STUCK IN TRAFFIC: MEASURING CONGESTION EXTERNALITIES WITH NEGATIVE SUPPLY SHOCKS

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Abstract

Traffic congestion is one of the most challenging issues of urban agglomeration. Congestion costs are often higher than their socially optimal levels, and little is known about the key parameters needed to design optimal congestion policies. This paper addresses this issue exploiting an exogenous reduction in for-hire vehicle supply in New York City. I estimate the effect of a vehicle on congestion and document substitution patterns to other transportation modes. A 9.1 percent reduction in the number of active vehicles decreases congestion by 0.46 minutes per mile. As vehicles leave the streets, for-hire trips decrease, resulting in increased waiting times and people switching to other transportation modes. Welfare increases for those who travel by vehicle because travel time is reduced. However, welfare decreases for those who face increased wait times or switch to a less-preferred transportation mode. A calibration exercise suggests daily net welfare gains between $8 and $13 million.

Keywords: Congestion, externalities, transportation, travel speed, for-hire vehicles, welfare trade-offs
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1 Introduction

Traffic congestion is one of the most challenging issues of urban agglomeration. People residing in large, medium, and small cities all report that congestion is their primary concern (Bloomberg, 2018). Traffic causes substantial costs. For example, in 2018, across the 25 most congested cities in the United States, the average driver spent 106 more hours traveling than they would have in free-flow conditions, at a total cost of $72.6 billion (Reed and Kidd, 2019). These costs are unavoidable as they are a consequence of the concentration of economic activity in urban areas, and they reduce one of the most important benefits of cities: the ability to easily connect with others (Glaeser, 2011). The problem is that congestion costs are often higher than their socially optimal levels because of a missing market problem: roads are generally not priced. Thus, individuals favor private and for-hire vehicles that offer on-demand and personalized travel experiences without internalizing the negative externalities (increased travel times due to congestion, pollution) associated with the use of these vehicles.

To address this problem, cities have implemented a range of measures to limit the use of on-demand vehicles. The effectiveness of these policies depends on how closely they approximate the optimal level of a Pigovian tax on road usage. However, relatively little is known about the key parameters needed to design an optimal congestion policy, such as quantification of how an additional vehicle affects travel speed in a city grid and measurement of substitution patterns across other transportation modes. Evaluating these parameters presents an identification challenge. The number of active vehicles in a city is endogenously determined by interactions across demand for different transportation modes (including private vehicles), supply of for-hire vehicles, and supply and demand of other commercial vehicles. Given this market, identifying how an additional vehicle affects speed and other transportation modes requires varying the number of vehicles whilst holding demand constant.

This paper estimates the effect of a vehicle on traffic congestion and documents the substitution patterns to other transportation modes caused by changes in the number of on-demand vehicles in a city. I study these effects in New York City during the period 2009–2017. Because the number of vehicles in a city is endogenous, the ideal setup for identifying effects on congestion would be to randomly take cars off the streets in a way that is not anticipated by demand and commercial agents. I exploit a natural experiment that mimics this ideal intervention. According to the Taxi and Limousine Commission (TLC, 2018), 57.5 percent of taxi drivers and 33.1 percent of other for-hire drivers in New York City come from countries with large Muslim populations. This suggests that Islam is the main religion of for-hire drivers, while only three percent of the city's overall population is Muslim (PEW Center, 2014). Islam has two major holidays of similar significance to Christmas for Christians, and their dates change every year following the lunar calendar. For example, one of these holidays occurred on Sunday, November 6 in 2011, Friday, October 26 in 2012, and Tuesday, October 15 in 2013. This fact makes it difficult for non-Muslims to anticipate these holidays. Thus, we can expect that the number of vehicles on the road in the city decreases during Muslim holidays because many drivers do not work on those days, while the city's population is oblivious to them. In this context, the identifying assumption is that all other determinants of the number of active vehicles are orthogonal to the dates of Muslim holidays. Intuitively, this means that during Muslim holidays, demand for for-hire vehicles and other transportation modes does not change, and I show evidence supporting this identifying assumption. Thus, any change in travel speed in the city should correspond to the exogenous reduction in the number of for-hire vehicles on these days.

Measuring how an additional vehicle affects congestion requires a travel speed measure that can capture changes across the city. Due to the complexities of traffic as a dynamic and nonlinear phenomenon, engineering models and traditional speed measures focus only on small subsets of streets (Bando et al., 1995; Wen, 2008). However, this approach does not capture congestion externalities that propagate throughout the whole city grid. A jammed street can increase or decrease travel speeds in different sections of the city, making the average speed of a trip that crosses multiple sections uncertain. This overall speed is the relevant measure for congestion because individuals care about their total travel time. I capture the effect of an additional vehicle on total travel speed by estimating effects on the average speed of taxi trips in the city. New York City reports detailed data on every trip made by taxis and other for-hire vehicles, including the average speed. Taxi speed captures congestion spillovers in the city because these trips cover different areas in the city and the destinations are unknown to the driver before the trip starts, which prevents selection.

The results show that taking vehicles off the streets significantly increases travel speed in the city. The estimates indicate that the number of active taxis decreases by 1,000 (9.1 percent of the total) during Muslim holidays, which decreases time per mile traveled (the inverse of speed) by 0.46 minutes (7.1 percent of a baseline of 6.5 minutes per mile). These effects imply an elasticity of 0.78. The results are robust to accounting for noise in the data generation process using randomization inference. Also, I rule out the possibility that effects on travel speed can be explained by changes in the composition of the for-hire driver workforce during Muslim holidays, and I present suggestive evidence that traffic flow increases as the number of active vehicles in the city decreases.

Fewer vehicles on the streets imply that people will substitute across transportation modes. People have other, less attractive, transportation alternatives. The results show that during Muslim holidays, taxi and other for-hire trips decrease between 1.6 percent and 16.4 percent. Moreover, the estimates indicate that the number of passengers per taxi trip decreases by 1.2 percent, suggesting that some people are not willing to wait because of increased waiting time. People who cannot find a taxi or for-hire vehicle have to switch to other transportation modes. During Muslim holidays travel distance in taxis increases between 2.1 and 3.4 percent. Since the median trip travels 1.8 miles, these estimates suggest that people who want to go somewhere reasonably near might switch to walking. Using data on bike and subway ridership, I find there is no effect on bike usage, and the estimates are too imprecise to quantify effects on subway rides.

While limiting on-demand vehicles increases travel speed, it also implies a welfare loss because some people cannot use their preferred transportation mode and have to switch to a second-best alternative like public transportation. Moreover, in some cities, public transportation operates close to its full capacity and taking a large influx of new passengers would lower its quality (Moss et al., 2018). This would translate into further welfare losses. Thus, to define an optimal traffic regulation policy, it is important to quantify and balance the welfare trade-offs between congestion costs and substitution of transportation modes (Stopher, 2004). Understanding these trade-offs is also important to asses the political acceptability of congestion-managing policies which tends to be limited (Small et al., 2007).

I quantify the welfare trade-offs driven by the reduction of for-hire vehicles during Muslim holidays. Conceptually, from the demand side, the change in consumer surplus is ambiguous. For those who still travel via vehicle, welfare increases because travel time is reduced. But those residents who face increased wait times or who switch to a less-preferred transportation mode will suffer from reduced welfare. I follow Anderson's (2014) transportation demand model that allows matching the parameters that define consumer surplus changes to the reduced-form estimate of the speed change. Welfare calibrations that consider the trade-off between travel speed and waiting times suggest that consumer surplus in the city increases between \$8 and \$13 million per day depending on assumptions about wait time. An important caveat is that this calibration recovers the welfare changes of a short-term, unanticipated reduction in the number of active vehicles. A long-lasting reduction could magnify substitution effects that lead to a reduction of consumer surplus. In this sense, the calibrations in this paper represent an upper bound of potential welfare changes from congestion.[1]

This study's findings contribute to two literatures. The first is a literature on policies and economic factors that affect traffic congestion. The majority of this research focuses on the effects of policies that restrict the number of vehicles on pollution, but do not estimate effects on congestion directly (Small and Gomez-Ibanez, 1999; Small et al., 2007; Davis, 2008; Gallego et al., 2013; Chen et al., 2013; Viard and Fu, 2015; Carrillo et al., 2016). A second group studies the effects of public transportation on ridership, congestion and related outcomes (Baum-Snow et al., 2005; Anderson, 2014; Bauernschuster et al., 2017). These studies find that public transit helps reduce driving times in major freeways and decreases total car hours in an economically significant way. Finally, Mangrum and Molnar (2018) study the effect of new taxis on congestion. The authors estimate the local effect of the introduction of the green taxi program in the outer boroughs of New York City, focusing on the boundary of this program in northern Manhattan. They find lower travel speeds in the vicinity of the boundary due to these new taxis, and use aerial photographs to quantify taxi supply and extrapolate this effect to lower Manhattan.

My study contributes to this literature in several ways. First, this paper quantifies the effect of an additional vehicle on total travel speed, a missing parameter for the design of congestion policies. The measure of travel speed and the nature of the supply shock capture all congestion spillovers that propagate throughout the whole city grid. As discussed above, focusing on congestion locally using a subset of roads, does not capture speed changes in other sections of the city indirectly affected by that congestion. Hence, the estimated effect on travel speed represents the change in total travel

[1]This calibration does not include welfare gains through lower air pollution (Currie and Neidell, 2005; Currie and Walker, 2011; Chen and Whalley, 2012; Bento et al., 2014; Bauernschuster et al., 2017; Simeonova et al., 2018).

time, which is welfare relevant, and can be directly used by policymakers to design Pigovian taxes for roads that reduce congestion externalities to their optimal levels. Second, the estimates can be informative in other contexts, insomuch as the general characteristics of traffic in New York City by borough and day time extend to many metropolises in the world. I estimate the change in total travel speed for different sections of the city and day times to capture how it varies when overall vehicle density changes. This can help match the estimated changes in travel speed to other locations by vehicle densities, expanding the external validity of the results. Third, quantifying the welfare trade-offs of the reduction of vehicles during Muslim holidays provides a relevant bound to guide the design of policies that seek to decrease congestion and evaluate their political viability.

