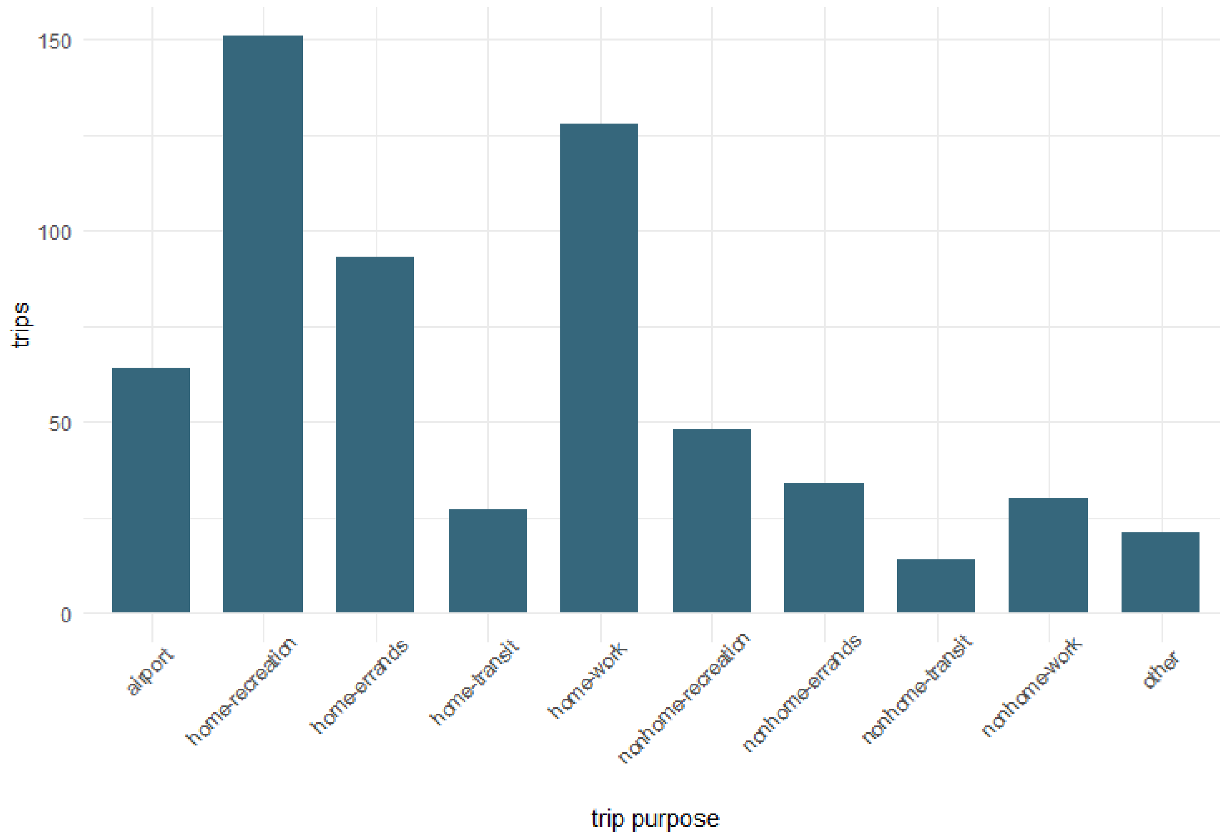


*Figure 4.2. Trip purposes for survey respondents' last ride-hailing trips*

When do people use ride-hailing services

Figure 4.3 shows the trip distribution by time of day for weekdays and weekends. In the survey, weekdays and weekends have roughly the same number of ride-hailing trips (320 for weekdays versus 290 for weekends). Weekdays and weekends see very different ride-hailing usage patterns. On weekdays, mid-day (between 10 am and 4 pm) see the most ride-hailing use, followed by the morning (7 am to 10 am) and evening (4 pm to 7 pm) peak commute hours. In contrast, weekends see relatively balanced ride-hailing use throughout the day after 10 am, with a usage peak between 9 pm and midnight.

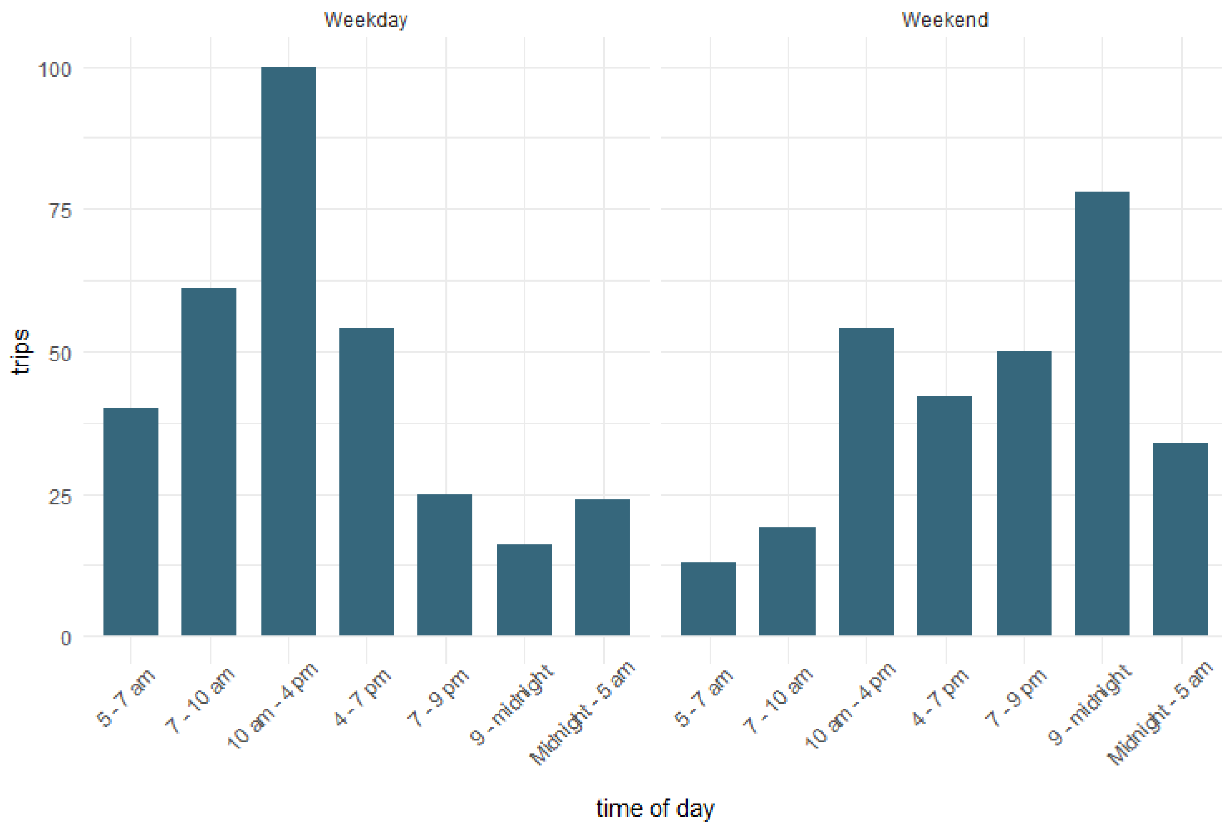


*Figure 4.3. Ride-hailing trip distribution by time of the day for weekdays and weekends*

The temporal distribution of ride-hailing trips reflects the activity patterns by time of day, as illustrated in Figure 4.4. For example, ride-hailing services are most heavily used for commute purposes during the morning and evening peaks on weekdays. On weekends, recreation trips make up the majority of ride-hailing trips between late afternoon and early morning of the next day, when weekend recreation activities tend to intensify.

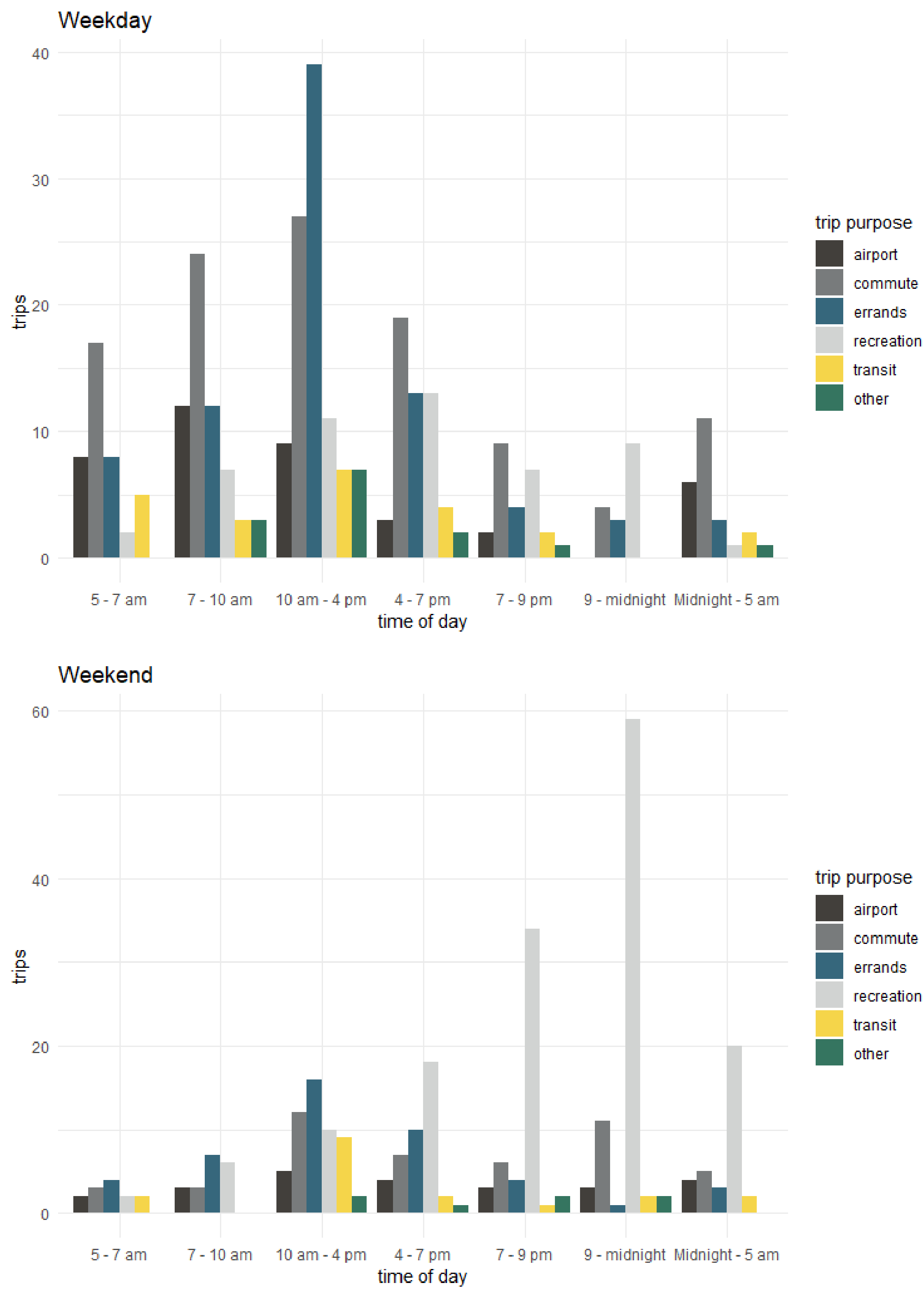


*Figure 4.4. Ride-hailing trip purpose by time of the day for weekdays and weekends*

