

Disruptor of Transportation:
Uber's Effect on Public Transportation In England

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Abstract

Technology is changing how people work and move. One of the quickest services to be created by technology is the gig economy; in turn, the gig economy is shaking the foundations of the transportation market. Leading the way is Uber, a Transportation Network Company, that has successfully used technology to provide cheap and convenient transportation service. Its success is disrupting common ways to travel and commute in private vehicles and public transportation. This paper uses a fixed effect approach to analyze Uber's effect on public transit consumption across England. The results find that collectively, Uber is a substitute for public transportation, but the effect varies by specific public transit mode. Uber is a replacement for bus travel, but it increases rail travel. The goal of this paper is to contribute more information for policymakers as they work with Uber and regulations.

1 Introduction

The convivence that technology brings has changed the market of services. The “gig” or “sharing” economy is one such service that is on the rise. The success of the gig economy stems from the ease and quickness consumers can receive products. The gig economy relies on the use of applications that provide the information on goods and

services, provide the payment method, and offer the consumer and suppliers to rate the service and each other. The largest feature of the gig economy, to other traditional services, is the low cost of employees. Employees working for start-ups such as UberEats, Airbnb, and Deliveroo are paid directly by the consumer while the company takes a portion of the payment. This low-cost model is disrupting traditional service markets.

The rapid growth and high popularity of these services has caused concern over their economic and social effects. Particularly in the transportation sector, the new services of Uber, Lyft and Kabbee are challenging the status quo of traditional transportation. Concern has grown over these companies, that they are reducing the viability of public goods and perhaps eventually replacing existing public transit systems with private alternatives, which could be less inclusive. Lack of regulation and oversight of these companies are being noted, notably with recent issues with licensing for ride-hailing drivers in London. There is also concern that these companies will lure riders away from public transit.

These Transportation Network Companies (TNC), an umbrella term for non-taxi ride-hailing services, argue that their product fills a need in the market where public transportation is falling short. TNCs contend that they solve the first/last mile problem that plagues public transit and are making consumers rethink the need to own a car.

How are the convenience and low costs of TNCs changing the behaviors of consumers regarding the use of public transportation?

This paper looks at the effect TNCs have on public transit ridership in England. Research on the effects of TNCs on public transit ridership has focused almost entirely in the United States, with little to no research on its effects on ridership in England. This is a large shortcoming in the research since England has a long and rich history of public transportation, especially compared to the United States. England has a larger share of its population riding on buses and using passenger rail for travel. This paper aims to unveil any changes in public transit ridership due to the introduction of TNCs. I use a fixed effects regression model to examine the disruption TNCs has caused on public transit ridership. With lower pricing and higher convenience, I find that ride hailing companies are a substitute, drawing riders away from public transportation.

1.2 Background

The transportation shared economy is full of different options including ride sharing, car sharing, bike sharing, and rentable electric scooters. Each of these options plays a role in a consumer's decision to use or not use public transit. This paper will focus on ride-hailing service of Uber. I refer to ride-hailing companies as Transportation Network Companies. The Association of Commuter Travel defines a Transport Network

Company as an “online platform that allows entrepreneurial drivers to find passengers who are seeking one-way rides. [TNCs] use an app-based platform and riders pay the driver using a virtual wallet”¹. Uber is the most prominent example of a TNC. As it was one of the earliest companies to enter the market, it has the largest TNC market share; however, others are beginning to offer competition.

The process of using a TNC closely resembles the process of hailing a taxi, where an individual requests a pick-up from one location to a drop-off at another location.

While TNCs and taxi services are similar in that regard, the higher convenience and lower costs of TNCs are causing taxis to lose market share². It is important to make the distinction between ride hailing and ride sharing. These two services are different.

Transit Magazine defines ride sharing as:

*Ride sharing, to many, is a synonym for carpooling—literally sharing a ride with another passenger. Some “ride-sharing purists” even argue that it is not motivated by profit, but instead for the sake of a social mission—mobility, environmental protection and cost savings.”*³

Of the TNCs currently in operation, this study analyzes Uber specifically because of its early introduction in England and the size of its market share. Uber currently has

¹ Association for Commuter Transportation. “Understanding Commuter Transportation Terms.” September 18, 2014

² USA Today. “Lyft gains on Uber while taxis tank: survey.” July 27, 2017

³ Quoted. “Ride-sharing vs. Ride-hailing: What’s the Difference?” April 13, 2016.

the largest market share among TNCs in England. Riders were first introduced to Uber in San Francisco, California in 2010. The company expanded rapidly worldwide and arrived, only two years after its initial launch, in London in 2012. Since then, Uber has entered all regions of England and is moving into the other areas of the United Kingdom.

Uber's success has been mostly driven by its primary features - flexibility and convenience - relative to private car ownership and public transit. Owning a car incurs significant costs when insurance, maintenance, gases, and taxes are taken into consideration while public transportation requires the user to walk to a station and walk to the final destination. Public transportation often also requires the user to make transfers, possibly from rail to bus or bus to bus. These costs are mirrored by Uber's ability to pick up a passenger with minimal required walking and is able to drop them off directly, with no transfers, at the desired location for similar costs and time.

It is important to define public transportation. Public transportation, also known as public transit, are systems of travel available to the public⁴. They are (Ben-Akiva & Morikawa, 2002) on a schedule and operate on fixed routes. The most common public transit systems include one or more modes, including buses, urban rail, and longer distance passenger rail. Bus travel is the most accessible mode for passengers through dense networks of routes while passenger rail is typically concentrated on specific corridors.