Additionally, this study contributes to the nascent literature on taxis and other for-hire vehicles. Research on taxis has focused on understanding supply behavior, market frictions, and moral hazard.[2] Most recent research has focused on Uber and other ride-sharing companies, evaluating their effects on drunk driving and fatalities, their interrelation with taxis and public transportation, labor supply, and consumer surplus.[3] This paper adds to this literature by quantifying how for-hire vehicles affect travel speeds in a dense city.

2 Travel Speeds and For-Hire Vehicles in New York City

2.1 Travel Speed in New York City

Travel speed in the city, measured by taxis' traveling speed, has decreased since the third quarter of 2013. Figure 1 shows that until that point, travel speeds were stable and fluctuated around 13 miles per hour. The summer quarter experiences a boost in speed consistent with fewer vehicles. However, since the third quarter of 2013, travel speeds decreased in the city, reaching an average close to 11 miles per hour by the end of 2017. Changes in velocity in Manhattan drove this decrease. Up to 2013, travel speed in Manhattan fluctuated close to 12 miles per hour and decreased to less than 10 miles per hour by the end of 2017. Conversely, speed in the outer boroughs has remained stable in 2009–2017, fluctuating around 16 miles per hour.

[2] See Camerer et al. (1997); Farber (2005, 2008, 2015); Jackson and Schneider (2011); Haggag et al. (2017); Buchholz (2017); Frechette et al. (2018); Thakral and Tô (2019).

[3] See Moskatel et al. (2017); Peck (2017); Dills and Mulholland (2018); Barrios et al. (2018); Cramer and Krueger (2016); Hall et al. (2018); Brodeur and Nield (2018); Hall and Krueger (2017); Cook et al. (2018); Cohen et al. (2016).

[Figure 1 about here]

2.2 Taxis in New York City

There are two types of taxis in New York City: yellow taxis and green taxis. The TLC determines the number of vehicles, driver licenses, and fares for both types of taxis. There are 13,587 yellow taxi medallions. Of these medallions, 58 percent operate through fleet garages that lease taxis to individual drivers with hack licenses. Drivers lease a car for a fixed period, usually 12 hours, paying a fixed fee plus fuel (Farber, 2015). The driver keeps the fare and tips. The rest of the yellow taxi medallions (42 percent) are individually owned and may or not be driven by its owner.

Traditionally, yellow taxis concentrated in Manhattan, south of 110th Street and in the airports, leaving the rest of the city with limited coverage. To address this issue, the TLC introduced green taxis to New York City in August 2013. These taxis work like yellow cabs but can only pick up passengers in the outer boroughs excluding the airports, or north of East 96th Street and West 110th Street in Manhattan. In 2017, there were 4,245 licensed green taxis.

Until September 4, 2012, taxi fares consisted of an initial charge of \$2.50 plus \$0.40 per every fifth of a mile when traveling above 12 miles per hour or per every 60 seconds at lower speeds including stops. From September 4, 2012, the TLC increased the travel charge to \$0.50. Additionally, there is a \$0.50 night surcharge (8 pm to 6 am), a \$1 rush-hour surcharge (4 pm to 8 pm), a \$0.30 improvements surcharge, and since February 2019, a congestion surcharge of \$2.50 (\$2.75 for green taxis) if the trip passes through Manhattan south of 96th Street. Trips from and to JFK Airport have a \$52 rate plus \$4.50 in rush hours, and trips to Newark Airport have an extra \$17.50 charge on the regular fare.

2.3 Uber and Other For-Hire Vehicles in New York City

Since 2011, ride-sharing companies disrupted the for-hire vehicle market in New York City. In May 2011, Uber started operating in the city, and it introduced its ride-sharing service UberX in April 2013. It was joined by Via in 2013, Lyft in 2014, and Juno in 2016. As Parrot and Reich (2018) point out, these companies' business model relies on attracting a large number of drivers who flexibly determine their driving hours. This model allowed these companies to avoid regulatory limits on the number of for-hire vehicles in the city. Ride-sharing companies set prices using algorithms that account for supply and demand of rides in local areas. Prices surge when demand is high, or supply is low. Thus, these companies constantly look for new drivers to increase their supply and keep prices low. Given this business model, low prices tend to increase a company's market share. Most drivers who work with these companies work full time shifts (Parrot and Reich, 2018).

Ride-sharing companies operate through cellphone apps that allow people to request a drive in real time. Cramer and Krueger (2016) find that in most markets this technology is more efficient than street-hailing to match drivers with a passenger. However, they also find that this is not true in New York City, where taxis and Uber have similar capacity utilization rates making them close substitutes. The authors argue that this could be the result of the city's high population density.

[Figure 2 about here]

The entry of ride-sharing changed travel in New York City. Figure 2 shows the total number of taxi and other for-hire vehicle rides in 2009–2017. Until 2015, there were approximately 40 million taxi rides per quarter of the year. With the entry of Uber and other ride-sharing companies, taxi rides fell to around 30 million per quarter in 2017. Additionally, ride-sharing companies captured an extra 40 million rides from other transportation modes. The growth of rides from Uber and other for-hire vehicles goes in line with the increasing number of these vehicles in the city. According to the TLC (2018), the number of active for-hire vehicles increased from 24,995 in January 2015 to 90,436 in December 2017.

The growth of for-hire vehicles spurred a policy debate in New York City. Policymakers increasingly worry about how the increasing number of for-hire vehicles affects congestion, safety, and income of taxi and for-hire drivers in general. In August 2018, the TLC temporarily froze new vehicle licenses for one to study the effects of the growth of these vehicles. Since then, New York has adopted three policy measures. First, the TLC mandated new per-mile and per-minute rates for all drivers of ride-sharing companies with the goal of increasing their earnings to at least $27.86 per hour. The new rates were applied in February 2019. Second, as mentioned above, the state of New York imposed a congestion fee for taxis and for-hire vehicles that enter Manhattan south of 96th Street. Third, in March 2019 the city and the state authorized a plan to implement congestion tolls in 2021.

2.4 Driver Ethnicity and the Supply of For-Hire Drivers

According to TLC (2018), taxi and other for-hire vehicle drivers are predominantly men (97 percent) with an average age of 46 years. The TLC reports that these drivers have a diverse ethnic background. Only nine percent of all drivers were born in the United States and 57.5 percent of taxi drivers and 33.1 percent of other for-hire drivers come from countries with large Muslim populations like Bangladesh, Pakistan, India, and Egypt. This suggests that while Muslims represent only three percent of New York City's population (PEW Center, 2014), Islam is the main religion of for-hire drivers in the city. Thus, we can reasonably expect that many drivers respond to Muslim holidays, while the majority of the population in the city is oblivious to them.

Eid al-Fitr and Eid al-Adha are the two most important holidays in Islam. While specific traditions vary by country, Muslims in the United States celebrate and observe these holidays even though neither Eid al-Fitr nor Eid al-Adha are recognized as federal holidays.[4] Muslims celebrate by gathering with family and friends, similar to celebrating Christmas for Christians. Eid al-Fitr marks the end of Islam's holy month of Ramadan. In the United States, celebrations of Eid al-Fitr start in the evening breaking fasting with feasts with family and friends and continue with morning congregational prayers (Al-Islam, 2019; Khan, 2017; Huffington Post, 2017; Rojas, 2018). Eid al-Adha commemorates the willingness of Abraham to sacrifice his son. As with Eid al-Fitr, the celebration of Eid al-Adha in the United States is about gathering in community. This holiday involves dressing up, going to the mosque for prayers in the morning, following with a feast of meals, visiting family and friends and exchanging gifts (Pervez, 2015; Peyton, 2018). The dates of Eid al-Fitr and Eid al-Adha are determined by the lunar calendar and change every year (Appendix Table A1). In 2009–2017, Eid al-Fitr was mostly during the summer and Eid al-Adha was between September and November.

Given the significance of these two holidays, it is possible that Muslim taxi and for-hire drivers will either not work or reduce the length of their shifts. This should reduce the number of for-hire vehicles in the city, which would reduce congestion on those dates. Since Muslims are only three percent of the total population in New York City but potentially more than a third of the drivers, the drop in the number of vehicles due to these holidays would correspond to an exogenous shift

[4] New York Public Schools included Eid al-Fitr and Eid al-Adha as holidays starting in 2016.

in supply and not in demand of for-hire vehicles. Moreover, the fact that the date of the Muslim holidays changes every year implies that it is difficult for non-Muslims to anticipate these shocks to supply, making them as-good-as random for potential passengers. In the rest of the paper, I exploit this variation in the supply of for-hire vehicles to estimate how an additional vehicle affects travel speed, the substitution patterns that arise, and the welfare implications of these reduction in the supply of on-demand vehicles.

3 Emprical Approach to Study Effects of Changes in the Supply of For-Hire Vehicles

This section details the data I used in the analysis and the strategy to estimate the causal effects of the change in the supply of vehicles induced by Muslims holidays.