What are the cost and wait time of ride-hailing trips

On average, ride-hailing trips in the study area are cheaper than taxi trips and have shorter travel distance and wait time than transit. Respondents spent an average $11 on their last ride-hailing trips, with three-quarters of the respondents spending less than $14, including tips and surge pricing (dynamic price adjustments by time of day and travel demand). While the survey does not ask the travel distance of the ride-hailing trips explicitly, the average ride-hailing fare indicates that the trips are likely between 3 and 6 miles (estimated by author based on UberX's fare schedule in Philadelphia). For reference, without surge pricing or tips, an 11-minute, 5-mile trip on an UberX costs about $10 in Philadelphia. The average transit trip in the Philadelphia metropolitan area is 6.6 miles (Federal Highway Administration, 2017).

Ride-hailing users waited an average 5 to 6 minutes for their ride-hailing vehicles to arrive. Nearly 60% of respondents waited less than 5 minutes, whereas only 12% of respondents waited longer than 10 minutes. In comparison, the average wait time for transit in the Philadelphia metropolitan area is almost 9 minutes according to the NHTS. For reference, SEPTA categorizes bus routes with a base frequency of every 15 minutes as high frequency services. The most frequent SEPTA buses have peak period frequencies of 4 to 6 minutes and a base frequency of 10 minutes on weekdays. In other words, even the most frequent buses would likely require some passengers to wait longer than they would have for ride-hailing vehicles.

Somewhat surprisingly, the wait time for ride-hailing vehicles does not vary significantly throughout the day on both weekdays and weekends, as shown in Figure 4.5. The difference between the shortest (between 9 pm and midnight on weekdays) and the longest (between midnight and 5 am on weekends) average wait times is only 2 minutes (4.5 minutes versus 6.7 minutes). This observation points to the relatively high availability of ride-hailing services in the study area. For example, during the hours with the most ride-hailing trips (10 am to 4 pm on weekdays and 9 pm to midnight on weekend), ride-hailing customers had an average wait time of less than 6 minutes. Meanwhile, even the most frequent transit services operate at a 10-minute headway during these hours. Furthermore, the average ride-hailing user wait no longer than 7 minutes for their ride-hailing vehicles between midnight and 5 am on weekdays and weekends, when most transit services are no longer available (only a small number of SEPTA's buses provide 24-hour service, with late night services operating at very low frequency).

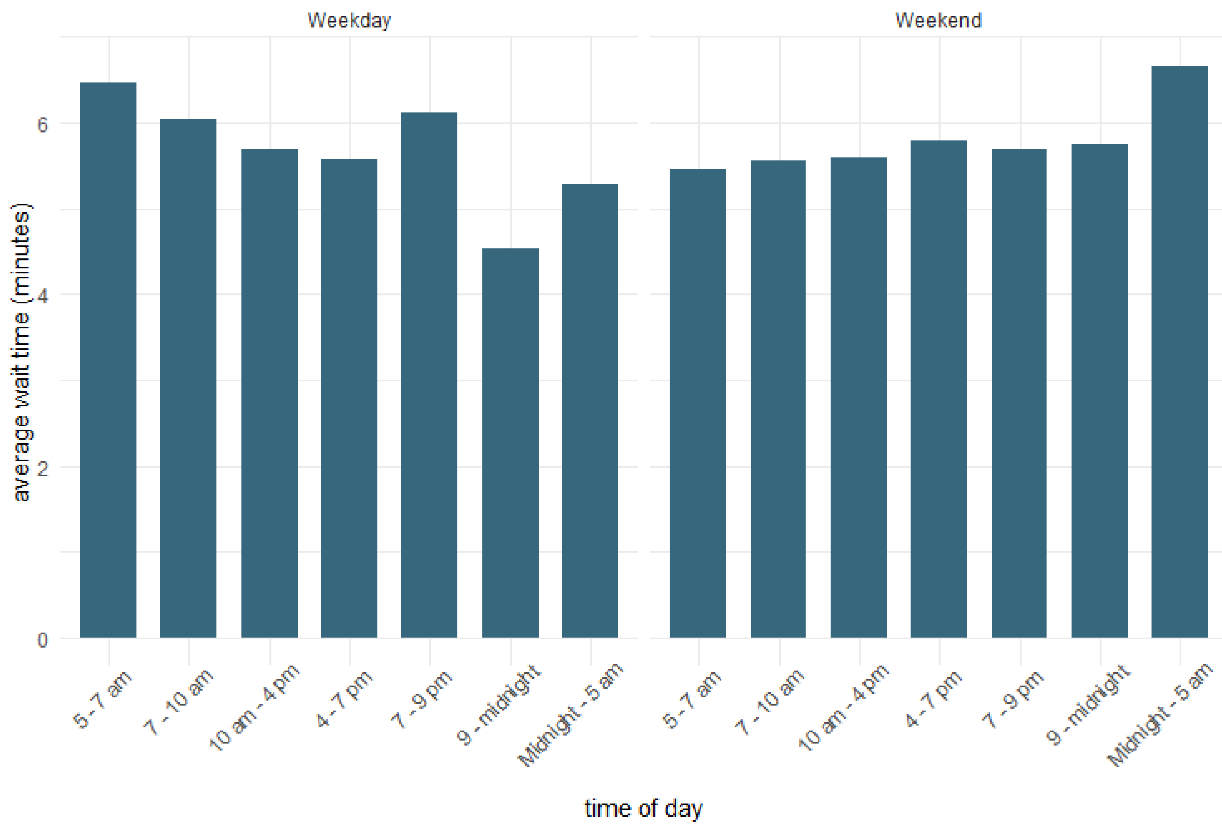


*Figure 4.5. Average ride-hailing wait time by time of day for weekdays and weekends*

## 4.3.4. Mode shift between ride-hailing services and other modes

Mode shift from transit to ride-hailing services

Survey results indicate a noticeable mode shift from transit to ride-hailing services for various trip purposes. Figure 4.6 shows what mode the respondents would have taken had ride-hailing services not been an option for their last ride-hailing trips. Overall, 27% of the respondents reported that they would have taken transit for their last ride-hailing trip, if ride-hailing services had not been available, a larger percentage than any other travel modes. Mode shift from transit to ride-hailing services is especially common for work or school commute trips and home-based errand, appointment, or shopping trips, with one-third of the respondents choosing ride-hailing services over transit for either types of trips. These findings, along with the observation that only a small share of ride-hailing trips was for transit connection, suggest that many respondents in the study area replaced transit with ride-hailing services. Ride-hailing services might not complement transit even for trips to or from transit stations, as more than a quarter of the respondents indicate that they would have taken transit to make the connection had ride-hailing services not been available.

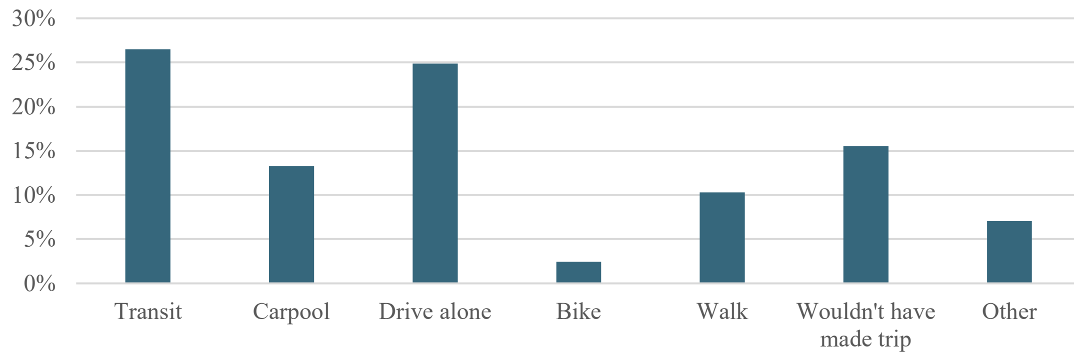


*Figure 4.6. What mode respondents would have taken had ride-hailing services not been available for their last ride-hailing trips*

Respondents with lower income have a higher substitution rate for transit than those with higher income. Among those who make $30,000 or less, 29% replaced transit with ride-hailing services on their last ride-hail trips, compared to 21% among those with an income of $70,000 or more. On one hand, this finding could indicate that ride-hailing services do not exclude lower-income residents. On the other hand, it could suggest that for some lower-income residents, transit service might not be convenient enough to compete with ride-hailing services on certain occasions, even though transit is almost certainly cheaper than ride-hailing services. For the nearly one-third of respondents who replaced transit with ride-hailing services and are financially constrained by their daily travel, having to rely on ride-hailing services due to the absence of good transit could be especially burdensome.