⁴ International Association of Public Transportation "UITP Public Transport Trends Report" 2019

Passenger rail is harder to access since riders must go to specific station, but it provides more frequent services than buses in most travel corridors (Ben-Akiva & Morikawa, 2002). Urban rail is a combination of light rail, trams, and subways, which only service metropolitan areas, while buses and passenger rail operate everywhere.

1.3 Literature Review

Public transportation offers two critical missions: (1) offering an alternative to car travel to reduce the externalities of cars and (2) to provide a level of mobility for all persons, especially the disadvantaged (Guilono, 2011). High level of car travel and car dependence has detrimental effects on society in terms of human physical health and the environment. Cars accounted for over 1,700 deaths in 2018⁵ in the UK, while a typical passenger vehicle emits over 4.6 metric ton of carbon dioxide a year⁶

Public transportation is a more environmentally friendly mode of transportation. It has better fuel efficiency, measured in Person-Miles Per Gallon (PMPG) than single-occupancy vehicles. The average PMGP for buses is 38.3 while passenger trains average PMGP is 71.6. This compare with 37.5 PMPG of a single-occupancy vehicle⁷. A study by the State of Delaware’s transit agency, DART, found that buses with as few as seven

⁵ Department of Transport “Reported Road Casualties in Great Britain” 8 November 2018

⁶ Environmental Protection Agency “Greenhouse Gas Emissions from a Typical Passenger Vehicle” 2020

⁷ True Cost Blog “Fuel Efficiency: Modes of Transportation Ranked by MPG” 2020

passengers are more fuel-efficient than average single-occupancy vehicles when used for commuting. Buses use 8.7% less energy per passenger mile and passenger rail uses 23.7% less energy per passenger mile than a car⁸.

The argument is for public provision of basic mobility. A function of resources, households adapt to limited mobility services by taking fewer trips (Guilono, 2011). The amount of car usage is most affected by income than any other demographic variable. Using the National Travel Survey, Stokes and Lucas (2011) discovered that almost 50% of low-income households reported they did not own a car and did not drive. The assumption made from their research was that the lack of car ownership is a result of low income rather than low income is a result of not owning a car.

Research by Garrett and Taylor (1999) found that there is a relationship between income and mode of transit used. Lower-income riders tended to travel by bus while higher-income riders used light rail or commuter rail. While there is a difference in mode of transit by income levels, a study by Belmonte (2014) found that low-income and high-income riders consume public transit at similar rates.

Most transportation planning theory has been based on the assumption of future universal car ownership (Stokes & Lucas, 2011). This assumption resulted in land-use patterns that are difficult for non-car owners to navigate (Ciommo & Shiftan, 2017). It

⁸ Division of Waste and Hazardous Substances, "The Environmental Benefits of Riding Public Transit"

wasn't until 2003 that it was identified that certain groups were being disadvantaged as a result. The Social Exclusion report identified how transportation policy was exacerbating social and economic inequalities (Stokes & Lucas, 2011). More attention with transportation is focused on increasing public transportation for the disadvantaged.

The impact of TNC spans equity and economics. Transportation planning is running into challenges with the rise of TNCs as technology that is now making it easier for a person to choose to ride in a car over taking bus or rail, safety is a significant issue. Roger (2017) examines Uber's effect on consumer welfare and finds that Uber significantly reduced drunk driving accidents and fatalities and mitigated discrimination against its riders, a problem common with traditional taxis. Roger (2017) reveals that there are safety concerns among Uber drivers and riders and that local governments lack the proper regulations due to Uber's youth in the transportation industry.

Uber's general economic effect is still being understood. Cohen et al. (2016) attempt to capture Uber's impact on the economy through consumer surplus. Using a regression discontinuity design, Cohen et al. (2016) find that Uber generated \$6.8 billion in overall consumer surplus. They see that the demand for Uber is inelastic with consumers insensitive to fare changes, but demand for Uber is more affected by characteristics that are harder to measure, including time of day, weather, or close substitutes.

The disruptions of TNCs are part of the rising sharing economy. Uber is able to mitigate costs by requiring its drivers to provide their own transportation. Taxi and Private Hire Vehicles (PHVs) accounted for only 1.4% of all trips in 2016, which includes ridesharing and ride-hailing services. (TfL, 2018). In London, PHVs have increased to over 77,000 by 2016 (TfL, 2016) with Uber reporting 3.5 million users of its service in London. Berger et al. (2017) exploited Uber's rollout throughout the United States to compare taxi driver wages and employment before and after Uber's entrance. Through difference-in-difference research approach they found that Uber did not affect taxi drivers, mainly due to increase in a shift of drivers switching to Uber.

There is disagreement over the effect of TNCs on transit ridership. Uber could be either a compliment or substitute for public transit. At a quick glance, it is easy to decide that Uber would take riders away from public transit. Hall et al. (2018) show that UberX, a premium Uber service, offers 20-30% reduction in price than that of a traditional taxi. Uber is also more convenient through its smartphone application. Although Uber fares are typically higher than public transit (Hall et al., 2018) the speed of service and the convenience could be enough to outweigh the higher fare cost. Graehler's et al. (2018) inspection of the decrease in public transit ridership in American cities found that when TNCs enter a market, passenger rail ridership fell by 1.3% and the bus ridership fell by 1.7%. Kern (2018) finds evidence through difference-in-

difference that Uber decreased bus ridership but found that Uber increased passenger rail ridership.