3.1 Data

To estimate the effect of changes in the supply of taxis and other for-hire vehicles on congestion and its welfare implications, I use data provided by the TLC, the Metro Transit Authority (MTA) and the City of New York from 2009–2017.[5]

The TLC reports data for every trip in a for-hire vehicle in the city. The details and period vary depending on the vehicle type. For yellow taxis, the TLC reports pick-up and drop-off dates and times, pick-up and drop-off locations, trip distances, itemized fares, payment types, and driver-reported passenger counts for each ride in 2009–2017. For 2009–2013, I also have daily tabulations of the number of yellow taxis that made at least one trip and the number of drivers who made at least one trip.[6] For green taxis, the TLC reports the same information on rides as for yellow taxis for 2013–2017. For other for-hire vehicles, including ride-sharing companies, the TLC reports the dispatching base license number (which identifies the firm that provided the ride), the pick-up date and time, and pick-up location for each ride in 2015–2017. With these data, I calculate the daily number of rides for each type of for-hire vehicle and the average income a yellow taxi driver makes

[5] These data can be downloaded from `https://opendata.cityofnewyork.us/`, `https://www1.nyc.gov/site/tlc/about/tlc-trip-record-data.page`, and `http://web.mta.info/developers/turnstile.html`

[6] Until 2013, the trip data also included anonymized medallion and driver identifiers that are not public anymore. I have access to the complete data only for 2013. I am grateful to Henry Farber for sharing these daily tabulations made from the original TLC data.

per day.

I also use the TLC data to define a measure of travel speed in New York City. Traffic behaves in a complex and nonlinear way, depending on the interactions of a large number of vehicles driven by humans. Congestion and traffic jams affect vehicle density differently across the city grid, in some parts density can increase, while it decreases in others. Consequently, congestion in one street can increase or decrease speed in different sections of the city. Focusing on congestion in a particular road will not capture how speed changes in other streets, which is important from a welfare perspective because individuals care about total travel time. To address this issue, I calculate the duration of each yellow taxi trip and combine it with the distance of the trip to obtain the inverse of the average speed of the trip (minutes per mile).[7] Since taxis travel across the entire city, the average speed of the taxi trips will capture the effect of all changes in speed in the grid.

The City of New York also reports data on motor collisions and flow counts in several streets in the city for 2012–2017. I use these data for robustness analyses.

To study substitution effects triggered by changes in the number of active vehicles, I use MTA data on the number of entries and exits from subway stations in the city from 2010–2017. These data are aggregated in four-hour intervals per turnstile and include the station name, date, time, cumulative entries, and cumulative exits. With this information, I calculate the daily number of subway rides. Also, the City of New York reports every trip of the bike sharing system in Manhattan. These data report pick-up and drop-off dates, times, and locations, which I use to calculate the daily number of bike trips.

3.2 Driver and Vehicle Patterns over Time

[Figure 3 about here]

In this section, I describe the evolution of the daily number of drivers and vehicles over a year. I focus on 2013 as a case study, although I will be using the entire sample in my main analysis.[8] To address the lack of public data from ride-sharing companies on the daily number of drivers and vehicles, I assume that the dynamics of taxis over the year is representative of the whole for-hire market. This assumption relies on three facts. First, as mentioned above, taxis and ride-sharing

[7] See Appendix B for details.

[8] The same patterns appear in every year available in the data. See Appendix Figures C1 and C2.

vehicles in New York City have similar efficiency levels (Cramer and Krueger, 2016), making them close substitutes. Second, there is anecdotal evidence that drivers in New York City switch between taxis and ride-sharing vehicles (Tangel, 2015). Finally, in 2013, taxis represented the majority of the for-hire vehicle market (Figure 2). As a test of this assumption, I find that the trips on Uber and other for-hire vehicles also decrease during Muslim holidays (Section 5).

Figure 3 panel (a) shows the daily number of drivers who made at least one trip. We can observe seasonal trends across the year. Notably, the number of drivers decreases during the summer, from June to August, and increases in September–December and January–May. These changes could reflect underlying patterns of demand for rides over time. Also, there is substantial variation within the week. Sundays have the lowest number of drivers, followed by Saturdays. During the workweek, the number of drivers increases from Monday to Friday. Federal holidays are among the days with the fewest number of active drivers. This drop could merely reflect the lower demand for rides on those days. However, during Eid al-Fitr and Eid al-Adha, there is a drop of similar magnitude to federal holidays in the number of drivers. Only Muslims participate in these holidays, and Muslims are a small minority of the city's population. Thus, the decrease in the number of drivers in those days is mainly a supply shock because a large share of drivers are Muslim. Figure 3 panel (b) shows the same patterns as in panel (a) in terms of the number of active vehicles.

In summary, the data indicate that the supply of for-hire vehicles in New York City drops during Muslim holidays. In the next section, I discuss the empirical approach to estimate the effect of these supply shocks on congestion.

3.3 Identification Strategy

The identifying assumption to estimate the effect of changes in the supply of for-hire vehicles is that the drop in supply during Muslim holidays is not correlated with the demand for for-hire vehicles, the number of private vehicles circulating, the number of other commercial vehicles, and other determinants of outcomes. Under this assumption, a first approach to estimate the effects of this supply shock could be to compare outcomes in the day of the Muslim holiday, to the same day in the weeks that surround it. This approach would address within-week trends, but it would not account for changes in the number of drivers and vehicles from one week to the next because of seasonal patterns, especially during the summer. Seasonal trends would bias the estimate upwards or downwards depending on the direction of the trend.

I implement the following empirical strategy to address these issues. First, due to the daily volatility in the data, for each year I take the period between May and December to be able to capture seasonal trends in traffic (Davis, 2008; Gallego et al., 2013; Anderson, 2014). This way, the period is long enough to capture trend changes during the summer, fall and December, and controls for extreme weather shocks in the winter and early spring that could bias the trends. Then, I flexibly capture seasonal and within-week trends using summer ($\delta_1 summer_t$), week-of-the-year (γ_{2wt}), and day-of-the-week (γ_{1dt}) fixed effects. I also use dummies to control for holidays observed in New York City that affect transportation demand ($\delta_2 holidays_{dt}$).[9] I include interactions of all these dummies with year fixed effects to capture long term changes in the trends caused by the entry of ride-sharing companies. Finally, previous research shows that weather can affect transportation demand and supply (Davis, 2008; Farber, 2015; Brodeur and Nield, 2018). I control for weather including daily temperature, precipitation, and dummies for the days affected by Hurricane Irene in 2011 and Super Storm Sandy in 2012. The estimating equation is

$$\begin{aligned} y_{idwt} &= \alpha_0 + \gamma_{1dt} + \gamma_{2wt} + \delta_1 summer_t + \delta_2 holidays_{dt} + \delta_3 temp_{dt} + \delta_4 precip_{dt} \\ &\quad + \delta_5 Irene_{dt} + \delta_6 Sandy_{dt} + \theta_1 Eid1_t + \theta_2 Eid2_t + u_{idwt} \end{aligned} \tag{1}$$

where $Eid1_t$ and $Eid2_t$ are dummy variables that mark Eid al-Fitr and Eid al-Adha in every year, respectively. I allow separate effects for each holiday because they happen at different times of the year. For instance, Eid al-Fitr happened mostly during the summer in the study period, when traffic is lighter because people leave the city for vacation. A lower level of congestion at that time of the year would imply that removing the same number of for-hire vehicles has a smaller effect on travel speed. Also, Eid al-Fitr festivities are mainly during the evening of the previous day and morning, while Eid al-Adha is a whole-day event (Section 2.4). Thus, in Eid al-Fitr supply decreases when vehicle density in general is low in the city.

[Figure 4 about here]

[9] I use dummies for Memorial Day weekend, the week of the Fourth of July (interacted with the day of the week), Labor Day weekend, Columbus Day, Yom Kippur, Thanksgiving week (interacted with the day of the week), Christmas week, and Christmas Day. I also control for special events: Halloween and a visit from the Pope in 2015.

I study the effect of the for-hire vehicle supply shock caused by the Muslim holidays on two types of outcomes. First, outcomes aggregated by day: number of drivers, number of taxis, number of rides in every type of for-hire vehicle, subway rides, bikes rides, number of collisions, average driver income, and the average number of rides per driver. Second, outcomes at the individual trip level: speed of a taxi trip, distance traveled, number of passengers, and the number of injuries and deceased in every accident. The dynamic nature of traffic potentially implies that the error terms are serially correlated within a day. The results of Bertrand et al. (2004) imply that heteroskedastic-robust standard errors are appropriate for the aggregated outcomes. For the disaggregated outcomes, I cluster the standard errors at the day level.

This empirical strategy compares outcomes during the Muslim holidays to other days, while controlling for weekly and seasonal trends, holidays, and meteorological conditions. Giving this design, the main concern for identification would be the presence of unobserved shocks that coincide with the Muslim holidays. The fact that the dates of these holidays change every year following the lunar calendar makes a coincidence unlikely. Moreover, as mentioned above, the changing dates imply that it is challenging for non-Muslims to keep track of these holidays. Also, to account for noise in the data generation processes, I calculate two-sided Fisher p-values by reassigning the date of the Muslim holidays within a range of one month before and one month after the actual dates following the formula derived by Young (2018). The date of the Muslim holiday should be a valid instrument for the number of for-hire vehicles active in the market.[10] In the next section, I present the first stage results of the effect of Muslim holidays on the number of drivers and vehicles.