Ride-hailing services often replace transit during times when transit is not operating at peak frequency. For the ride-hailing trips that replaced transit, 34% and 25% took place during mid-day (10 am to 4 pm) on both weekdays and weekends. During this period, transit operates on the base frequency, which can typically be at least 10 minutes for trolleys and the most frequent buses. The average respondent waited 5 minutes for their ride-hailing vehicles to arrive during this period.

While the survey does not ask explicitly about the quality of the transit trips being replaced, respondents appear to favor ride-hailing services over transit for its better service and availability. Conforming to existing findings (Feigon & Murphy, 2018; Rayle et al., 2016), respondents cite ride-hailing services' shorter travel time, wait time, and walk time as the most common reasons for choosing ride-hailing services over transit, as illustrated in Figure 4.7. Ride-hail's better service, however, comes at a cost. Overall, the ride-hailing trips that replaced transit cost the respondents an average $10.6, a much higher price than the base transit fare of $2.5. In addition to service quality, 43% of the respondents claim that transit was not available for their last ride-hailing trips either due to the lack of service coverage or because the trip took place outside transit's service hours. For those who chose ride-hailing services over transit due to the lack of transit service, two-thirds suggest that they would have consider taking transit if it had been available.

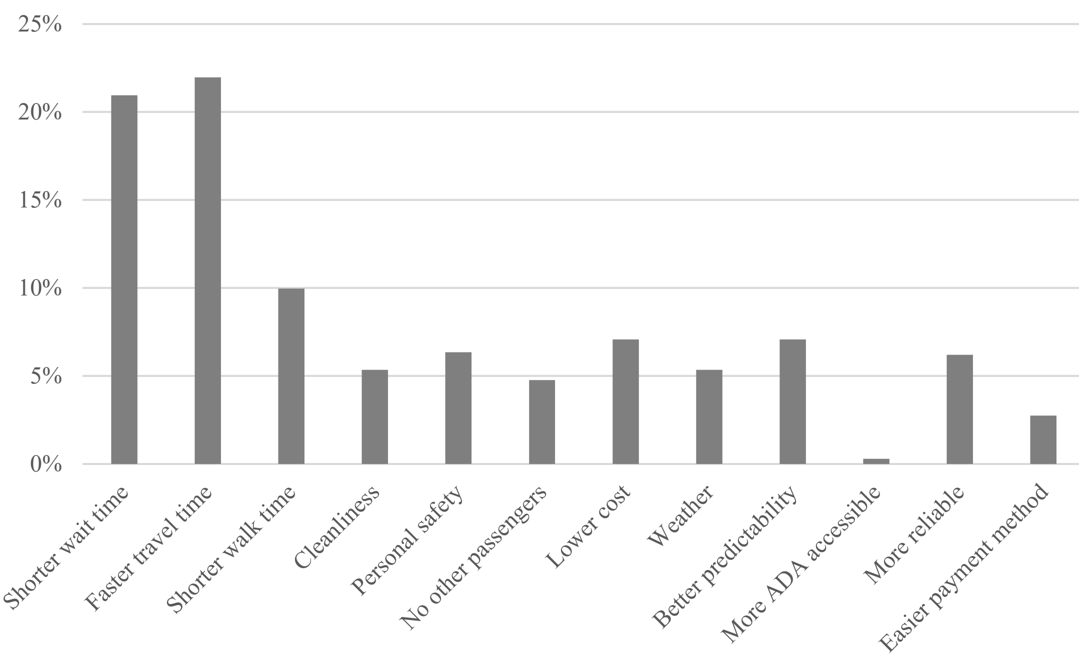


*Figure 4.7. Reasons why respondents chose ride-hailing services over transit for their last ride-hailing trips (respondents can choose up to 3 options)*

Mode shift from driving to ride-hailing services

In addition to transit, ride-hailing services also replaced trips that had previously been traveled by driving and carpooling. Overall, ride-hailing services replaced either driving alone or carpooling on nearly 40% of the respondents' last trips, as shown in Figure 25. Ride-hailing services' substitution effect on driving is especially prominent for recreation trips. Almost 60% of the respondents would have driven or carpooled on their last ride-hailing trips for recreation purposes had ride-hailing services not been available. Among respondents who took ride-hailing services to or from transit stations, nearly 40% would have chosen park-and-ride or kiss-and-ride without ride-hailing services. By replacing driving or carpooling, ride-hailing services can take cars off the road, since the same vehicle usually continue to pick up passenger(s) after dropping off the current passenger(s). However, since ride-hailing vehicles would need to travel from another location to pick up the next passenger(s) who requested the ride, the VMT from ride-hailing vehicles are almost certainly higher than what they would have been had the respondents chosen to drive their private vehicles or carpool for the surveyed trips. Furthermore, according to the NHTS, driving trips are often longer than trips on other modes in the Philadelphia region. It is therefore unsurprising that ride-hailing trips that replaced driving alone and carpooling tend to be more expensive than ride-hailing trips that replaced other modes, costing an average $12.

While the respondents' reasons for choosing ride-hailing services over driving vary throughout the day, the high cost of parking stands out as the biggest concern. On weekdays, parking being too expensive or difficult to find is the most common reason for the respondents to prefer ride-hailing services to driving for all periods but late evening. This finding suggests that the high cost and inconvenience of parking discourages driving while prompting a mode shift to ride-hailing services. Given the common use of ride-hailing services for recreation purposes, it is perhaps not surprising that avoiding driving when respondents might consume alcohol becomes a main reason for taking ride-hailing services instead of driving in late weekday evenings and throughout the day and into late night on weekends.

Mode shift from walking and biking to ride-hailing services

Ride-hailing services likely put more cars on the road by replacing trips that would have been made by active transport modes, including walking and biking. For respondents whose last ride-hailing trips were for travelling between home and work or school, 21% would have walked or biked had ride-hailing services not been available, as shown in Figure 25. The substitution is even greater for transit connection trips, where 27% of the respondents would have walked or biked to or from transit stations without ride-hailing services. While substituting ride-hailing services for active transport modes could mean shorter travel time and perhaps even more pleasant travel experience for some respondents, it comes at an average price of almost $9, a cost that could have been more expensive than the transit ride itself. Furthermore, while it is unclear whether replacing active transport modes with ride-hailing services would put more cars on the road, since those ride-hailing vehicles might already have been roaming the streets waiting for passenger requests, the substitution certainly contributes to greenhouse gas emissions by replacing zero-emission modes such as walking and biking.

### 4.3.5. Changes in vehicle ownership

Consistent with existing findings, the majority of the respondents did not change their vehicle ownership at all after adopting ride-hailing services. Vehicle ownership remained the same for 63% of current car owners and 62% of non-owners after adopting ride-hailing services. While 21% of the respondents either decided not to buy or lease a car, or postponed owning or leasing a car, 11% purchased or leased a car after they started using ride-hailing services. It is unclear whether the change in vehicle ownership was a direct response to adopting ride-hailing services.

### 4.3.6. Changes in trip making

Ride-hailing services prompted users to make trips that they previously would not have made, and thus likely contributed to the increasing VMT in the study area. Nearly 16% of the respondents would not have made their last ride-hailing trips had ride-hailing services not been available, even though more than 80% of these respondents live in household with at least one vehicle. Respondents who made the trips enabled by ride-hailing services have a lower median household income ($45,000) than the sample as a whole ($55,000). More than one-third (34%) of those respondents are financially burdened by daily travel, compared to 28% for the sample. These findings provide evidence that ride-hailing services could enhance access by allowing users, including lower income users, to make trips that would have been inconvenient or even infeasible to make otherwise. Lyft even claims that nearly 70% of the company's rides in Philadelphia either began or ended in an underserved or low-income neighborhood (Laughlin, 2018a). On the other hand, the finding that residents are making trips that they would not have made otherwise because of ride-hailing services suggests that ride-hailing services likely induce travel demand and subsequently increases VMT in the study area.

Ride-hailing services' potential impact on trip making varies by trip purpose. Figure 4.8 shows the change in the number of trips respondents took after adopting ride-hailing services for various trip purposes. Overall, the majority of respondents did not change the number of trips they make for each type of trips after adopting ride-hailing services. This finding points to the substitution of ride-hailing services for other travel modes, leaving the total number of trips unchanged. Noticeably more customers took more recreation and errand trips than those who made fewer such trips. While the survey did not ask whether the change in respondents' trip making is directly linked to the use of ride-hailing services, the fact that the trips that saw the biggest net increases (i.e., recreation and social trips) happen to be the most common ride-hailing trip types suggests that the ride-hailing services likely contributed to at least some of the increases in such trips. For transit connection and commute trips, the percentages of respondents who took more and fewer trips are roughly equal.

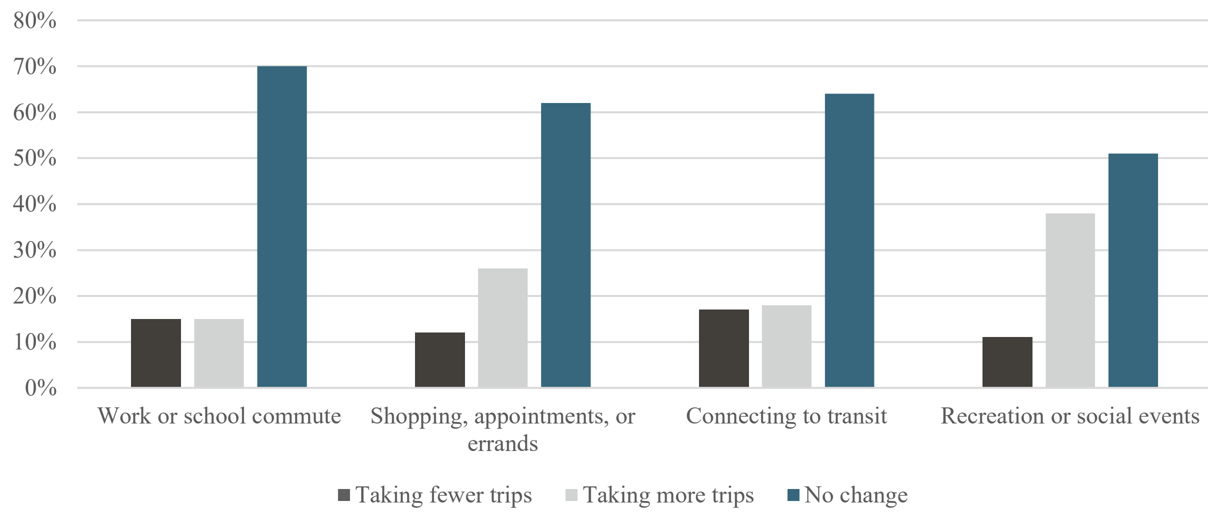


*Figure 4.8. Change in the number of trips for various activities after adopting ride-hailing services*

Figure 4.9 shows respondents' frequency of driving and taking transit for various purposes after adopting ride-hailing services. Most respondents did not change the usage of their current modes for commute and recreation or errand trips. More than 20% of the respondents use transit for commute more often after adopting ride-hailing services, possibly because ride-hailing services offer a feasible alternative for the return trip. Nearly a quarter of the respondents took transit and drove less for recreation and errand trips, the most common trips for ride-hailing services in the study area. This finding points to ride-hailing services' potential substitution effect on transit and driving for recreation and errand trips. It is unclear if the change in travel behavior is a direct response to ride-hailing use.