Uber could be a compliment of public of public transportation. Uber itself touts that its service helps public transit solve the first/last mile problem. The first/last mile problem refers to the last part of a person's travel. The issue arises because public transit cannot take a rider exactly where they need to go. Often the first and last portions of trips can take the longest, so substituting this with Uber can reduce the time and cost of using public transit (Hall et al., 2018). Hoffmann and Ipeiritis (2016) look at Uber's relationship with the subway in New York City. They find that the increase in Uber pickups and increase in subway usage are positively correlated. TNCs can increase the flexibility of a rider's travel. Public transit relies on fixed timetables. Transit cannot respond to the flexibility a car offers for a person to respond to emergencies or changes in work schedules. Uber fills that flexibility role. Tremblay (2012) found that Uber is complementary to transit but that it takes a long period of time for the relationship to emerge. A combination of TNCs and public transit could make it possible to complete all trips without owning a car.

The remainder of the paper is organized as follows. In section 2, I discuss the data and descriptive statistics. In Section 3, I discuss the hypothesis, the methodology,

and the econometric specifications used in this paper. In section 4, I present the main results of this paper and in section 5, I conclude and discuss areas of future research.

2 Data and Descriptive Statistics

I create our own data base with regional level macro data from various sources. There are nine regions in England: East of England, East Midlands, London, West Midlands, North West, North East, South West, South East, and Yorkshire and the Humber. These regions are non-administrative and are used mostly for statistical purposes⁹. The observations are collected between the years 2004 to 2018. This yearly

⁹ Britannica “Traditional Regions” 2020

range is selected because one data set significantly changed its estimation methods in 2004.

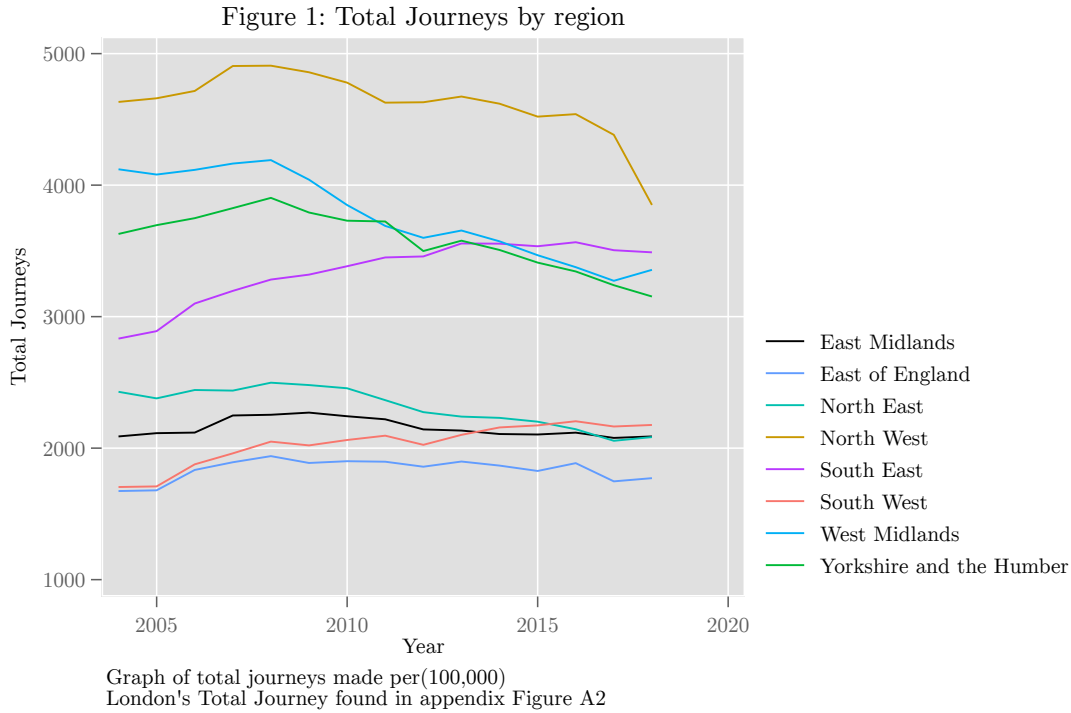


Figure 1 show's each regions' average total journeys per year from 2004 to 2018. Some regions have experienced decline in total transit ridership and other regions show increase in ridership. Due to London's larger ridership number's, it is omitted from this graph. Its average total journeys taken is found in the appendix of Figure A2.

Followed below is a brief description, definitions, and sources of the variables used in the paper. I provide the summary statistics of the variables used in Tables 1 and 2, while Table 3 shows the correlations among the different variables. Table A4 of the cross-correlations of the control variables is found in the appendix.