3.4 Change in the Supply of For-Hire Vehicles

[Table 1 about here]

Before presenting model-based estimates, I present a graphical analysis of the identification strategy. Figure 4 plots the residualized number of taxis and drivers in 2013 after controlling for day-of-the-week, week and holiday fixed effects, and meteorological conditions.[11] Controlling for these fixed effects identifies the variation of Muslim holidays on taxi supply. After accounting for

[10] While the exclusion restriction holds, in the analyses, I focus on reduced form estimates because I have data on the number of drivers and vehicles only for taxis and only in 2009–2013.

[11] See Appendix Figures D1, D2,D3, and D4 for 2009–2012.

confounders, the number of active drivers and vehicles reaches a minimum in both Eid al-Fitr and Eid al-Adha. The reduction in drivers and vehicles is similar in both holidays.

Table 1 presents estimates of the change in supply caused by these holidays in 2009–2013, based on the model described in Equation 1. The number of active drivers decreased by about 3,300 during Eid al-Fitr (15.9 percent of the baseline) and by about 3,900 during Eid al-Adha (18.9 percent of the baseline). The difference between both holidays is not statistically significant. Correspondingly, the number of active taxis decreased by about 1,000 during Eid al-Fitr (8.7 percent of the baseline) and by about 1,100 during Eid al-Adha (9.1 percent of the baseline). The Fisher p-values are 0.014 for both outcomes. In the next section, I study how this change in the supply of for-hire vehicles affects congestion in New York City.

4 Effects on Congestion

The results in Section 3.4 show that during Muslim holidays the supply of taxis (and potentially other for-hire vehicles) decreases. As long as this shock in supply is unanticipated by demand, meaning that people do not switch to private cars in those days, I can exploit it to identify how taking vehicles off the streets affects congestion.

[Table 2 about here]

Table 2 shows how travel speed in the city changes during Muslim holidays.[12] For 2009–2017, time per mile (inverse of speed) decreased by 0.18 minutes in Eid al-Fitr (2.8 percent of baseline, Fisher p-value=0.096) and by 0.46 minutes in Eid al-Adha (7.1 percent of baseline, Fisher p-value=0.014). This effect is driven by changes in speed in Manhattan (Appendix Table E1).[13] Couture et al. (2018) show that longer distance trips have higher speed. Controlling for distance does not affect these results (Appendix Table E2).

These estimates are statistically different from each other, even when supply decreases by almost the same number of vehicles in both holidays. This difference is consistent with two facts. First, in the sample period, Eid al-Fitr was mainly during the summer months, when people leave the city for vacation and overall vehicle density decreases. Thus, travel speed increases during the

[12] Appendix Figures E1, E2, and E3 show the residualized travel times.
[13] Manhattan is defined as the areas south of East 96th Street and West 110th Street.

summer (see baselines in Table 2), implying that taking out the same number of vehicles during the summer should have a smaller effect on speed than during the rest of the year. Table 2 also presents estimates for 2009–2013 and 2014–2017. In the first period, Eid al-Fitr was mainly in the late summer, when vehicle density is at its lowest, while in the latter period it was in the early summer with a higher vehicle density. Consistent with the changes in density, for 2009–2013, time per mile (inverse of speed) decreased by 0.09 minutes in Eid al-Fitr (1.5 percent of the baseline), while for 2014–2017, time per mile decreased by 0.3 minutes per mile (4.7 percent of the baseline).

Second, the difference in the effect between the two holidays is consistent with the nature of the celebrations. Eid al-Adha is a whole-day event, while Eid al-Fitr festivities are mainly during the evening of the previous day and morning (Section 2.4). Thus, in Eid al-Fitr supply decreases when there are fewer vehicles in general in the city and higher average speeds. Appendix Table E3 shows that during Eid al-Fitr, speed gains happened during the early morning, continue during the day, and disappear in the evening, while during Eid al-Adha, speed gains started at 6 am and continue during the whole day and night.

[Figure 5 about here]

While average time per mile increased from 2009–2013 to 2014–2017, the estimates in Table 2 also indicate that the size of the effect of reducing the supply of for-hire vehicles during Eid al-Adha is stable. During 2009-2013, time per mile in this holiday decreased by 7.2 percent of the baseline, similar to the 7.1 percent decrease for 2014-2017. This similarity suggests that at least the same proportion of for-hire vehicles left the streets in 2014-2017 as in 2009-2013, making elasticity estimates in 2009–2013 lower bounds informative for the later period.

Figure 5 plots a back-of-the-envelope calculation of the congestion elasticity for 2009–2013. In this graph, I take all the hourly estimates for 2009–2013 that are significant at the one percent level for both holidays (Table E3), divide them by the average travel time, and scale them with the percentage change in the supply of for-hire vehicles implied by the estimates in Table 1.[14] This elasticity measures the effect of a change in the number of active vehicles on average travel time. The elasticity increases non-linearly as travel time increases, which reflects higher vehicle density on the streets. For instance, during Eid al-Adha between 7 and 9:59 pm, a 9.1 percent decrease in supply

[14]This calculation assumes that the estimated reductions in supply in Table 1 correspond mainly to the periods when the effects on travel time are significant at the one percent level.

corresponds to a 7.2 percent decrease in time per mile, which results in a congestion elasticity of 0.79. The average travel time was 6.17 minutes per mile, which is similar to travel times in Manhattan during the night in 2017. Thus, these elasticity estimates can be taken as conservative lower bounds of how changes in the supply of for-hire vehicles today would affect travel speed in New York City.

4.1 Robustness Check: Effects on Motor Collisions

[Table 3 about here]

During Muslim holidays, not only does the number of active vehicles in the streets decrease, but the composition of drivers changes. A competing explanation to the effects on travel speed could be that remaining for-hire drivers drive faster or take faster routes to take advantage of lower competition in those days. To rule out this story, I exploit the fact that higher speeds imply higher severity of traffic accidents (Hauer, 2009). If this explanation is true, then the severity of accidents that involve taxis should increase, while there should be no effect on collisions where no taxis are involved.[15]

The City of New York reports every motor collision in the city since 2012.[16] Using these data, Table 3 panel (a) presents the effect of Muslim holidays on motor collisions in the city. Column 1 shows that during both holidays there is no significant change of the number of collisions (1.3 percent of baseline with a Fisher p-value=0.752 and 1.4 percent of baseline with a Fisher p-value=0.621). However, the estimates in Column 2 suggest that the severity of collisions increases by 0.03 injuries or fatalities (11.6 percent of baseline, Fisher p-value=0.031) during Eid al-Adha, when travel speed had the largest increase. There is no significant effect during Eid al-Fitr (3.4 percent of baseline, Fisher p-value=0.457) when the increase in speed is lower than during the other holiday. Columns 3 and 4 show that the effect on injuries and fatalities was driven by accidents that *did not* involve taxis. This result is consistent with higher driving speeds in general and not with a change in

[15]There is no clear prediction on how increasing travel speed affects the likelihood of having an accident (Nilsson, 1982; McCarthy, 1993, 1994; Peltola, 2000). The results of Dills and Mulholland (2018) suggest another channel through which a reduction in the supply of for-hire vehicles may affect the number of motor collisions. Fewer for-hire vehicles may increase alcohol-related crashes. However, this channel would require people having access to their cars after drinking in bars, which is not common in New York City, particularly in Manhattan. Census data shows that 23 percent of household own a car in Manhattan, while the nation-wide average rate is 92 percent.

[16]The data include date, time, location, number of people injured or killed, contributing factors, and type of the vehicles involved.

driving behavior by remaining taxi drivers. These results are robust to a Poisson specification (Table 3 panel b).

4.2 Is There Hypercongestion in New York City?

Recent theoretical developments show the importance of a second channel through which increases in the number of vehicles affects travel in a dense urban area (Daganzo, 2007; Geroliminis and Daganzo, 2008; Daganzo et al., 2011; Fosgerau and Small, 2013; Fosgerau, 2015; Arnott et al., 2016; Hall, 2018). The basic intuition is that drivers adapt their routes to avoid the most congested areas in a city. This process equalizes congestion through the city grid. As vehicle density increases, this process reduces vehicle flow (throughput) in an urban area creating hypercongestion.[17] Thus, congestion not only decreases travel speed, but it also affects flow in a city. Hypercongestion would have important implications for the design of congestion policy, but there is limited empirical evidence of its existence.

To provide a suggestive test on the existence of hypercongestion in New York City, I use traffic counts in several streets in the city. These data include the number of vehicles that crossed particular street segments in the city every hour of the day. For example, the data reports the number of vehicles that crossed on Broadway between Leonard and Gerry Street. However, these data have several limitations. First, the data do not cover the entire year. There are months in every year without any measurement. Second, each segment is measured for at most one week, and it is not necessarily measured again in other years. Third, the measurements coincided with a Muslim holiday only in October 2012. These limitations prevent me from using the estimation strategy detailed in Equation 1.

[Table 4 about here]

To address these issues, I take flow counts during Eid al-Adha (October 26, 2012) and every other Friday in October 2012. Under the assumption that seasonal trends are stable during October, this approach controls for day-of-the-week variation in traffic flows. I control for street segment fixed effects and cluster the standard errors at this level. Table 4 presents these estimates. These results suggest that reducing the number of active vehicles in Muslim holidays increases traffic flow, which

[17] Vehicle flow is defined as the number of vehicles that crosses through an area in a specific period.

is consistent with hypercongestion. However, the estimates are imprecise and do not allow drawing strong conclusions.

To summarize, the results in Section 4 indicate that the reduction in the supply of for-hire vehicles during Muslim holidays increased travel speed in New York City. In line with this result, the severity of motor collisions also increases during these dates. In the next section, I study how the decrease in the supply of active vehicle affects ridership in this and other modes of transportation.