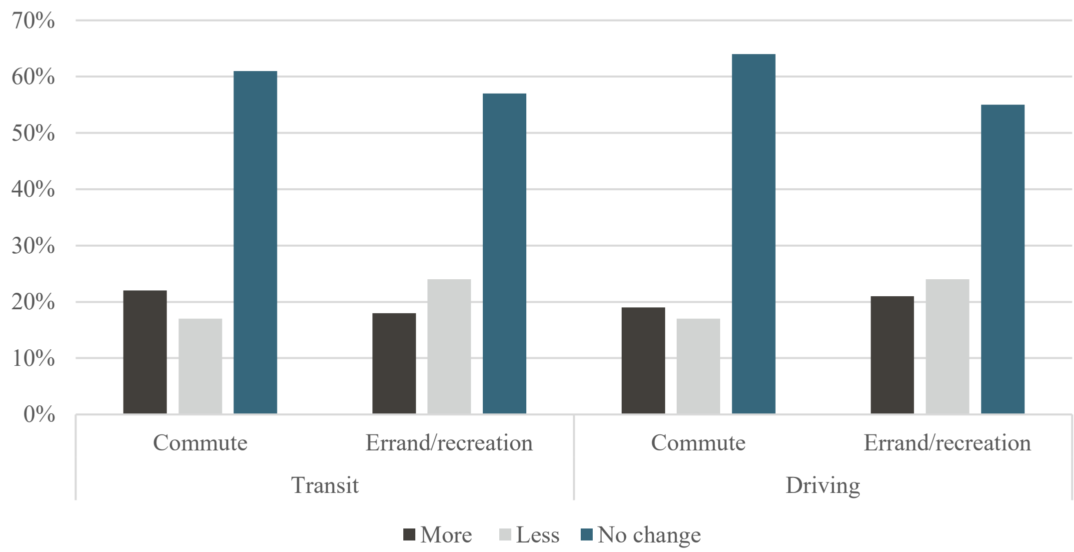


*Figure 4.9. Post-ride-hailing change in transit use and driving across activities*

## 4.4. Conclusion

In this chapter, I examined ride-hailing user and trip characteristics, as well as how customers' vehicle ownership and travel behavior changed after adopting ride-hailing services. Consistent with existing findings, respondents use ride-hailing services to fill occasional rather than regular travel needs. Younger and lower-income respondents tend to use ride-hailing services more frequently than older and higher-income respondents. Many ride-hailing trips are short and for recreation and errand purposes in urban area. The temporal distribution of ride-hailing trips reflects the activity patterns throughout the day on both weekdays and weekends. More than a quarter of the respondents replaced transit with ride-hailing services on their last ride-hailing trips. Ride-hailing services also replaced some driving, walking, and biking trips and subsequently contributed to the increase in VMT in the study area. Meanwhile, ride-hailing services can enhance access by enabling users, including lower-income users, to make trips that they would not have made without ride-hailing services. Last, most of the respondents did not change the overall number of trips they make or their vehicle ownership after adopting ride-hailing services.

The finding that many respondents took ride-hailing services for trips that they would have made by transit highlights ride-hailing services' substitution, rather than complementary, effect on transit. In the next chapter, I zoom in on individual ride-hailing users to investigate what socio-demographic and trip specific factors affect their choices between ride-hailing services and transit.

# Chapter 5. Trade Uber for the Bus[3]

## 5.1. Individual Preferences Between Ride-Hailing Services and Transit

In this chapter, I explore ride-hailing customers' willingness to choose ride-hailing services versus transit based on results from the choice experiments in the ride-hailing user survey. By investigating the associations between mode choice and individuals' socio-demographic background and travel mode specific factors, I answer the questions, who favor ride-hailing services over transit, and what factors do they value the most when choosing between ride-hailing services and transit? As transit agencies aim to retain customers amid the growing influence of ride-hailing services, understanding the factors that affect individual preferences between ride-hailing services and transit could help transit operators identify strategies and improve service to make transit more attractive for ride-hailing users.

Findings suggest that respondents' age, income, gender, and current transit usage are significantly associated with their willingness to choose one mode over the other. Longer overall trip time, including in-vehicle travel time, wait time, and walk time to access transit, as well as the presence of transfers in a trip are significant deterrents to travel by transit and prompt the respondents to choose ride-hailing services over transit. While respondents' willingness to choose either mode decreases as trip cost increases, reducing transit fares alone might not be enough for ride-hailing users to switch to transit.

## 5.2. Choice Experiments

### 5.2.1. Choice Scenarios

The choice experiment section in the survey asks each respondent to imagine a situation where he/she needs to make a trip home and the only available options are non-shared ride-hailing services, such as UberX, and transit. It then asks each respondent to choose between ride-hailing services and transit in 12 scenarios with different combinations of attributes, including monetary

[3] A modified version of this chapter was published in the *Journal of American Planning Association*.

cost, in-vehicle travel time, out-of-vehicle wait time, total walk time to and from transit stop/station, number of transfers for transit, and carbon dioxide emissions in pounds per passenger mile for each mode. Figure 5.1 gives an example of a scenario presented to the respondents. The survey provides the following explanation of the attributes in the beginning of the choice experiment section.

In the game, you will see each option described in terms of

Cost: Total monetary cost (including tips) for using ride hail or transit fare.
Wait time: Time spent waiting for your ride hail or transit vehicle to come.
Travel time spent in vehicle: Time spent traveling in ride hail or transit vehicle for the trip.
Total walk time: Total amount of time spent walking to AND from transit stop/station.
Number of transfers: Number of transfers involved in the transit trip.
CO2 emissions: CO2 emissions per mile for the trip using each option.

In the following section, imagine that you need to make a trip to return home. You do not have access to a car and the only available options are non-shared ride hail (e.g., UberX and Lyft) and transit. Twelve different scenarios will be presented to you. Each scenario contains information about the two options. Please make your choice considering all the information presented.

| | Ride hail | Transit |
|---|---|---|
| Cost | $20 | $1.5 |
| Wait time | 6 minutes | 12 minutes |
| Travel time spent in vehicle | 20 minutes | 40 minutes |
| Total walk time to and from transit stop/station | | 10 minutes |
| Number of transfers | | Direct trip, no transfer |
| $CO_2$ emissions per mile | 0.57 pounds | 0.37 pounds |

*Figure 5.1. Example of a choice scenario presented to the survey respondents in the choice experiments*

I consulted the mode choice literature when choosing mode specific factors to include in the choice experiments. Trip duration and monetary cost are often included in mode choice studies and have proven relevant for travelers when making mode decisions (see for example (Yang et al., 2009)). Ride-hailing survey studies have suggested that time saving is a main advantage of ride-hailing services over transit (see for example (Rayle et al., 2016)) and therefore could affect customers' preference between the two modes. Scholars have had extensive discussions on the disutility of transfer penalties in the transit literature (see for example (Guo & Wilson, 2004; Liu et al., 1997)). The online survey was distributed to respondents in four waves between March 18 and April 19, 2019. The first three waves were pre-tests for calibration of the choice experiments. Responses from the pre-tests are included in the survey sample.

## 5.2.2. Attribute Level Calculation

I calculated the values that describe each attribute (i.e., attribute levels) in the choice experiments based on data from the NHTS (Federal Highway Administration, 2017), SEPTA (Southeastern Pennsylvania Transportation Authority, 2019c), the Federal Transit Administration (Federal Transit Administration, 2010), ride-hailing literature (A. Brown, 2018), and ride-hailing price schedule (Lyft Inc., n.d.). I then calibrated the attribute levels based on the three pre-tests among respondents in the study area. I used an efficient design to create the combination of attribute levels in the choice experiments. The choice experiments were created using the Ngene survey design software developed by ChoiceMetrics.

Tables 5.1 and 5.2 show the attribute levels used to construct the choice scenarios in the different waves. The first three waves had 57, 43, and 50 responses, respectively. The attribute calculation methods explained in this section were used to calculate the attribute levels in the initial pre-test.