Table 1: Summary Statistics of Dependent Variables

(1)					
	mean	sd	min	max	count
Total Journeys (100,000)	6515.757	10197.24	1673.846	38108.12	135
Bus (100,000)	4959.799	6117.491	1672.606	23840.86	135
Rail (100,000)	1.669	2.272	.106	9.597461	135
Urban Rail (100,000)	2357.629	4888.872	44	15433	89

Table 2: Summary Statistics of Control Variables

(1)					
	mean	sd	min	max	count
Uber	.281	.451	0	1	135
Population	5876141	1765534	2540000	9121000	135
Area Km ²	14475.44	6133.008	1572	23837	135
Population Density	890.566	1525.545	210.681	5661.578	135
GDPpc	25958.01	7741.431	17216.54	54735.28	135
Unemployment Rate	6.135556	1.870688	3.1	10.8	135
GDHI	17047.19	3563.451	11752	29362	135

Table 3: Cross-Correlation between total journeys and control variables

(1)						
	Total Journeys	Uber	Unemployment Rate	GDP	GDHI	Population Density
Total Journeys	1					
Uber	0.186	1				
Unemployment Rate	0.226	-0.304	1			
GDP	0.910	0.400	0.00170	1		
GDHI	0.691	0.498	-0.157	0.922	1	
Population Density	0.996	0.174	0.236	0.893	0.665	1
<i>N</i>	135					

2.1 Dependent Variables

The variables measuring bus passenger journeys¹⁰ and urban rail journeys¹¹ are from the Department of Transportation (DfT) or the Office of Rail and Road (ORR)¹². The regions are the smallest unit of observation publicly available and are important to control for region specific effects.

Bus passenger journeys is the measure of unlinked journeys made by year.

The journeys are provided by the PSV operators survey. It provides information on

¹⁰ Bus statistics available from https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/852284/bus0108.ods

¹¹ Urban Rail Journeys available from https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/894620/lrt0101.ods

¹² Rail statistics available from <https://dataportal.orr.gov.uk/statistics/usage/regional-rail-usage/>

passenger journeys, vehicle miles, and operating costs¹³. *Rail passenger journeys* is the measure published by the ORR using the LENNON (Latest Earnings Earned Nationally Networked Over-Night) which is the rail’s ticketing and revenue system and has been used to calculate regional rail usage since 2003. The *urban rail journeys* data set is compiled by the DfT using responses to the Light Rail and Tram Survey. This survey collects information on light rail and tram system (urban rail) use and covers urban systems that sit outside the UK national rail network¹⁴. I exclude the systems that are not part of the nine regions of England.

2.2 Uber Variable

There is no official data set of compiled areas that Uber is operating. The closest is a list of cities in which it operates. Due to the passenger journey data being restricted to the regions, we assume that if Uber operates in the cities in the region, it is operating in the entire region. When Uber entered a market was collected through official Uber press releases and/or local news articles. *Uber* is coded as a binary variable with 0 when Uber is not present in the region and switches to 1 when Uber arrives into the region.

¹³ Department of Transport “Bus Statistics Quality Report”, 2019

¹⁴ Department of Transport “Light Rail and Tram Statistics: Quality Report” 2019

2.3 Control Variables

GDP (GDP per Capita) is the gross domestic product of the region divided by its population. The data is in pounds and is provided by the Office of National Statistics¹⁵

Population refers to the total population of each of the regions each year. Population estimates were provided by Eurostat. The population variable is used to calculate GDP per capita and the population density. **Population Density** is the population divided by the Km^2 of each region.

The unemployment rate was provided by the Office of National Statistics (ONS). The unemployment rate gathered by the ONS through the Labour Force Survey. Unemployment measures people without a job have been actively seeking work within the last four weeks. ONS reports the regional estimates for the unemployment rate are more volatile compared to the country rate.

GDHI (Gross Disposable Household Income) is obtained by the ONS. The gross disposable household income (GDHI) is the amount of money that individuals have available to spend or save after they paid taxes and received any direct benefits. It is considered a reflection of “material welfare”¹⁶. Regional GDP numbers was also provided by the ONS. The ONS uses estimates of VAT returns to calculate a regions gross domestic product.

¹⁵ONS: <https://www.ons.gov.uk/>

¹⁶ Office of National Statistics “Regional Gross Disposable Household Income” 2018

3 Methodology

3.1 Hypothesis

Opportunity costs, substitution and income effects, and normal and inferior goods are noted as key economic concepts consumers consider when deciding on a travel mode. These concepts are considered when developing a hypothesis on TNCs and its relationship to public transit. Does the emergence of Uber affect the regions consumption of public transit? If so, is it a compliment or substitute? Does the mode of transit - bus, urban rail, or passenger rail - determine if Uber is a compliment or substitute? Considering the economic theories, the main hypothesis is H_1 : Uber will have a negative impact on the public transit ridership across England and by region. H_2 : Uber will have a larger negative impact on bus ridership than the other modes of transit. H_3 : Uber will have a positive impact on both urban and passenger rail ridership.

H_1 , as the main hypothesis, is predicting that Uber's lower costs and higher convenience will have a statistically significant negative impact on the consumption of public transit. Uber will act as a substitute since buses have the highest opportunity costs when looking as a function of income, distance, and travel of the different transit modes. This makes it the most likely of the three to be replaced with a more convenient form of travel. Based on the literature, Uber's ability to resolve the first/last mile problem that faces rail travel. Uber will be a complimentary good for both types of rail, making it easier

for commuters to arrive at the rail stations. I suspect Uber's effect on urban rail will be more ambiguous compared to buses and passenger rail. There is less research conducted on TNCs and urban rail. Due to the nature of its smaller service area, the results may be insignificant to the size of the regions used in my analysis.