5 Effects on Ridership and Substitution to other Transportation Modes

The reduction in the supply of for-hire vehicles induced by Muslim holidays should decrease the number of daily trips. From the demand's side, as the waiting time (or price) for getting a taxi or other for-hire vehicles increases, some people might stop looking and switch to other modes of transportation. I study these issues in this section.

[Table 5 about here]

Table 5 presents how ridership in for-hire vehicles changes during Muslim holidays (Equation 1).[18] In 2009–2017, on average, daily yellow taxi rides decreased by about 22,000 during Eid al-Fitr (5.2 percent of baseline, Fisher p-value=0.047) and by almost 30,000 trips during Eid al-Adha (6.8 percent of baseline, Fisher p-value=0.014). This is consistent with a reduction in supply. Similarly, in 2013–2017 green taxi rides decreased by around 2,000 during Eid al-Fitr (4.6 percent of baseline, Fisher p-value=0.080) and by approximately 3,900 rides during Eid al-Adha (11.1 percent of baseline, Fisher p-value=0.014).

Until 2014, yellow taxis were the dominant type of for-hire vehicle in New York City. Since then taxi drivers faced faced increasing competition from ride-sharing companies. Higher competition may affect how taxi drivers respond to Muslim holidays, but the direction of this effect is uncertain (Brodeur and Nield, 2018). The results show that in 2009–2013 yellow taxi rides decreased by 6.3 percent of the baseline in Eid al- Fitr and by 7.9 percent of the baseline during Eid al-Adha (Column 2), while they decreased 3.6 and 4.2 percent of the baseline in 2014–2017 (Column 3).

[18] Appendix Figures F1, F2, F3, F4, F5, F6, F7, F8, F9, F10, and F11 show trips and the residualized trips.

This is consistent with competition increasing the cost of taking a day off. For 2009–2013 these estimates imply reduced-form trip elasticities of 0.72 and 0.87, respectively, with respect to the supply of for-hire vehicles.

Trips in ride-sharing companies should also decrease because they have a significant share of Muslim drivers (Section 2.4). However, we should expect smaller effects than for taxis because as taxis leave the market, increased demand increases a ride's price in ride-sharing companies increasing the driver's opportunity cost of taking a day off. Hence, the estimated effects on trips with these companies are less precise. In 2014–2017, Uber trips decreased by about 3,300 during Eid al-Fitr (2.2 percent of baseline, Fisher p-value=0.539) and by 8,600 trips during Eid al-Adha (4.1 percent of baseline, Fisher p-value=0.260). For Lyft, in 2015–2017, rides decreased by approximately 6,300 in the first holiday (16.4 percent of baseline, Fisher p-value=0.047) and by 700 rides in the second holiday (1.6 percent of baseline, Fisher p-value=0.670). There is no significant effect on other types of for-hire rides.

[Table 6 about here]

As people cannot find a ride in a taxi or other for-hire vehicle, they must switch to their second-best mode of transportation to get to their destination. Table 6 explores the substitution patterns triggered by an unanticipated reduction in the supply of for-hire vehicles during Muslim holidays.[19] The number of passengers per taxi trip decreased by 0.01 people (0.8 percent of baseline, Fisher p-value=0.096) in Eid al-Fitr and by 0.02 people (1.2 percent of baseline, Fisher p-value=0.014) in Eid al-Adha. The magnitudes of the effects are small and suggest that some people are not willing to wait to share a taxi ride, which is consistent with increased waiting times.

Column 2 shows that during Muslim holidays the distance traveled in a taxi increased. In Eid al-Fitr, distance traveled increased by 0.05 miles (1.7 percent of baseline, Fisher p-value=0.047) and by 0.1 miles in Eid al-Adha (3.4 percent of baseline, Fisher p-value=0.014). Longer trip distances suggest that people who want to go somewhere reasonably near are not willing to wait long (or pay much) for a for-hire trip, while people traveling longer distances are willing to wait longer (or pay more). This effect is driven by the upper quantiles of the distance distribution (Appendix Table F1). Given that 50 percent of all trips travel up to 1.7 miles, increased travel distances during Muslim

[19] Appendix Figures F12, F13, F14, F15, and F16 show residualized subway and bike trips.

holidays for longer trips suggest that walking is a potential substitute for short for-hire trips.

Table 6 also shows how subway and bike trips change in Muslim holidays. Unfortunately, the reduction in for-hire trips during these days falls within the normal variation of daily subway trips. Thus, the estimates are too imprecise to be informative. For 2010–2017, subway rides decreased by 18,500 in Eid al-Fitr (0.4 percent of baseline, Fisher p-value=0.801) and increased by 3,800 during Eid al-Adha (0.1 percent of baseline, Fisher p-value=0.900). Regarding bike trips from the bike sharing system in Manhattan, there is no significant change during Muslim holidays. In Eid al-Fitr, these rides increased by 700 (2.1 percent of baseline, Fisher p-value=0.736) and decreased by 850 in Eid al-Adha (2.5 percent of baseline, Fisher p-value=0.736). These results suggest that bicycles are not a substitute for for-hire vehicles.

In summary, the results in this section show that a shock that reduces the supply of for-hire vehicles causes higher waiting times and some substitution effects for passengers. These effects together with the changes in travel speed studied in Section 4 imply that the welfare of both passenger and drivers should be affected. I study the welfare implications of this supply shock in the next section.

6 Welfare Implications

In this section, I study the welfare implications of the reduction in the supply of for-hire vehicles during Muslim holidays. The design of policies that address traffic congestion is complex because mismatch between individual preferences and social costs. All else equal, individuals favor using vehicles that offer on-demand and personalized travel experiences. However, if roads are not priced, using on-demand vehicles imposes social costs in the form of increased travel times and other negative externalities. In this sense, policies that limit on-demand vehicles implies a welfare loss because some people cannot use their preferred transportation mode and have to switch to a second-best alternative like public transportation. Thus, to formulate traffic regulation policies, it is important to quantify and balance the welfare trade-offs between congestion costs and substitution of transportation modes. These trade-offs could determine the political viability of congestion policies.

The results in sections 4 and 5 indicate that the reduction in the supply of for-hire vehicles affects both demand-side and supply-side outcomes related to welfare. On the one hand, as for-hire vehicles leave the streets, travel speed increases. There is evidence that people place a high value on the time they spend stuck in traffic (Small et al., 2007; Abrantes and Wardman, 2011). Thus, increased travel speed would increase the welfare of both riders of for-hire vehicles and people driving private cars. On the other hand, as the supply of for-hire vehicles decreases, waiting times increase and some people may have to switch to another mode of transportation that was not their preferred choice.[20] These factors would decrease welfare. Thus, the final effect on consumer surplus is uncertain. From the supply side, less competition could imply a transfer from drivers who take those days off to drivers who work. Lower competition can increase trips per driver and lead to higher income for the remaining drivers.

6.1 Supply-Side Transfers

[Table 7 about here]

During Muslim holidays, Non-Muslim drivers face less competition as some Muslims opt not to work those days. Lower competition should imply more trips per driver, and subsequently, daily income per driver should increase. The estimates in Table 7 confirm this intuition.[21] Rides per driver increased by 2.8 trips in Eid al-Fitr (12.6 percent of baseline, Fisher p-value=0.014) and by 3.2 in Eid al-Adha (14.5 percent of baseline, Fisher p-value=0.014). These estimates are not significantly different from each other. Scaling these results with the change in the number of drivers (Table 1) yields elasticities of 0.79 and 0.77, respectively. As the number of trips increases, daily income per driver also increases. During Eid al-Fitr, average income per driver increased by $35 (12.7 percent of baseline, Fisher p-value=0.047) and by $44 in Eid al-Adha (15.6 percent of baseline, Fisher p-value=0.014).

These results with previous work on the labor supply of taxi drivers suggest that the duration of drivers' shifts might also increase during the Muslim holidays (Farber, 2005, 2008, 2015; Thakral and Tô, 2019). Unfortunately, the available data only allows for testing this hypothesis in 2013. The estimates in the third column of Table 7 show that shift duration increased by 0.5 hours in Eid al-Fitr (5.8 percent of baseline) and by 0.07 hours in Eid al-Adha (0.8 percent of baseline).[22]

[20] See Hoffmann et al. (2018) and Saia (2019) for more evidence on substitution patterns.
[21] Appendix Figures F19, F20, F17, and F17 show the residualized trips per driver and income per driver.
[22] Appendix Figure F21 presents the residualized shift duration.

However, using only one year does not allow us to control adequately for noise in the data generation process. The estimates lose significance when calculating the p-values with randomization inference (Fisher p-value= 0.08 and Fisher p-value=0.506, respectively). Consequently, it is not possible to draw definite conclusions about changes in shift duration.