*Table 5.1 Attribute levels used to construct choice scenarios in the choice experiment section in the first and second waves of survey*

| Attributes | Ride-hail | Transit |
|---|---|---|
| **Cost (in dollars)** | 13, 16, 20 | 1.25, 2, 3 |
| **Wait time (in minutes)** | 2.5, 5, 7.5 | 4, 7, 12 |
| **Travel time spent in vehicle (in minutes)** | 15, 20, 30 | 20, 40, 60 |
| **Total walk time to and from transit stop/station (in minutes)** | | 10, 15, 20 |
| **Number of transfers** | | Direct trip, no transfer/One transfer to another line |
| **$CO_2$ emissions per mile (in pounds)** | 0.57 | 0.37, 0.46, 0.6 |

*Table 5.2 Attribute levels used to construct choice scenarios in the choice experiment section in the third and final waves of survey*

| Attributes | Ride-hail | Transit |
|---|---|---|
| **Cost (in dollars)** | 10, 15, 20 | 1.5, 3 |
| **Wait time (in minutes)** | 2, 6 | 4, 12 |
| **Travel time spent in vehicle (in minutes)** | 15, 20, 30 | 20, 40, 60 |
| **Total walk time to and from transit stop/station (in minutes)** | | 10, 20 |
| **Number of transfers** | | Direct trip, no transfer/One transfer to another line |
| **$CO_2$ emissions per mile (in pounds)** | 0.57 | 0.37, 0.46, 0.6 |

Wait times for ride-hailing services

I estimated wait time for ride-hail based on Brown's (A. Brown, 2018) analysis, which suggests that more than 50% of wait time was shorter than 5 minutes and 90% was shorter than 9 minutes.
Wait times for transit

Wait time for transit was calculated based on the weighted median, 25th and 75th percentile of transit wait time for the Philadelphia region from the NHTS.

In-vehicle time for ride-hailing services

I calculated the in-vehicle time for ride-hail based on the weighted median, 25th and 75th percentile of taxi (including ride-hail) travel time for the Philadelphia region from the NHTS.

In-vehicle time for transit

The in-vehicle time for transit was calculated based on the weighted median, 25th and 75th percentile of transit travel time for the Philadelphia region from the NHTS.

Walk to and from transit time

This attribute was calculated based on the sum of the weighted median, 25th and 75th percentile of transit access and egress time for the Philadelphia region from the NHTS.

Transfer

I did not present more than 1 transfer in the choice experiments because the majority of transit passengers in the Philadelphia region make no more than one transfer on their trips. In the NHTS, the weighted median transfer for the Philadelphia region is 0 while the 75th percentile transfer is 1.

Distance

Trip distance is calculated as the weighted median travel distance for ride-hail (including taxi) and transit for the Philadelphia region from the NHTS. This variable does not appear in the choice experiments but was used to calculate the monetary cost of trips.

Monetary cost for ride-hailing services

I calculated the costs for ride-hailing services based on the price schedule published by Uber and Lyft. By the time the survey was designed (in 2018), the Philadelphia Parking Authority had levied a 1.4% tax on revenue from ride-hailing trips. I applied the tax to the calculation of ride-hailing cost. In the choice experiments, the attribute levels were adjusted based on the base ride-hailing rate with and without a 1.5-time surge pricing.

Transit fare

Transit fare in the choice experiments were calculated based on the SEPTA's fare structure in 2018. The base fare for SEPTA is \$2 to \$2.5, depending on the payment method. Transfer costs an additional \$1. Reduced fare for riders with disabilities is \$1.25. The fare calculation did not include paratransit and Regional Rail, whose fares are higher than those for the other transit modes.

CO2 emission

The Federal Transit Administration estimates the per passenger mile CO2 emission for single occupancy vehicle to be 0.96 pounds (Federal Transit Administration, 2010). The survey assumes the average ride-hailing vehicle occupancy to be 1.67 persons, consistent with the average vehicle occupancy from the NHTS. Transit emissions were calculated based on the emission profile for SEPTA's various transit modes (Southeastern Pennsylvania Transportation Authority, 2019c).

## 5.3. Individual Willingness to Choose Ride-Hailing Services Versus Transit

### 5.3.1. Modeling framework

I use a mixed multinomial logistic regression (mixed logit) modeling framework to analyze respondents' mode choices in the choice experiments. The mixed logit is a popular extension of the multinomial logistic regression (Sarrias & Daziano, 2017). It is a very flexible model that can approximate any random utility model (McFadden & Train, 2000). Furthermore, it does not exhibit the independence of irrelevant alternatives property encountered in multinomial logit (Sarrias & Daziano, 2017). Mixed logit allows parameters to vary randomly over individuals (Train, 2009), a relevant attribute to the current analysis as respondents might value factors such as in-vehicle travel time differently due to different tastes. It also allows each respondent's personal preference to apply to each of the 12 choice experiments (Train, 2009). The mixed logit models for this analysis are estimated using the mlogit package (Croissant, 2019) in R.

### 5.3.2. Modeling Specification

The models include travel mode specific factors and/or respondents' socio-demographic and economic characteristics. Each model allows the coefficients of certain time components to be different between the two modes, and to vary across individuals to reflect different tastes.

The first model only includes trip related factors and excludes demographic variables. This model allows the coefficients for in-vehicle travel time and walk time to and from transit stations/stops to vary randomly across individuals following the normal distribution to reflect individuals' different tastes. It also allows the coefficient for transit's wait time to be different from the coefficient for ride-hailing services' wait time (i.e., alternative specific coefficients) to capture wait time's different disutility, or burden, between the two modes. Model 2 includes both trip related factors and demographic variables. The specification for trip related factors is identical to that for Model 1. In terms of demographic variables, a quadratic age term was included to capture the potential non-linear relationship between age and willingness to use ride-hailing services. Transit usage was divided into three categories. Given that the average transit usage rate among the respondents is 2.5 times per week, the model treats respondents who reported using transit 1 to 4 times as the reference category. Respondents in this category were compared to those who use transit more and less. Income was calculated using the mid-point of each income interval. For respondents who preferred not to reveal their income, I imputed their income using the average income of the respondents' home county from the 2017 5-year ACS. The final data set has 40 observations with imputed incomes. Model 3 allows the generic coefficient for walk time to vary across individual following a normal distribution to reflect different tastes. It also allows the coefficients for travel time and the coefficients for wait time between the two modes to be different. All three models assume generic coefficients for monetary cost, walk time, and the number of transfers. Gender, age, income, and transit usage rates are individual specific variables and are estimated as such in Models 2 and 3. I used the backward stepwise method to select variables to include in the final models.

I also estimated models with CO2 emission profile, number of household vehicles, education attainment, urban/suburban typology of respondents' home counties, and the interaction between income and age. These variables were dropped from the final models due to inconsistent statistical significance across the models.

The final models presented in this paper rely on 1,000 Halton draws. Models with 500 and 2,000 Halton draws did not produce significantly different results from the reported models. I direct interested readers to Chapter 9 in Discrete Choice Methods with Simulation (Train, 2009) for a discussion on the Halton sequence. The models use a panel structure to account for the potential correlations in each respondent's responses as a result of the repeated choice experiments presented to each respondent. Transit is the reference category in all three models. The final data set excludes 20 observations for missing answers for gender and some other variables and contains 590 observations.

In the choice experiments, respondents chose ride-hailing services 4,085 times (58%) and transit 2,995 times (42%). Since the survey only sampled ride-hailing users, estimates of preferences reflect how travel mode related attributes are valued within this specific subpopulation.

## 5.3.3. Interpretation of parameter estimate

Table 5.3 presents the parameter estimates and the odds ratios from the final models. Parameter estimates have indirect interpretations as odds ratios. For example, according to Models 1 and 2, a one dollar increase in monetary cost of a trip corresponds with an -0.09 or an 8.6% (the exponent of -0.09 minus 1) decrease in the odds of choosing either mode, all else being equal. For categorical variables such as transit usage and gender, the odds ratios of the coefficients are compared to the reference category. For example, in Model 3, the odds of choosing ride-hailing services over transit is 25% (the exponent of 0.22 minus 1) higher for female than for male respondents.

*Table 5.3 Parameter estimates and odds ratios from three models with different variables and coefficient specifications*

| | Model 1 | | Model 2 | | Model 3 | |
|---|---|---|---|---|---|---|
| | Estimate (S.E.) | Odds ratio | Estimate (S.E.) | Odds ratio | Estimate (S.E.) | Odds ratio |
| **Intercept (ride-hail specific)** | -0.361* (0.176) | 0.697 | -1.065** (0.373) | 0.345 | -1.314** (0.421) | 0.269 |
| **Cost** | -0.091*** (0.008) | 0.913 | -0.091*** (0.008) | 0.913 | -0.081*** (0.008) | 0.922 |
| **Transfer** | -0.497*** (0.073) | 0.608 | -0.500*** (0.072) | 0.607 | -0.473*** (0.068) | 0.623 |
| **Walk time** | -0.073*** (0.007) | 0.930 | -0.066*** (0.007) | 0.936 | -0.064*** (0.007) | 0.938 |
| **In-vehicle travel time** | -0.037*** (0.002) | 0.963 | -0.037*** (0.002) | 0.964 | | |
| ***Ride-hail*** | | | | | -0.030*** (0.007) | 0.971 |
| ***Transit*** | | | | | -0.033*** (0.003) | 0.968 |
| **Wait time** | | | | | | |
| ***Ride-hail*** | -0.007 (0.017) | 0.993 | -0.008 (0.017) | 0.992 | -0.010 (0.016) | 0.990 |
| ***Transit*** | -0.034*** (0.009) | 0.966 | -0.037*** (0.009) | 0.964 | -0.036*** (0.008) | 0.964 |
| **Gender (ride-hail specific)** | | | 0.206* (0.082) | 1.239 | 0.219** (0.077) | 1.245 |
| **Income (ride-hail specific)** | | | 0.006*** (0.001) | 1.006 | 0.006*** (0.001) | 1.006 |
| **Age (ride-hail specific)** | | | -0.030 (0.017) | | -0.028 (0.016) | |
| **Age$^2$ (ride-hail specific)** | | | 0.001* (0.000) | | 0.000* (0.000) | |
| **Transit usage (ride-hail specific)** | | | | | | |
| ***Above average*** | | | -0.025 (0.093) | 0.976 | 0.010 (0.088) | 1.010 |

| | | | | | | |
|---|---|---|---|---|---|---|
| ***Below average*** | | | 1.057*** (0.086) | 2.877 | 1.042*** (0.081) | 2.834 |
| **Random Parameters** | | | | | | |
| ***Walk time*** | 0.147*** (0.005) | | 0.127*** (0.005) | | 0.124*** (0.004) | |
| ***In-vehicle travel time*** | -0.034*** (0.002) | | -0.032*** (0.002) | | | |
| **AIC** | 7,434 | | 7,363 | | 7,456 | |
| **McFadden's $R^2$** | 0.23 | | 0.24 | | 0.23 | |
| **Significance levels: < 0.001 ***, < 0.01 **, < 0.05 *** | | | | | | |

# 5.4. Discussion of Findings

## 5.4.1. Who You Are Matters

In the choice experiments, respondents' willingness to choose ride-hailing services over transit has significant associations with their demographic characteristics. The models suggest that respondents under 30 years old are decreasingly willing to choose ride-hailing services over transit, with those in their late 20s being the least willing. The probabilities for choosing ride-hailing services gradually increase for respondents over 30. The finding that the willingness to choose ride-hailing services increases with age for respondents over 30 could indicate a growing acceptance of ride-hailing services among people in the older age groups, perhaps as a result of increasing familiarity with smartphone technology and ride-hailing services, even though older respondents have not used the service as often as respondents in the younger age groups. Alternatively, the findings could also suggest a lack of enthusiasm toward transit among older respondents. Indeed, the respondents' transit usage rate decreases with age, reflecting a national trend for people over 20 years old (Federal Highway Administration, 2019a).