3.2 Empirical Model

Empirically, I want to identify the effect Uber's entrance has on public transit ridership. The basic econometric specification is given by equation (1) below:

$$Y_{i,t} = \beta_0 + \beta_1 Uber_{i,t} + \beta_{i,t} \sum X_{i,t} + \alpha_i + \gamma_t + \epsilon_{i,t}$$

where Y_{it} is the passenger journeys Y in region i in year t . $Uber_{i,t}$ is the indicator variable of Uber's presence in region i and year t , which is our main variable of interest. $X_{i,t}$ represents the observable time varying control variables such as GDP and GDHI. α_i represents the regional fixed effects, γ_t represents year fixed effects, and $\epsilon_{i,t}$ is the error term which includes any omitted variables not controlled for in the model or by regional and yearly fixed effects.

The main coefficient of interest is β_1 , which represents the effect Uber has on passenger journeys. Following my hypothesis in section 3.1 and motivated by the

previous literature I expect β_1 to be negative and significant for total passenger journeys but positive and significant for rail and urban rail travel. I also expect β_1 to be negative and significant for bus passenger journeys.

To obtain a consistent estimation of β_1 I rely on panel identification with region fixed effects and year fixed effects. The inclusion of these controls is supported by the literature to be important for determining public transit ridership.

To accommodate outliers in the data, I take a log of my control variables. Figures A3 to A6 show that the logged control variables become normally distributed. Since I want to measure the elasticity, I take the logs of our dependent variables *log_total*, *log_bus*, *log_rail*, *log_urban*.

4 Results

4.1 Baseline Specification – Region and Time Fixed Effects Model

In this section I provide the main results of our paper following the specification of equation (1). A Hausman test confirms that fixed effect is preferred over random effects. All specifications in this section include regional fixed effects in addition to other controls. I always use robust standard errors clustered at the regional level.

I begin by running our dependent variable *log_total* of the total ridership of the three modes of public transit. We observe that Uber significantly decreases public

transit journeys by between 5% to 7%. This is demonstrated in the first column and the subsequent columns, which we add different time varying controls.

Table 5: Effect on Uber on Total Passenger Journeys

	(1)	(2)	(3)	(4)
	log total	log total	log total	log total
1.uber	-0.0725** (0.0174)	-0.0650** (0.0137)	-0.0639** (0.0173)	-0.0554* (0.0186)
GDPpc	0.254 (0.206)	-0.616** (0.168)	-0.617** (0.166)	-0.162 (0.483)
Pop Density	-	2.784*** (0.327)	2.777*** (0.376)	3.085*** (0.304)
Unemployment	-	-	0.00223 (0.0308)	0.0278 (0.0432)
GDHI	-	-	-	-0.510 (0.430)
_cons	17.18*** (2.087)	8.895** (2.217)	8.938** (2.132)	7.344* (2.337)
<i>N</i>	135	135	135	135
adj. <i>R</i> ²	0.070	0.337	0.332	0.342

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In column 2, I add population density and observe that it is the denser the region, the less the impact Uber has on journeys. In columns 3 and 4, I add unemployment rate and GDHI respectively and I see that adding both slightly reduces Uber's effect on journeys. Column 4 is chosen as my preferred specification since it includes a wide set of controls that the literature found to be important.

In table 6, I analyze the effects that Uber has on the different modes of public transportation journeys. Each of the columns represents a different mode of transportation. I observe that Uber has a negative and significant effect on bus journeys, reducing journeys by 6.5% when uber enters a region. In column 3, I find that Uber has a positive and significant effect on rail journeys. When Uber enters a region rail journeys increase by 7.6%. Uber's effect on urban rail is insignificant. This may be due to the form of urban rail itself. Subways and trams are often used by tourism or light traveling than for commuting, which means consumers are seeking these modes for different reason than they would be for seeking bus or rail. Thus, Uber's introduction does not affect these systems.

Table 6: Effect on Uber by Transit Mode

	(1)	(2)	(3)	(4)
	Total	Bus	Rail	Urban Rail
1.uber	-0.0554 [*] (0.0186)	-0.0658 ^{**} (0.0144)	0.0764 ^{**} (0.0214)	0.134 (0.121)
GDPpc	-0.162 (0.483)	-0.169 (0.462)	1.889 ^{**} (0.535)	2.463 [*] (0.923)
Pop Density	3.085 ^{***} (0.304)	2.716 ^{***} (0.391)	-0.498 (1.146)	1.612 (1.886)
Unemployment	0.0278 (0.0432)	0.0350 (0.0420)	0.311 ^{**} (0.0836)	-0.0145 (0.0783)
GDHI	-0.510 (0.430)	-0.434 (0.436)	-0.0924 (0.504)	-2.237 [*] (0.609)
_cons	7.344 [*] (2.337)	8.846 ^{**} (2.389)	-4.412 (4.390)	-7.740 (6.308)
<i>N</i>	135	135	135	89
adj. R^2	0.342	0.325	0.857	0.368

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5 Conclusion and Further Research

This paper examines the effect that Uber's presence in England has on public transportation ridership. Through use of regional fixed effects, I show that Uber does have a significant effect on public transportation ridership. On aggregate, Uber negatively effects passenger journeys but when broken by mode the results vary. For bus

transit, Uber still causes a decrease in ridership but increases ridership for rail journeys, while there is no significant effect on urban rail.

It is clear that the dynamics of public transit are changing, and it is clear that TNCs are the cause. Uber is taking passengers away from one mode and taking them to another, but it is not clear if Uber is an absolute substitute or compliment for public transportation. This has major implications for public transportation planners and policymakers. The equity view, if bus services are restricted or even cut due to lower ridership, the poor will be most affected. They are most reliant on buses for work commuting and other transport needs. While policymakers, who want to reduce single car use, could partner with Uber to get more people to train stations to use rail.