6.2 Demand Model

For the demand side, data limitations prevent me from estimating the demand of transportation modes and using those estimates to calculate changes in consumer surplus.[23] I address this limitation in two ways. First, I focus on 2009–2013, when taxis were the dominant for-hire vehicle. Since taxis and ride-sharing companies are close substitutes in New York City, the welfare implications should still be informative today. Second, to approximate welfare changes, I follow Anderson (2014) and assume that person i has quasilinear preferences over a composite good X and transportation costs of mode of transportation j and faces a budget constraint:

$$U_{ij} = X_i - v_i \left[\sum_{j \in J} I_{ij} \Big(\frac{m_i}{s_j} + c_j(a_j + w_{ij}) \Big) \right] \tag{2}$$

$$\textit{such that } Y_i = X_i + m_i \sum_{j \in J} p_j I_{ij} \tag{3}$$

where v_i is the individual's value of time while traveling, m_i is the distance to travel, s_j is the travel speed of mode of transportation j, a_j is the access and egress time associated to mode of transportation j, w_{ij} is the time person i waits for mode of transportation j, c_j is a multiplier that captures the disutility of waiting for a mode of transportation, and p_j is the price per mile of transportation mode j. I_{ij} is an indicator for the mode of transportation chosen by person i. I consider four types transportation modes: taxis ($j = t$), transit ($j = s$), private car ($j = c$), and walking ($j = p$). Using private cars, taxis or walking does not require spending time on access or egress ($a_c = a_t = a_p = 0$). Furthermore, using a private car or walking does not imply a waiting time ($w_{ic} = w_{ip} = 0$). Additionally, I assume $c_s > c_t = c_c = 1$, $s_t = s_c = s$, and $p_p = 0$. Replacing

[23] In addition to the data available, estimating demand would require waiting times for taxis and prices, waiting times, distance, and duration of the trip for Uber and other for-hire companies.

Equation 1 in Equation 2 yields

$$U_{ij} = Y_i - m_i \sum_{j \in J} p_j I_{ij} - v_i \left[\sum_{j \in J} I_{ij} \left(\frac{m_i}{s_j} + c_j (a_j + w_{ij}) \right) \right] \tag{4}$$

People choose the transportation mode that maximizes Equation 4.[24] I define consumer surplus as the difference in utility between the preferred choice j and the second-best alternative k.

Given that the reduction in supply during Muslim holidays is difficult to anticipate, it is reasonable to assume that people do not learn about the increase in speed unless they use a car or take a for-hire vehicle, and that they do not find out that waiting times for for-hire vehicles increased unless they decide to take a taxi. These assumptions imply that people use their ex-ante knowledge to make their choice and realize the consequences of the reduction of taxis only after they make a decision. Thus, even though the ex-ante ranking of the modes of transportation is not affected by the unanticipated shock, welfare can change because of it. Under these assumptions, we can calculate the change of consumer surplus due to the reduction of taxis for four types of people defined by their preferred mode of transportation:

People who usually choose private cars: For people who prefer to drive their private vehicles, consumer surplus is given by

$$CS_{ick} = m_i (p_k - p_c) + v_i \left(\frac{m_i}{s_k} - \frac{m_i}{s} \right) + v_i c_k (a_k + w_{ik}) \tag{5}$$

During Muslim holidays travel speed increases for every vehicle in the city. Let $s' > s$. The change in consumer surplus for people who use their cars is

$$\Delta CS_{ick} = v_i \left(\frac{m_i}{s} - \frac{m_i}{s'} \right) > 0 \tag{6}$$

People who usually choose transit: People who choose to use the transit system (mainly subway) during Muslim holidays are not aware of the change of speed. Also, the estimates in Section 5 suggest that the number of people who switch from taxis to subway during Muslim holidays falls within the usual fluctuations in subway usage. This would imply that for people who

[24] This utility specification does not consider individual characteristics like disabilities that restrict the choice set.

always use the subway there is no change in their access/egress time or waiting time. Thus, their welfare is not affected because the change in the supply of for-hire vehicles does not affect any of the times associated with subway usage.

People who usually choose to walk: The reduction of the supply of for-hire vehicles does not affect people who usually choose to walk. Thus, their welfare is not affected.

People who usually choose a taxi: To define the second best alternative for people who usually choose a taxi, it is important to note that according to the ACS only 22 percent of New Yorkers use their private car to commute (6.3 percent in Manhattan). Also, only 22 percent of households in Manhattan own a vehicle, while more than 90 percent of taxi trips occur in Manhattan. These numbers suggests that private cars are not the main substitute of taxis in the presence of an unanticipated reduction of their supply. Thus, I assume that walking is the second-best alternative for trips with a travel distance less than $\bar{m}$ and that public transit is the second best alternative for trips with a travel distance greater than $\bar{m}$. For people for whom the alternative is walking, consumer surplus of taking a taxi is

$$CS_{itp} = v_i\Big(\frac{m_i}{s_p} - \frac{m_i}{s}\Big) - m_i p_t - v_i w_{it} \tag{7}$$

During the Muslim holidays a person may or not have found a taxi. If the person found a taxi, then she would benefit from the change in speed but could have waited for longer than usual to get the taxi. It is reasonable to suppose that people have a maximum waiting time $\bar{w}_i$ before switching to their second-best alternative. Hence, the change in consumer surplus is bounded between

$$v_i\Big(\frac{m_i}{s} - \frac{m_i}{s'}\Big) + v_i(w_{it} - \bar{w}_i) \leq \Delta CS_{itp} \leq v_i\Big(\frac{m_i}{s} - \frac{m_i}{s'}\Big) \tag{8}$$

If the person did not find a taxi, that would mean that she waited $\bar{w}_i$. Thus, the change in consumer surplus is

$$\Delta CS_{itp} = v_i(w_{it} - \bar{w}_i) < 0 \tag{9}$$

For people whose alternative was to take the subway, consumer surplus is given by

$$CS_{itk} = m_i(p_s - p_t) + v_i\left(\frac{m_i}{s_s} - \frac{m_i}{s}\right) + v_i[c_s(a_s + w_{is}) - w_{it}] \tag{10}$$

The same scenarios regarding the change in consumer surplus apply for these individuals (Equations 8 and 9). The difference is that they might be willing to wait for a cab longer than people who could just walk to their destination.

In the next section, I explain the procedure to quantify Equations 6, 8, and 9 and present the changes in welfare.

6.3 Welfare Changes of Decreasing the Supply of For-Hire Vehicles

[Table 8 about here]

Table 8 summarizes the parameter values used to calculate welfare changes. Under the utility specification in Equation 4 aggregate demand exists, so without loss of generality, we can consider the behavior of a representative or average agent. This allows us to match the parameters that define the changes in welfare to the reduced form estimates. Mainly, the term $\left(\frac{1}{s} - \frac{1}{s'}\right)$ is the change in travel time estimated in Section 4.

The other key parameter to quantify Equations 6, 8, and 9 is the value of travel time, v_i. I follow a revealed preference approach to obtain a measure of this value. By definition, v_i should be greater or equal than the amount paid by taxi riders. To approximate v_i for a representative agent, I use the average total amount paid per minute in the sample of taxi rides (Appendix Figure G1). This value will provide a conservative estimate of the welfare gains due to higher travel speed.

With this approximation of the value of commuting time, I can recover the maximum waiting time ($\bar{w}$) from the data. By definition, $\bar{w}$ is the waiting time that makes Equations 7 and 10 equal to zero. To calculate this value, first, for each second-best alternative (walking and transit), I calculate access, egress, waiting and traveling times as required by inputting taxi trip pickup and drop-off coordinates in a trip planner application calibrated with official travel data from the MTA.[25] Then, I solve for $\bar{w}$ using a value of 1.8 (Parry and Small, 2009; Anderson, 2014) for c_s in Equation 10,

[25] `http://www.opentripplanner.org/`. This open access trip planner is used by the state of New York to supply travel information in the state. The software uses the input coordinates to automatically define if walking or transit is the best option. See details in Appendix G.

and take the average from the sample. These calculations yield an average maximum waiting time of 3.68 minutes for people whose second-best alternative was walking and 12.83 minutes for people whose second-best alternative was transit.

Equations 8 and 9 also require an estimate of the average real waiting time. Frechette et al. (2018) estimate the distribution of waiting times in 2013. I calculate the average of this distribution (2.57 minutes). Additionally, I use the average wait time to define two extra counterfactual scenarios where the waiting time increases 10 and 25 percent of the real waiting time to 2.83 and 3.21 minutes.

Finally, Table 8 reports the average distance of a taxi trip by second-best alternative, and the average distance traveled while commuting by a private car in the city. Table 8 also includes the average number of taxi trips, of commuting trips in private cars, and the reduction in taxi trips during Muslim holidays estimated in Section 5. I use these values to scale the changes in welfare from an individual trip level to the city level.

[Table 9 about here]

Panel (a) of Table 9 presents the welfare changes by trip associated with the reduction in the number of active vehicles during Muslim holidays. The estimated gain in travel speed increases consumer surplus on average by $0.56 per mile traveled. With this input, we can quantify welfare changes by choice of transportation mode:

People who travel on their private cars. These individuals only benefit from the speed gain (Equation 6). Multiplying $0.56 times the average distance traveled on a private car yields a surplus gain of $6.29 per trip.

People who chose a taxi and were able to find one. According to Equation 8, for these individuals the change in consumer surplus depends on both the gain in travel speed and potentially higher waiting times. If waiting times do not change, then consumer surplus would increase by $0.46 per trip for individuals whose second best option is walking and by $1.84 per trip for those whose second best is transit (the difference comes from travel distances). However, Table 9 shows that these welfare gains quickly fade if waiting time increases as a consequence of reducing the number of vehicles. In the limit, if people have to wait the maximum time they are willing to for a taxi, on average consumer surplus would decrease by \$0.90 per trip for individuals whose second best option is walking and by \$10.75 per trip for those whose second best is transit.

People who chose a taxi and were *not* able to find one. For these individuals, Equation 9 implies that they waited for a cab up to their maximum and then switched to the second-best option. In this case, consumer surplus would decrease by \$1.36 per trip for individuals whose second best option is walking and by \$12.59 per trip for those whose second best is transit.