In the choice experiments, respondents with higher incomes are more likely to choose ride-hailing services over transit than those with lower incomes, even though the actual ride-hailing usage among the survey respondents is not significantly different across income groups. For the average respondents, each additional $1,000 in annual household income corresponds with a 0.6% increase in the odds of choosing ride-hailing services over transit. High-income respondents' higher willingness to use ride-hailing services conforms to existing findings on the relationship between ride-hailing adoption and income (Clewlow & Mishra, 2017; Feigon & Murphy, 2018). In the last chapter, I explained that lower-income respondents use ride-hailing services more often than higher-income respondents. The findings that lower-income respondents use ride-hailing services more frequently, even though they might be more reluctant to use the service could signal a shortage of convenient, affordable travel options for low-income residents, forcing them to rely on ride-hailing services to meet certain travel needs. There is a weak correlation between respondents' incomes and ages, with a coefficient of determination (i.e., R2) of 0.03, and the interaction between income and age did not significantly correspond with respondents' mode choices across all three models.

The models also indicate that female respondents have higher willingness to choose ride-hailing services over transit than male respondents, even though the actual ride hailing usage between male and female respondents are comparable (1.8 versus 1.6 rides per week). The odds of the average female respondents choosing ride-hailing services instead of transit are 1.2 times the odds (or 20% higher odds) for the average male respondents. The difference in the willingness to use ride-hailing services over transit between genders could be a result of women's concerns when making mode choice decisions. In the survey, a larger proportion of female than male respondents were concerned about traveling with small children and how much they were carrying when making mode choice decisions for commute and shopping/errand trips. Furthermore, conforming to the literature on the relationship between gender and transit use (Hsu et al., 2019; Namgung & Akar, 2014), a greater proportion of female (18%) than male (15%) respondents cited personal safety as one of their biggest concerns about taking transit. Some customers might favor ride-hailing services over transit for its on-demand, personalized service might help mitigate some of their concerns.

Less frequent transit users are more willing to choose ride-hailing services over transit. Compared to respondents whose transit usage rate is around the sample average, the odds of choosing ride-hailing services over transit for respondents who use transit less often are almost three times as high. In contrast, the difference in the odds of choosing ride-hailing services is not statistically significant between the average and frequent transit users. Although this study assumes that people make rational decisions based on the attributes of the two modes, respondents' past and current mode choices could affect their decisions (Daly & Rohr, 1998; Nerhagen, 2003). For instance, some frequent transit riders might have chosen transit over ride-hailing services simply due to their habit of taking transit, instead of transit having more favorable attributes than ride-hailing services.

Carbon dioxide emission profile of each mode is not significantly related to respondents' mode choice. In the survey, nearly 60% of respondents indicated that they either were not aware of or did not care about the difference in the environmental impact between ride-hailing services and transit. Only around 18% of respondents agreed with the statement that transit consumes less gasoline and emits less greenhouse gases than ride-hailing services. Respondents who were unaware of or did not care about the difference in the environmental impact between the two modes chose ride-hailing services 20% more than they chose transit. Among respondents who considered transit a more environment-friendly travel mode, transit was chosen as frequently as were ride-hailing services.

The insignificant association between vehicle availability and mode choice in the choice experiments is consistent with the lack of clear patterns in the actual ride-hailing usage among respondents with different household vehicle availability. These results could suggest that not having a car does not necessarily make someone transit dependent (Jarrett Walker + Associates, 2018) or more willing to take transit. In Philadelphia, nearly one third of the households are carless. My findings could be particularly relevant for planners when studying the post-ride-hailing travel demand of the city's residents.

### 5.4.2. Time and Money Matter

The probabilities of choosing ride-hailing services and transit decrease as trips become more expensive. For each additional dollar, the odds of the average respondents choosing either modes decrease by 7.8% (Model 3) to 8.7% (Model 2). From a utility standpoint, a one dollar increase in the monetary cost of the trip corresponds to a 0.08 to 0.09 decrease in the observed utility of travel. While longer wait time, in-vehicle time, and in the case of transit, walk time to and from the stations/stops all lower the probabilities of choosing either mode, respondents do not value the various time components of a trip equally. The models estimate that nearly 90% of the respondents consider time spent in-vehicle a burden. Every additional minute spent traveling in a vehicle lowers the odds of choosing either modes by 4%. Despite the different comfort and privacy levels offered by ride-hailing services and transit, respondents consider the monetary values of the time spent traveling in either modes to be almost equal, ranging from $22 per hour for ride-hailing services to $25 per hour (Model 3) for transit. For reference, the average pre-tax hourly wage among the respondents is approximately $32.

Respondents consider wait time to be more onerous for transit than for ride-hailing services, as indicated by the more negative coefficients for transit's wait time across all three models. On average, waiting for transit (valued at $22 in Model 1 to $27 per hour in Model 3) is 4 to 5 times as costly as waiting for ride-hailing vehicles (valued at $4 to $7 per hour). This finding is intuitive as passengers can usually wait for their ride-hailing vehicle in a comfortable environment such as at home or in a restaurant, as opposed to waiting for transit at a bus stop or a train station, sometimes exposed to the elements. Ride-hailing apps also allow users to track their ride, thus providing greater certainty for the waiting customers. While real-time transit arrival/departure displays help to reduce the perceived wait time for transit passengers (Dziekan & Kottenhoff, 2007; Yoh et al., 2011), they are not common at transit stations/stops in the study area. Waiting for ride-hailing vehicles therefore might be less of a deterrent than waiting for transit for individuals making mode choice decisions. Differing from existing studies suggesting that wait time is usually considered to be more burdensome than in-vehicle travel time for transit (Cervero, 1990; Iseki & Taylor, 2009; Reed, 1995; Yoh et al., 2011), respondents for the present survey value the two time components almost equally. This discrepancy could be the result of the unique trip purpose specified by the choice experiments or the lack of context beyond the trip related factors provided in the choice scenarios.

Walk time to and from transit are considered to be more burdensome than in-vehicle time and wait time for transit and ride-hailing vehicles. For each additional minute spent on walking to and from transit, the odds of choosing transit decrease by 6% to 7% for the average respondents. Respondents find walking to and from transit ($44 to $48 per hour) to be twice as onerous as waiting for transit or traveling in a transit or ride-hailing vehicle, and as many as 11 times as onerous as waiting for ride-hailing vehicles. On average, respondents would pay an average $8 to avoid 10 minutes of walking. Findings on the value of walk time generally falls within the range suggested by previous studies (Iseki & Taylor, 2009). Despite walking's high average disutility, not all respondents consider it a burden. In fact, approximately 30% think positively about walking to and from transit. Among the possible reasons for transit users to consider the time spent walking to and from transit beneficial rather than burdensome, transit walking's health benefits have been well-studied. Studies have shown that transit walking helps transit users attain the recommended level of daily physical activity (Besser & Dannenberg, 2005; Freeland et al., 2013). Scholars also find associations between transit use and reductions in body mass index and the odds of becoming obese over time (MacDonald et al., 2010).

Findings on the value of time from the choice experiments are consistent with respondents' revealed preferences. In the survey, respondents cite ride-hailing services' shorter travel time, wait time, and walk time as the most common reasons for choosing ride-hailing services over transit. The fact that respondents who replaced transit with ride-hailing services on their last trips spent an average $8 more for their trip suggests that the respondents were willing to pay higher price for better transport service.

Lastly, transfers discourage individuals' willingness to take transit. A transit trip with one transfer lowers the odds of the average respondents taking transit by 39%, compared to a direct trip with no transfer. The negative association between transfer and the likelihood of choosing transit echoes findings on the impedance of transfer to travel (i.e., transfer penalties) (Guo & Wilson, 2004; Liu et al., 1997; Yoh et al., 2011). Depending on the modes of transit involved in a transfer, existing studies suggest that transfer penalties are estimated to be 1.4 minutes to almost 50 minutes of in-vehicle travel time (Guo & Wilson, 2004). In the sample, respondents consider the "cost" of a transfer to be equivalent to spending 13 minutes traveling in vehicle or 15 minutes waiting for transit. Since the present survey does not take into account SEPTA's one-dollar transfer fee, the estimated cost of a transfer in the choice experiments is almost certainly lower than the actual cost.

## 5.5. Implications for Planning

In this section, I discuss the planning and policy implications of the key findings from the survey analysis. I also explain the limitations of the current study and examine the lessons for future survey studies on this topic.

### 5.5.1. Transit Fare Reductions Without Shorter Trip Time May Not Be Enough

Despite the significant burden of trip cost on travel, transit fare reductions alone may not prompt a meaningful mode shift from ride-hailing services to transit among ride-hailing users. Not considering reduced fares and transfer fees, reducing the base transit fare from the current $2.50 to $1.50, a 40% reduction, leads to a mere 1.2% higher average probability of choosing transit over ride-hailing services. In contrast, a 15% reduction in wait time, walk time, and in-vehicle time increases the average probability of choosing transit by 5%, while keeping other factors constant. Figure 30 illustrates how the average probabilities of choosing transit increase as wait time, walk time, and in-vehicle time for transit decrease. Indeed, among the respondents who indicated they could have taken transit for their last ride-hailing trips, ride-hailing services' faster travel time, shorter wait time, and shorter walk time are the most cited advantages over transit. This finding adds further evidence that passengers react more strongly to service improvements than fare reductions (Cervero, 1990).