This paper opens door for further research. Obtaining ridership data on the city level would allow researchers to conduct a difference-in-difference experiment to compare cities ridership levels before and after Uber's entry. There also warrants further investigating on commuting decision-making of individuals when a TNC is in the market.

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Appendix

Table A1: Summary Statistics of Dependent Variables

(1)					
	mean	sd	min	max	count
Total Journeys (100,000)	6515.757	10197.24	1673.846	38108.12	135
Bus (100,000)	4959.799	6117.491	1672.606	23840.86	135
Rail(100,000)	1.66854	2.271579	.1061926	9.597461	135
Urban Rail (100,000)	2357.629	4888.872	44	15433	89

Table A2: Summary Statistics of Control Variables

(1)					
	mean	sd	min	max	count
Uber	.2814815	.4513967	0	1	135
Population	5876141	1765534	2540000	9121000	135
Area Km^2	14475.44	6133.008	1572	23837	135
Population Density	890.5661	1525.545	210.6809	5661.578	135
GDPpc	25958.01	7741.431	17216.54	54735.28	135
Unemploye nt Rate	6.135556	1.870688	3.1	10.8	135
GDHI	17047.19	3563.451	11752	29362	135

Table A3: Cross-Correlation between total journeys and control variables

(1)

	Total Journeys	Uber	Unemploy ment Rate	GDP	GDHI	Populatio n Density
Total Journeys	1					
Uber	0.186	1				
Unemploy	0.226	-0.304	1			
GDP	0.910	0.400	0.00170	1		
GDHI	0.691	0.498	-0.157	0.922	1	
Population Density	0.996	0.174	0.236	0.893	0.665	1
<i>N</i>	135					

Table A4: Cross-Correlations between control variables

(1)

	Unemployment Rate	GDP	GDHI	Population Density
Unemployment Rate	1			
GDP	0.00170	1		
GDHI	-0.157	0.922	1	
Population Density	0.236	0.893	0.665	1
<i>N</i>	135			

Table A5: Effect on Uber on Total Passenger Journeys

	(1)	(2)	(3)	(4)
	log_total	log_total	log_total	log_total
1.uber	-0.0725** (0.0174)	-0.0650** (0.0137)	-0.0639** (0.0173)	-0.0554* (0.0186)
GDPpc	0.254 (0.206)	-0.616** (0.168)	-0.617** (0.166)	-0.162 (0.483)
Pop Density	-	2.784*** (0.327)	2.777*** (0.376)	3.085*** (0.304)
Unemploy ment	-	-	0.00223 (0.0308)	0.0278 (0.0432)
GDHI	-	-	-	-0.510 (0.430)
_cons	17.18*** (2.087)	8.895** (2.217)	8.938** (2.132)	7.344* (2.337)
N	135	135	135	135
adj. R^2	0.070	0.337	0.332	0.342

Table A6: Effect on Uber by Transit Mode

	(1) Total	(2) Bus	(3) Rail	(4) Urban Rail
1.uber	-0.0554 [*] (0.0186)	-0.0658 ^{**} (0.0144)	0.0764 ^{**} (0.0214)	0.134 (0.121)
GDPpc	-0.162 (0.483)	-0.169 (0.462)	1.889 ^{**} (0.535)	2.463 [*] (0.923)
Pop Density	3.085 ^{***} (0.304)	2.716 ^{***} (0.391)	-0.498 (1.146)	1.612 (1.886)
Unemploy ment	0.0278 (0.0432)	0.0350 (0.0420)	0.311 ^{**} (0.0836)	-0.0145 (0.0783)
GDHI	-0.510 (0.430)	-0.434 (0.436)	-0.0924 (0.504)	-2.237 [*] (0.609)
_cons	7.344 [*] (2.337)	8.846 ^{**} (2.389)	-4.412 (4.390)	-7.740 (6.308)
<i>N</i>	135	135	135	89
adj. <i>R</i> ²	0.342	0.325	0.857	0.368

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure A1: Total Journeys by region