Panel (b) of Table scales the previous values by the number of people who fall in each category in 2013. This calculation highlights that there is a welfare transfer from people who take taxis to people who drive their cars. If there is no change in waiting times, the reduction in the number of vehicles during Muslim holidays would have increased welfare by \$12.9 million per day. However, if waiting times increased to their maximum, the welfare gain would only be \$8 million per day.

7 Discussion

This paper finds that during Muslim holidays a reduction of approximately 1,000 vehicles in the streets (9.1 percent of the baseline) reduces the time per mile traveled by 0.46 minutes, representing a 7.1 percent gain in travel speed. These estimates imply an elasticity of congestion to the supply of for-hire vehicles of 0.78. This effect is driven by changes in speed in mid and lower Manhattan, south of East 96th Street and West 110th Street. This result is a key piece of evidence to guide the current efforts to implement congestion pricing in lower Manhattan. In particular, since this estimate corresponds to a reduction in for-hire vehicles, it is relevant to guide the current debate on regulations for ride-sharing companies. In the rest of the city, the effects are smaller, which is consistent with the fact that the outer boroughs have lower vehicle density than Manhattan. In these outer regions, the implied elasticities of congestion fluctuate between 0.2 and 0.3. These values are in line with the elasticities reported by Mangrum and Molnar (2018), whose estimates are based on speed changes at the boundary of East 96th Street and West 110th Street and do not capture speed changes in mid and lower Manhattan.

The results also suggest that as vehicles leave the streets, traffic flow (throughput) increased in Muslim holidays. This result is consistent with the existence of hypercongestion in the city, which would imply further welfare gains from reducing congestion (Hall, 2018). However, the data available do not allow for a detailed analysis of this issue, and the estimate's precision does not allow drawing definite conclusions. More research is needed to asses the existence of hypercongestion and its welfare implications.

Since most cities do not charge Pigovian taxes on road usage, the gain in travel speed suggests that reducing congestion in highly dense cities can convey significant welfare gains. This study documents a daily welfare gain that ranges between \$8 and \$13 million. However, it is important to discuss three caveats. First, this paper's calculations indicate that there is a welfare transfer from people who take taxis to people who drive their cars. This transfer implies that a reduction in the supply of for-hire vehicles makes driving a private car more attractive. Hence, policies that deviate from the Pigovian optimum focusing on decreasing a particular type of vehicle might prove less useful as people substitute to vehicles allowed to circulate without any restriction.

Second, it is important to highlight that reducing the number of active vehicles forces people to switch to less-preferred transportation modes. These changes imply a poorer travel experience which decreases economic welfare. This paper quantifies the substitution effects of a short-term shock unanticipated by demand. It is reasonable to assume that the effects of a lower travel experience would only get more substantial for a significant, permanent reduction in the number of active vehicles, which could magnify welfare losses. This implies that to mitigate welfare losses, before implementing congestion pricing policies it is important to ensure that public transportation improves both in terms of capacity and quality of the ride. In this sense, the results in this paper are an informative upper bound of the potential welfare gains of regulating traffic congestion.

Finally, the welfare calculations do not include pollution externalities. I conduct a back-of-the-envelope calculation to give a sense of the reduction in pollution during Muslim holidays. From the TLC data, on average, a taxi traveled 250 kilometers (156 miles) per day in 2013. Peitzmeier et al. (2017) report that a gasoline passenger vehicle emits 160 grams of CO_2 and 0.078 grams of NO_x per kilometer under fluid conditions, and 330 grams of CO_2 and 0.15 grams of NO_x per kilometer under stop-and-go conditions. Multiplying distance traveled by these emissions estimates yields that during Muslim holidays, CO_2 emissions decreased between 40.1 and 82.6 tons, while NO_x emissions decreased between 0.02 and 0.04 tons. These reductions in emissions imply benefits in terms of health and climate outcomes.

References

Abrantes, P. A. and M. R. Wardman (2011). Meta-analysis of UK values of travel time: An update. *Transportation Research Part A: Policy and Practice 45*(1), 1–17.

Al-Islam (2019). Eid-Ul-Fitr; a unique festival time of joy for Muslims. Retrieved on January 23, 2019 from `https://www.al-islam.org/fast-sayyid-saeed-akhtar-rizvi/eid-ul-fitr-unique-festival-time-joy-muslims`.

Anderson, M. L. (2014). Subways, strikes, and slowdowns: The impacts of public transit on traffic congestion. *American Economic Review 104*(9), 2763–96.

Arnott, R., A. Kokoza, and M. Naji (2016). Equilibrium traffic dynamics in a bathtub model: A special case. *Economics of Transportation 7*, 38–52.

Bando, M., K. Hasebe, A. Nakayama, A. Shibata, and Y. Sugiyama (1995). Dynamical model of traffic congestion and numerical simulation. *Physical Review E 51*(2), 1035.

Barrios, J. M., Y. V. Hochberg, and H. Yi (2018). The cost of convenience: Ridesharing and traffic fatalities. *University of Chicago, Becker Friedman Institute for Economics Working Paper* (2018-80).

Bauernschuster, S., T. Hener, and H. Rainer (2017). When labor disputes bring cities to a standstill: The impact of public transit strikes on traffic, accidents, air pollution, and health. *American Economic Journal: Economic Policy 9*(1), 1–37.

Baum-Snow, N., M. E. Kahn, and R. Voith (2005). Effects of urban rail transit expansions: Evidence from sixteen cities, 1970-2000 [with comment]. *Brookings-Wharton papers on urban affairs*, 147–206.

Bento, A., D. Kaffine, K. Roth, and M. Zaragoza-Watkins (2014). The effects of regulation in the presence of multiple unpriced externalities: Evidence from the transportation sector. *American Economic Journal: Economic Policy 6*(3), 1–29.

Bertrand, M., E. Duflo, and S. Mullainathan (2004). How much should we trust differences-in-differences estimates? *The Quarterly Journal of Economics 119*(1), 249–275.

Bloomberg (2018). 2018 American Mayors Survey. Bloomberg American Cities Initiative, accessed 4/19/2019 https://www.bbhub.io/dotorg/sites/2/2018/04/American-Mayors-Survey.pdf.

Brodeur, A. and K. Nield (2018). An empirical analysis of taxi, Lyft and Uber rides: Evidence from weather shocks in NYC. *Journal of Economic Behavior & Organization 152*, 1–16.

Buchholz, N. (2017). Spatial equilibrium, search frictions and efficient regulation in the taxi industry. Working paper.

Camerer, C., L. Babcock, G. Loewenstein, and R. Thaler (1997). Labor supply of New York City cabdrivers: One day at a time. *The Quarterly Journal of Economics 112*(2), 407–441.

Carrillo, P. E., A. S. Malik, and Y. Yoo (2016). Driving restrictions that work? Quito's Pico y Placa program. *Canadian Journal of Economics 49*(4), 1536–1568.

Chen, Y., G. Z. Jin, N. Kumar, and G. Shi (2013). The promise of Beijing: Evaluating the impact of the 2008 Olympic Games on air quality. *Journal of Environmental Economics and Management 66*(3), 424–443.

Chen, Y. and A. Whalley (2012). Green infrastructure: The effects of urban rail transit on air quality. *American Economic Journal: Economic Policy 4*(1), 58–97.

Cohen, P., R. Hahn, J. Hall, S. Levitt, and R. Metcalfe (2016). Using big data to estimate consumer surplus: The case of Uber. Working Paper 22627, National Bureau of Economic Research.

Cook, C., R. Diamond, J. Hall, J. A. List, and P. Oyer (2018). The gender earnings gap in the gig economy: Evidence from over a million rideshare drivers. Working Paper 24732, National Bureau of Economic Research.

Couture, V., G. Duranton, and M. A. Turner (2018). Speed. *Review of Economics and Statistics 100*(4), 725–739.

Cramer, J. and A. B. Krueger (2016). Disruptive change in the taxi business: The case of Uber. *American Economic Review 106*(5), 177–82.

Currie, J. and M. Neidell (2005). Air pollution and infant health: what can we learn from California's recent experience? *The Quarterly Journal of Economics 120*(3), 1003–1030.

Currie, J. and R. Walker (2011). Traffic congestion and infant health: Evidence from E-ZPass. *American Economic Journal: Applied Economics 3*(1), 65–90.

Daganzo, C. F. (2007). Urban gridlock: Macroscopic modeling and mitigation approaches. *Transportation Research Part B: Methodological 41*(1), 49–62.

Daganzo, C. F., V. V. Gayah, and E. J. Gonzales (2011). Macroscopic relations of urban traffic variables: Bifurcations, multivaluedness and instability. *Transportation Research Part B: Methodological 45*(1), 278–288.

Davis, L. W. (2008). The effect of driving restrictions on air quality in Mexico City. *Journal of Political Economy 116*(1), 38–81.

Dills, A. K. and S. E. Mulholland (2018). Ride-sharing, fatal crashes, and crime. *Southern Economic Journal 84*(4), 965–991.

Farber, H. S. (2005). Is tomorrow another day? The labor supply of New York City cabdrivers. *Journal of Political Economy 113*(1), 46–82.

Farber, H. S. (2008). Reference-dependent preferences and labor supply: The case of New York City taxi drivers. *American Economic Review 98*(3), 1069–82.

Farber, H. S. (2015). Why you can't find a taxi in the rain and other labor supply lessons from cab drivers. *The Quarterly Journal of Economics 130*(4), 1975–2026.

Fosgerau, M. (2015). Congestion in the bathtub. *Economics of Transportation 4*(4), 241–255.

Fosgerau, M. and K. A. Small (2013). Hypercongestion in downtown metropolis. *Journal of Urban Economics 76*, 122–134.