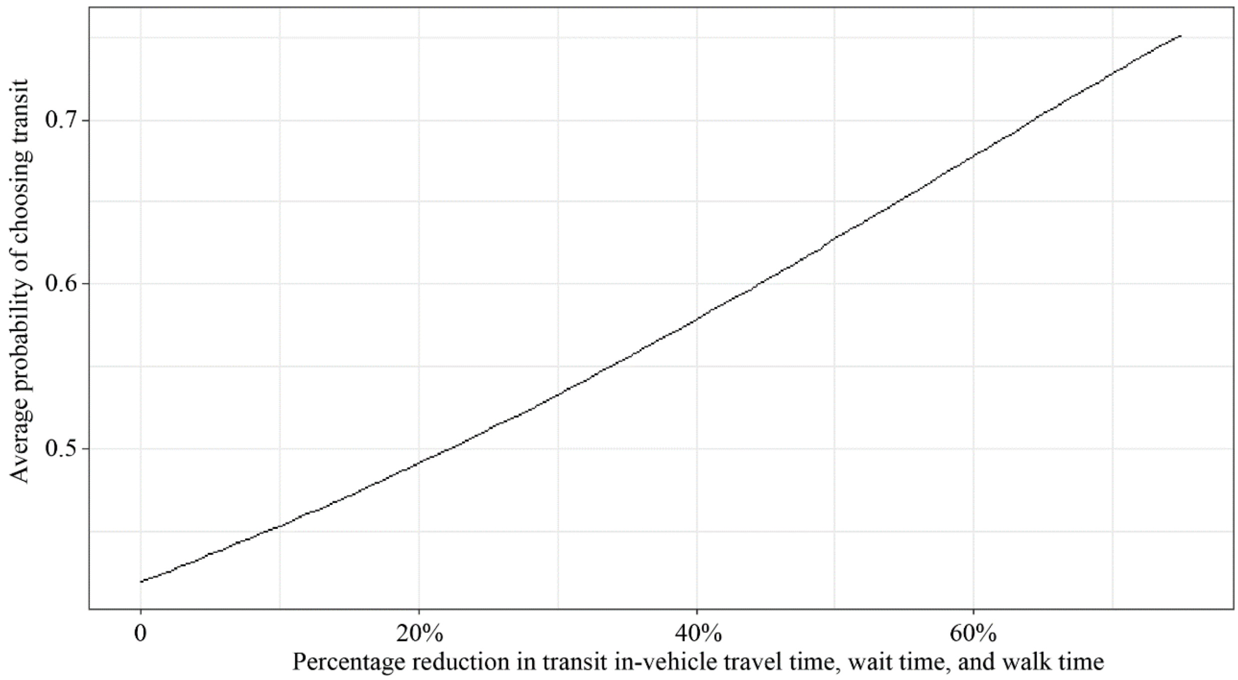


*Figure 5.2. Simulation of the average probability of choosing transit over ride-hailing services according to reductions in travel time, walk time, and wait time for transit*

The relationship between travel time and mode choices indicates that better scheduling, routing, and stop/station siting could help make transit a more attractive option by shortening trip duration. In addition to transit service improvements, cities should consider planning interventions such as dedicated bus lanes and transit signal priority to reduce transit in-vehicle travel time (Ben-Dor et al., 2018; Hu et al., 2014; National Academies of Sciences, Engineering, and Medicine, 2010; New York City Department of Transportation, 2018) and subsequently lessen passengers' travel burden.

Cities and transit agencies should also explore stop/station improvement strategies to enhance passengers' transit experience. For example, real-time information displays at transit stops/stations have proven effective in increasing transit predictability while reducing the perceived wait time (Dziekan & Kottenhoff, 2007). In addition, station/stop amenities such as schedule and route information, seating, and bus shelters become more important to passengers' transit experience as wait time for transit increases (Yoh et al., 2011).

Last, the burdensome walk to and from transit highlights the need to provide convenient transit access. Planners and transit officials who want to encourage transit use should consider incorporating measures that enhance sidewalk infrastructure and promote pedestrian-friendly street design (Mintesnot & Kent, 2016) in their planning toolbox to improve pedestrian access to transit.

## 5.5.2. Access for All

My findings on the relationships between the willingness to use ride-hailing services and income, age, and gender offer insights into the socio-demographic implications of ride-hailing services. The difference between the stated willingness and the actual ride-hailing usage across income groups highlights the potential unmet travel needs for low-income residents. By indicating that lower-income respondents use ride-hailing services more often than higher-income respondents, my survey adds evidence to existing findings that ride-hailing services do not exclude low-income neighborhoods and communities (Brown, 2019). Meanwhile, the results from the choice experiments suggest that lower-income respondents are more reluctant to choose ride-hailing services than higher-income respondents. My finding that lower-income respondents use ride-hailing services more frequently, even though they are less willing to use the service, could signal a shortage of convenient, affordable travel options for low-income residents, forcing them to rely on ride-hailing services to meet certain travel needs.

The relationship between age and ride-hailing services could have implications on transit ridership amid the increasing popularity of ride-hailing services. My finding that the willingness to use ride-hailing services increases with age for respondents over 30 could indicate a growing acceptance of ride-hailing services among people in the older age groups, perhaps as a result of increasing familiarity with smartphone technology and ride-hailing services, even though older respondents have not used the service as often as respondents in the younger age groups. Alternatively, the findings could suggest a lack of enthusiasm toward transit among older respondents. Indeed, respondents' transit use decreases with age, reflecting a national trend for people over 20 years old (Federal Highway Administration, 2019a). These factors remind transit agencies to identify challenges in the system that could prevent senior residents from considering transit as a viable travel alternative. Currently, people between 36 and 65 years have the highest number of average daily per person trips (McGuckin & Fucci, 2018) and make more than half of all person trips in the United States (Federal Highway Administration, 2019b). If the current relationship between age and ride-hailing use continues, then we may expect to see greater substitution of ride-hailing services for transit as people of the more tech-savvy generation start entering their 30s.

Last, women's higher willingness to choose ride-hailing services over transit urges transit agencies to pay greater attention to female riders' needs. In the survey, a larger proportion of female respondents were concerned about traveling with small children and how much they were carrying when making mode choice decisions for commute and shopping/errand trips. Furthermore, echoing the literature on the relationship between gender and transit use (Hsu et al., 2019; Namgung & Akar, 2014), a greater proportion of female respondents cited personal safety as one of their biggest concerns about taking transit. Transit agencies and cities should explore strategies that could improve safety or at least passengers' perceptions of safety, such as transparent bus shelters and stops/stations that are highly visible and easy to find (Loukaitou-Sideris et al., 2001; Lusk, 2002; Yavuz et al., 2007; Yoh et al., 2011). Female respondents' concerns about taking transit and their higher willingness to use ride-hailing services serve as another reminder for transit agencies to recognize and accommodate female riders' needs to make transit more user-friendly.

## 5.6. Survey Limitations

The survey design and sampling have several limitations. Not distinguishing the types of transit service in the choice experiments could present a challenge to some respondents when making mode choices. For example, one may choose transit over ride-hailing services if it means waiting for the subway in a station, instead of waiting for a bus at an unsheltered bus stop on the street. Furthermore, the survey presents a generic trip home from other activities to all respondents across the choice experiments. In reality, the trade-off between transit and ride-hailing services could vary by specific trip purposes and contexts. For instance, respondents might be more willing to wait 10 minutes for a transit bus in the afternoon on a fair weather day than in a cold winter night. There are also discrepancies between the demographic characteristics of the sample and the general population in the study area. For example, due to the skews of the internet demographics, my survey under-samples male residents. If the characteristics and preferences of the male ride-hailing users that were not surveyed were significantly different from those of the male respondents, then the analyses could produce estimates that are different from the study area's ride-hailing user population (Fowler, 2019). Respondents' revealed preferences could also be subject to recall bias.

## 5.7. Lessons for Future Research

The current study's findings and limitations should serve as lessons for future ride-hailing research. First, scholars should conduct more research on low-income residents' travel needs amid ride-hailing services' increasing presence. Low-income residents are the more frequent but less willing ride-hailing users. Planners and officials who aspire to further transport equity might find merit in exploring how to make ride-hailing services a viable travel option for low-income residents. Second, the current study presents all respondents the same travel scenario in the choice experiments. In future analyses, distinguishing the types of transit services, trip purposes, and travel contexts such as time of the day of travel and weather conditions might help researchers obtain more nuanced information about respondents' preferences between ride-hailing services and transit. Finally, extending the research scope beyond the current non-shared ride-hailing services versus transit dichotomy could enable scholars and practitioners to examine the relationship between different types of ride-hailing services and other modes of transport. Shared ride-hailing services such as Lyft Line, for example, offer cheaper rides for an increase in time spent picking up and dropping off other riders (Sarriera et al., 2017). Shared ride-hailing services' substitution effect on transit therefore might be different from that of non-shared services.

## 5.8. Conclusion

In this chapter, I investigated ride-hailing user characteristics and individual preference between ride-hailing services and transit based on the choice experiments from the online survey. Findings suggest that socio-demographic and mode-specific factors play a significant role in individuals' choices between ride-hailing services and transit. Older and higher-income respondents are more willing to choose ride-hailing services over transit in the choice experiments, even though they use these services less often than younger, lower-income respondents. Female respondents have higher probabilities of choosing ride-hailing services over transit. Additionally, more frequent transit users are more likely to choose transit over ride-hailing services than less frequent transit users. Furthermore, lower fares and shorter overall trip time for transit increase respondents' willingness to use transit over ride-hailing services. Fare reductions alone, however, may not be enough to generate meaningful mode shift from ride-hailing services to transit. A 40% fare reduction, for instance, only increases the average probability of choosing transit over ride-hailing services by 1.2%. In contrast, a 15% reduction in walk, travel, and wait time increases respondents' average probability of choosing transit by more than 5%. Echoing existing findings, my study suggests that respondents value the different time components in a trip differently, with time spent on walking to and from transit stops/stations being twice as burdensome as in-vehicle travel time and wait time for transit, and as many as 11 times as onerous as waiting for ride-hailing vehicles. Together, these findings add further evidence to the importance of shortening trip time in making transit a more attractive travel option.