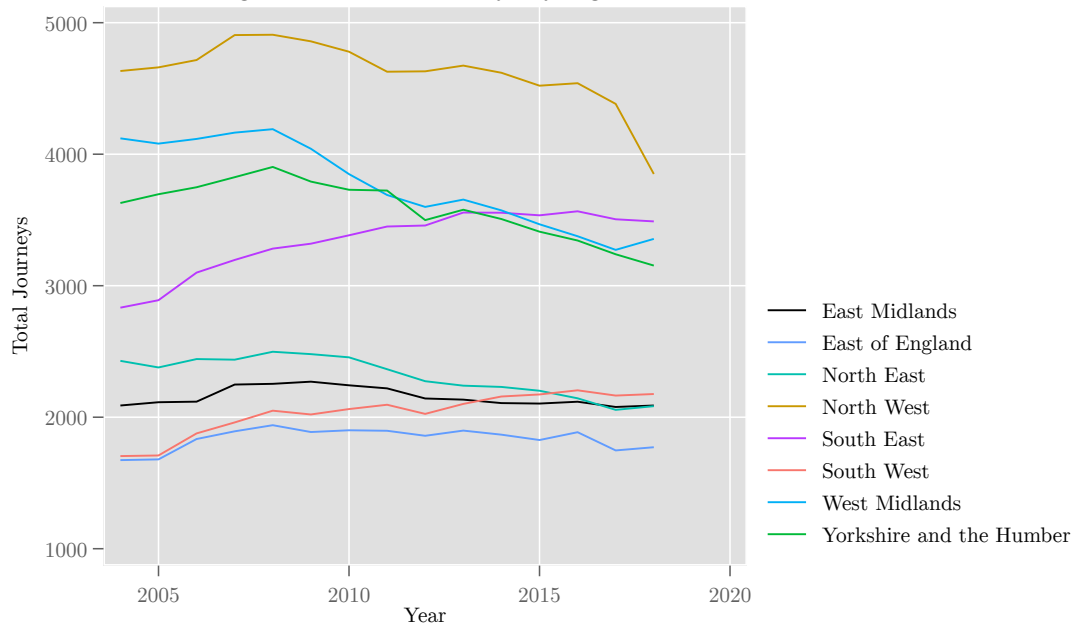


Figure A2: London
London

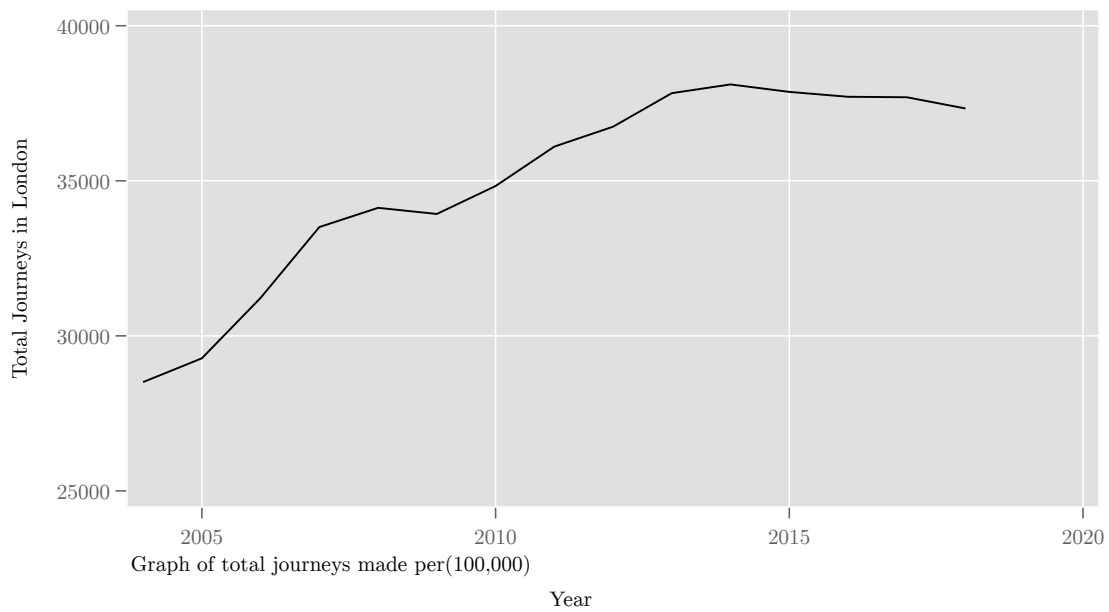


Figure A3: Histogram of Log GDP

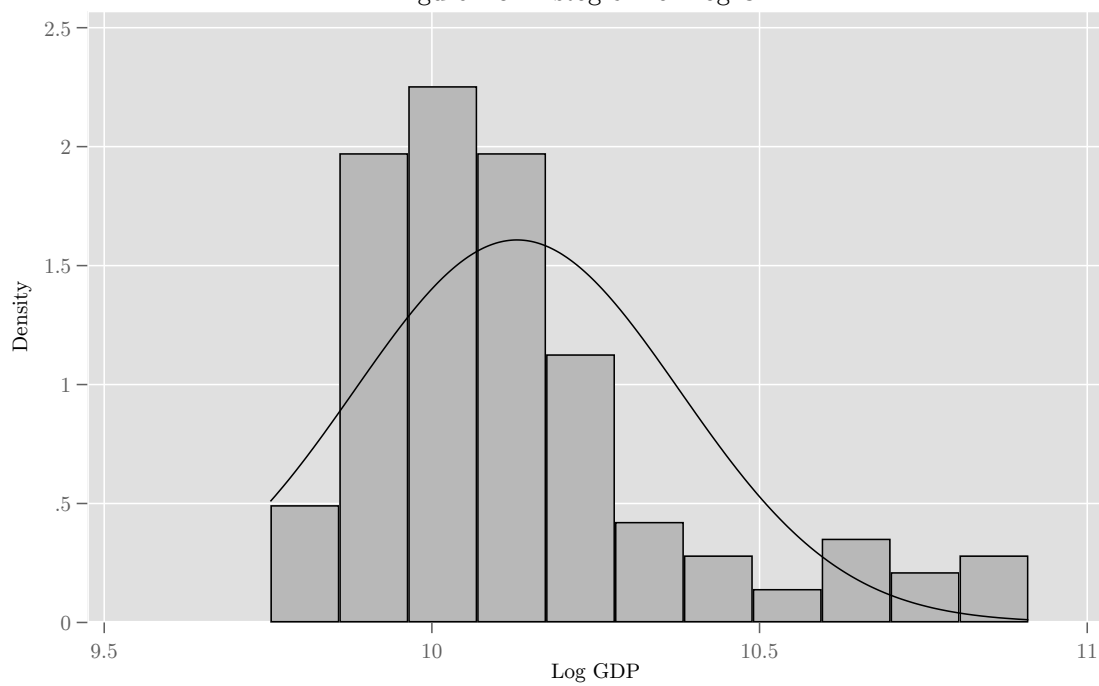