Despite the fact that some respondents in the sample replaced transit with ride-hailing services, planners and transit officials should find it encouraging that only 14% of the survey respondents would absolutely not consider taking public transportation under any circumstances.

# Chapter 6. Implications and Conclusion

## 6.1. Research Questions Revisited

Ride-hailing services that emerged in late 2014 have changed transit ridership and residents' travel behavior in the Philadelphia region. Although services such as Uber and Lyft still transport far fewer passengers than traditional transit, their popularity has increased significantly since their market entry. Coinciding with the rapid growth of ride-hailing services have been declines in transit ridership. Mirroring the national trend, ridership for SEPTA's four main transit modes, including buses, heavy rail, trolleys, and Regional Rail, declined to some of its lowest levels in the last decade, despite sustained population growth especially in Philadelphia over that period.

In chapters 2 through 5, I investigated the post-ride-hailing system-wide transit ridership trends, factors that are associated with ridership decline at bus stops, ride-hailing user and trip characteristics, and ride-hailing customers' mode choice between ride-hailing services and transit. Through the analyses, I answered the overarching question, what does ride-hailing services' growing popularity mean for transit use?, by addressing three interrelated sub-questions.

1. Have UberX and Lyft increased or lowered transit ridership in the Philadelphia region? What transit service factors and neighborhood characteristics are associated with the recent bus ridership decline?
2. Who uses UberX and Lyft in the Philadelphia region and more generally why?
3. What factors contribute to individuals' willingness to choose transit versus ride-hailing services in the Philadelphia region?

In the following paragraphs, I summarize the key findings and policy implications around the three questions.

## 6.2. Summary of Findings

### 6.2.1. Ride-Hailing Services and System-wide Transit Ridership

Ridership for all of SEPTA's four main transit modes in the study area declined after ride-hailing services' entry. Buses suffered the biggest ridership losses, with an average of more than 800,000 fewer trips per months after the entry of ride-hailing services than before. The ridership declines for heavy rail and trolleys are less severe than the decline for buses, suggesting that higher speed, more frequent, and more reliable rail transit services might be less prone to ridership losses than traditional buses amid the increasing influence from ride-hailing services. Only the ridership for Regional Rail showed signs of rebounding since the entry of ride-hailing services, although as of mid-2019, it had not returned to the ridership level in the two years prior to ride-hailing services' entry.

### 6.2.2. Ridership Change by Bus Stop

When it comes to ridership loss in the post-ride-hailing period, not all buses and bus stops are equal. Buses and bus stops that serve more passengers had greater ridership declines than less busy buses and smaller stops. Additionally, bus stops in neighborhoods with characteristics that are associated with higher bus ridership, such as higher job density and higher poverty rates, might be as prone to ridership losses as other bus stops. Bus ridership loss also differs between urban and suburban areas. Bus stops in urban neighborhoods are more likely to have gained riders in the post-ride-hailing period than those in suburban neighborhoods. This factor could indicate that bus ridership might be more resilient in certain urban neighborhoods than in suburban neighborhoods amid the growing popularity of ride-hailing services. Last, more frequent buses are more resilient to ridership decline than less frequent buses.

### 6.2.3. Ride-Hailing Service User and Trip Characteristics

Like users of ride-hailing services in other regions in the U.S., respondents in my study use ride-hailing services to fill occasional rather than regular travel needs. Many ride-hailing trips are for short recreation and errand purposes in urban area. Younger and lower-income respondents tend to use ride-hailing services more frequently than older and higher-income respondents. More than a quarter of the respondents replaced transit with ride-hailing services on their last ride-hailing trips. Some of those trips were for connecting to transit services. My findings provide evidence on ride-hailing services' substitution rather than complementary effect on transit.

### 6.2.4. Willingness to use ride-hailing services versus transit

In the choice experiments of the online survey, respondents over 30 years old and those with higher income are more willing to choose ride-hailing services over transit, even though they use ride-hailing services less often than younger, lower-income respondents. While female respondents use ride-hailing services as frequently as male respondents, they have higher probabilities of choosing ride-hailing services over transit in the choice experiments. More frequent transit users are more likely to choose transit over ride-hailing services than less frequent transit users.

High monetary cost, long travel time, and the presence of transfers are significant deterrents to travel. Echoing existing findings, my analyses suggest that respondents value the different time components in a trip differently, with time spent on walking to and from transit stops/stations being twice as burdensome as in-vehicle travel time and wait time for transit, and as much as 11 times as onerous as waiting for ride-hailing vehicles. While lower transit fares increase respondents' willingness to use transit over ride-hailing services, fare reductions alone may not be enough to generate a meaningful mode shift from ride-hailing services to transit without shortening overall travel time. This finding adds evidence to the importance of shortening trip time in making transit a more attractive travel option.

## 6.3. Key Policy Implications

First, there is a need to ensure that transit service is meeting the travel needs of lower-income residents adequately. This is particularly critical for poor, big cities like Philadelphia, where many lower-income residents rely on transit services for daily commute and other purposes. In the post-ride-hailing period, bus stops in neighborhoods with higher poverty rates are more likely to lose riders than those in more affluent neighborhoods, even though lower-income residents use transit more often than higher-income residents. While ridership decline in low-income neighborhoods could come from reduced travel demand, it is also possible that lower-income residents have replaced transit with other modes of travel. The ride-hailing user survey indicates that not only do lower-income respondents use ride-hailing services more often than higher-income respondents, but a greater percent of them replaced transit with ride-hailing services. Meanwhile, lower-income respondents are less willing to choose ride-hailing services over transit than higher-income respondents. My finding that lower-income respondents use ride-hailing services more frequently, even though they might be more reluctant to choose the services over transit than high-income respondents could signal a shortage of convenient, affordable travel options for low-income residents, forcing them to rely on ride-hailing services to meet certain travel needs. While ride-hailing services could enhance access of low-income residents, they are likely to be more expensive than transit and thus could add to the financial burden of travel facing low-income residents.

Second, improving transit service will require shortening travel time and reducing transfer. Long travel time is a significant deterrent to using transit. The time spent on walking to and from transit and waiting for transit vehicles to arrive is especially burdensome for transit riders. Additionally, passengers are less inclined to take transit when their trips require transfer from one transit line to another. Transfer could be particularly burdensome if the second transit vehicle of the trip does not arrive on time, thus increasing passengers' wait time and overall travel time. Besides the time penalty associated with transfer, SEPTA's one-dollar transfer fee adds financial costs to transfers, thus making transit less attractive. Improving transit service is particularly important for buses, which carry the most passengers, but have suffered the biggest post-ride-hailing ridership loss. To achieve the city's goal of increasing bus ridership by the mid-2020s, planners should explore strategies to shorten travel time and minimize the burden associated with transfers as the city and SEPTA continue to redesign the bus network. While implementing such strategies might require additional financial commitments from both the city and the state, delaying service improvements could have its own costs. If the current ridership decline continues, then the diminishing farebox revenue could strain SEPTA's coffers, which in the long term could force the agency to cut services, chasing away even more passengers.

Although my study focuses on the Philadelphia region, my findings offer insights for other large, multimodal American cities that are witnessing the rapid growth of ride-hailing services. Many big cities and their metropolitan areas have experienced transit ridership declines since the emergence of ride-hailing services. Meanwhile, more and more cities have begun to promote transit to combat the negative externalities of driving. Amid the growing influence of ride-hailing services, transit providers that aspire to stem transit ridership loss might find it crucial to reduce the travel burden of using transit to make transit a more convenient and attractive transport option. Furthermore, cities that aim to improve access for all need to ensure that transit service accommodates female and low-income residents' travel needs.

Finally, ride-hailing services have become and likely will continue to be an integral part of travel within megaregions by providing a convenient alternative transport mode to airports and train stations. My ride-hail survey shows that a significant proportion of ride-hailing trips are airport trips. Transit at airports and train stations might face challenges of recapturing passengers who have switched to ride-hailing services. Despite the popularity of ride-hailing services, however, research shows that reliable, high speed transit services that connects the airport with the city and its public transit system still plays a pivotal role (Dong & Ryerson, 2020). Such findings offer optimism about the future of high-quality transit service as a link in regional travel, especially as airport operators seek measures to reduce curb congestion at terminals while cities continue to promote transit.

## 6.4. Future Research

As ride-hailing services become more popular, there is a need for continued research on the relationship between the services and transit. Scholars might find it necessary to explore ride-hailing services' impact on transit at different time of day. Findings could offer valuable insights for transit agencies to adjust their services throughout the day effectively. As ride-hailing services continue to diversify, it is important to understand passengers' mode choice between transit and various types of ride-hailing services, such as shared ride services (i.e., Lyft Line). It is also crucial for researchers and practitioners to explore how ride-hailing companies might work with transit agencies to improve access for vulnerable populations without adding an undue financial burden to their daily travel.

During my research, I encountered the difficulty of obtaining trip data for ride-hailing services via FOIA requests. The lack of publicly available ride-hailing trip data prevents analyses that could enhance the understanding of the services' impact on transit and the transport system as a whole. This research gap in turn could hinder planners' and policy makers' efforts to design effective strategies in response to the ride-hailing services' increasing influence. SEPTA, for example, was unable to obtain ride-hailing trip data from its partnership with Uber. The lack of trip data makes it difficult to investigate the partnership's effectiveness in attracting customers to use Regional Rail. Currently, only a few cities in the United States require ride-hailing companies to disclose their trip records. To facilitate research and further the discourse on the impact of the increasingly popular ride-hailing services, local and state legislatures should consider requiring ride-hailing companies to share anonymized trip data.

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