Figure A4: Histogram Log GDHI

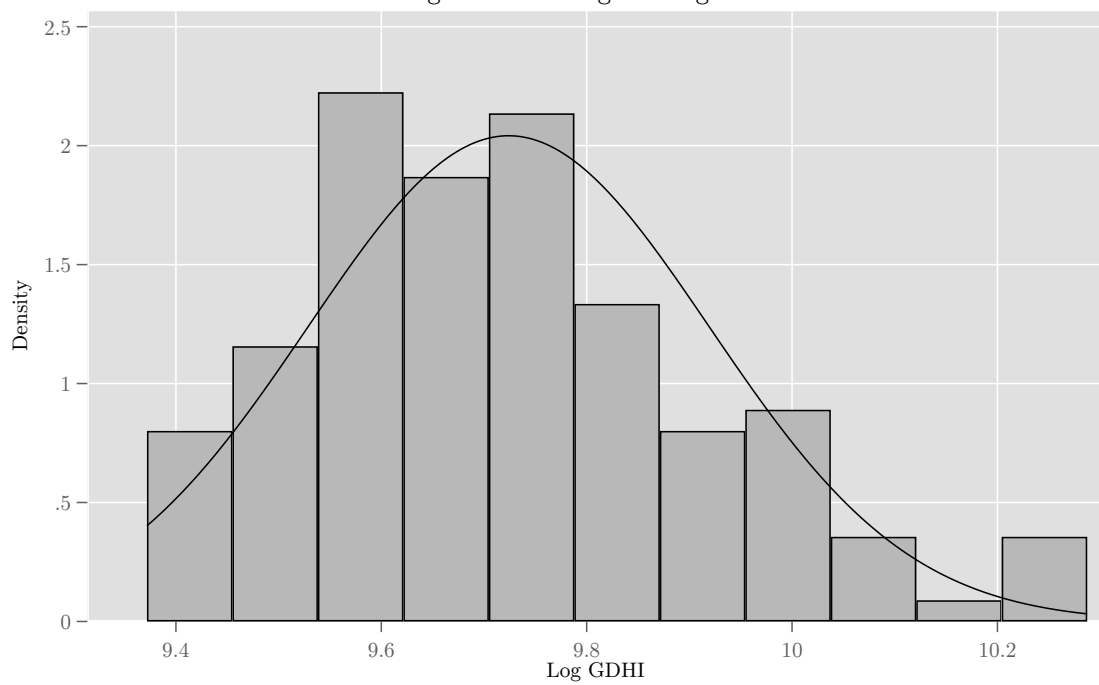


Figure A5: Histogram Log Unemployment Rate

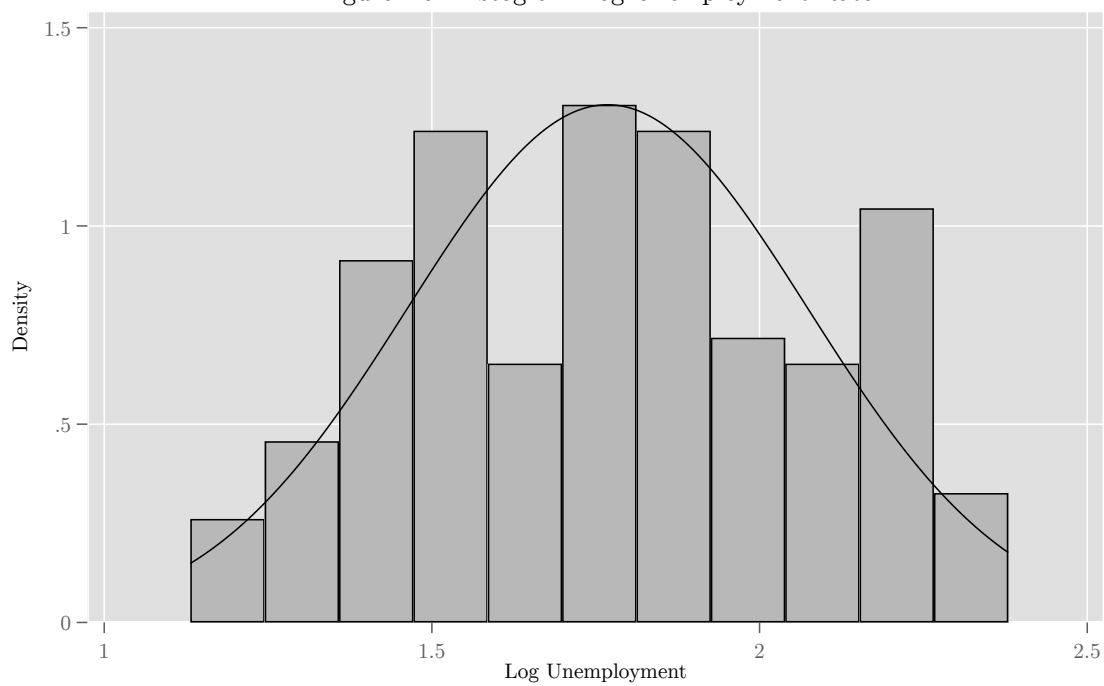


Figure A6: Histogram Log Population Density