Frechette, G. R., A. Lizzeri, and T. Salz (2018). Frictions in a competitive, regulated market: Evidence from taxis. Working Paper 24921, National Bureau of Economic Research.

Gallego, F., J.-P. Montero, and C. Salas (2013). The effect of transport policies on car use: Evidence from Latin American cities. *Journal of Public Economics 107*, 47–62.

Geroliminis, N. and C. F. Daganzo (2008). Existence of urban-scale macroscopic fundamental diagrams: Some experimental findings. *Transportation Research Part B: Methodological 42*(9), 759–770.

Glaeser, E. (2011). Cities, productivity, and quality of life. *Science 333*(6042), 592–594.

Haggag, K., B. McManus, and G. Paci (2017). Learning by driving: Productivity improvements by New York City taxi drivers. *American Economic Journal: Applied Economics 9*(1), 70–95.

Hall, J. and A. B. Krueger (2017). An analysis of the labor market for Uber's driver-partners in the United States. *ILR Review 71*(3), 705–732.

Hall, J., C. Palsson, and J. Price (2018). Is Uber a substitute or complement for public transit? *Journal of Urban Economics 108*, 36–50.

Hall, J. D. (2018). Pareto improvements from Lexus Lanes: The effects of pricing a portion of the lanes on congested highways. *Journal of Public Economics 158*, 113–125.

Hauer, E. (2009). Speed and safety. *Transportation Research Record: Journal of the Transportation Research Board* (2103), 10–17.

Hoffmann, K., P. Ipeirotis, and A. Sundararajan (2018). Ridesharing and the use of public transportation. Working paper.

Huffington Post (2017). How Muslims celebrate Eid al-Fitr, the end of Ramadan. Retrieved on January 23, 2019 from `https://www.huffingtonpost.com/entry/how-muslims-celebrate-eid-al-fitr-the-end-of-ramadan_us_59511e9ce4b02734df2bf6c9`.

Jackson, C. K. and H. S. Schneider (2011). Do social connections reduce moral hazard? Evidence from the New York City taxi industry. *American Economic Journal: Applied Economics 3*(3), 244–67.

Khan, G. (2017). See how American Muslims celebrate Islam's holiest holiday. National Geographic. Retrieved from: `https://www.nationalgeographic.com/photography/proof/2017/06/muslims-america-eid-ramadan`.

Mangrum, D. and A. Molnar (2018). The marginal congestion of a taxi in New York City. Unpublished. Accesed October 2018. https://alejandromolnar.github.io.

McCarthy, P. S. (1993). The effect of higher rural interstate speed limits in alcohol-related accidents. *Journal of Health Economics 12*(3), 281–299.

McCarthy, P. S. (1994). An empirical analysis of the direct and indirect effects of relaxed interstate speed limits on highway safety. *Journal of Urban Economics 36*(3), 353–364.

Moskatel, L. S., D. J. Slusky, et al. (2017). Did UberX reduce ambulance volume? Technical report, REPEC. University of Kansas, Department of Economics.

Moss, M. L., S. Schwartz, S. Rechler, K. Wylde, B. Rudin, J. Samuelsen, P. Ward, T. Prendergst, F. Ferrer, F. Flake, D. Paterson, D. Towns, J. Molinaro, K. Law, and S. Bellone (2018). Fix NYC Advisory Panel Report. Technical report, Fix NYC.

Nilsson, G. (1982). Effects of speed limits on traffic accidents in Sweden. Unpublished.

Parrot, J. and M. Reich (2018). An earnings standard for New York City's app-based drivers: Economic analysis and policy assessment. *Report for the New York City Taxi and Limousine Commission 5*.

Parry, I. W. and K. Small (2009). Should urban transit subsidies be reduced? *American Economic Review 99*(3), 700–724.

Peck, J. L. (2017). New York City drunk driving after Uber. Working paper.

Peitzmeier, C., C. Loschke, H. Wiedenhaus, and O. Klemm (2017). Real-world vehicle emissions as measured by in situ analysis of exhaust plumes. *Environmental Science and Pollution Research 24*(29), 23279–23289.

Peltola, H. (2000). Seasonally changing speed limits: Effects on speeds and accidents. *Transportation Research Record: Journal of the Transportation Research Board* (1734), 46–51.

Pervez, S. (2015). Eid is Muslim celebration of sacrifice. Islamic Circle of North America. Retrieved from: `http://www.icna.org/eid-is-muslim-celebration-of-sacrifice/`.

PEW Center (2014). Religious Landscape Study.

Peyton, L. (2018). At Eid al-Adha, Muslims celebrate a tradition of sacrifice. Houston Chronicle. Retrieved from: https://www.houstonchronicle.com/life/houston-belief/article/At-Eid-al-Adha-Muslims-celebrate-a-tradition-of-13171636.php.

Reed, T. and J. Kidd (2019). Global Traffic Scorecard. Technical report, INRIX Research, Kirkland, WA.

Rojas, N. (2018). Eid al-Fitr 2018: Celebration marking end of Ramadan brings feasts, new clothes and gifts. Newsweek. Retrieved from: https://www.newsweek.com/eid-al-fitr-2018-celebration-marking-end-ramadan-brings-feasts-new-clothes.

Saia, A. (2019). Trouble underground: Demand shocks and the labor supply behavior of New York City taxi drivers. Working Paper, Available at SSRN.

Simeonova, E., J. Currie, P. Nilsson, and R. Walker (2018). Congestion pricing, air pollution and children's health. Working Paper 24410, National Bureau of Economic Research.

Small, K. A. and J. A. Gomez-Ibanez (1999). Urban transportation. *Handbook of regional and urban economics 3*, 1937–1999.

Small, K. A., E. T. Verhoef, and R. Lindsey (2007). *The economics of urban transportation*. Routledge.

Stopher, P. R. (2004). Reducing road congestion: A reality check. *Transport Policy 11*(2), 117–131.

Tangel, A. (2015). Trading taxis for Uber, drivers riding a boom. The Wall Street Journal. Retrieved from: https://www.wsj.com/articles/trading-taxis-for-uber-drivers-riding-a-boom-1438389363?mod=e2fb&fbclid=IwAR3Yx-whAMqJcUg6DWwepkvXX8CiJy92wXO4dsc_xOnejRzCLvuNn4iNOwY.

Thakral, N. and L. T. Tô (2019). Daily labor supply and adaptive reference points. Forthcoming *American Economic Review*.

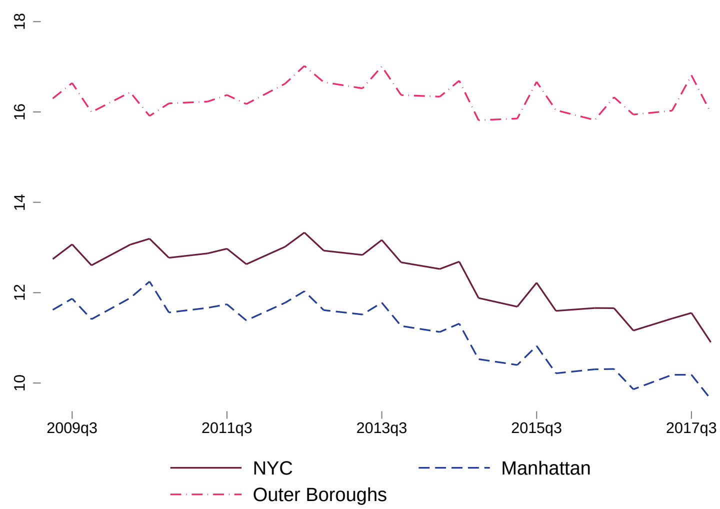
TLC (2018). 2018 Fact Book dataset. 2018 Fact Book dataset. Accesed January 2018. https://www1.nyc.gov/site/tlc/about/fact-book.page. New York City, NY: Taxi & Limousine Commission.

Viard, V. B. and S. Fu (2015). The effect of Beijing's driving restrictions on pollution and economic activity. *Journal of Public Economics 125*, 98–115.

Wen, W. (2008). A dynamic and automatic traffic light control expert system for solving the road congestion problem. *Expert Systems with Applications 34*(4), 2370–2381.

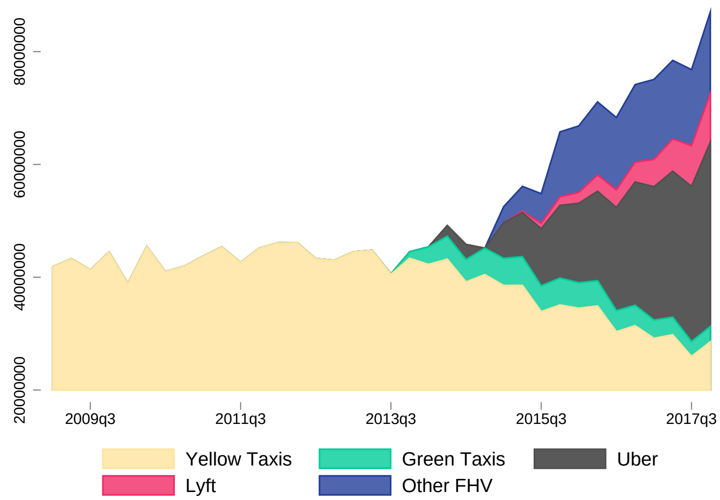
Young, A. (2018). Channeling Fisher: Randomization tests and the statistical insignificance of seemingly significant experimental results. *The Quarterly Journal of Economics 134*(2), 557–598.

Figure 1: Travel Speeds in New York City 2009–2017



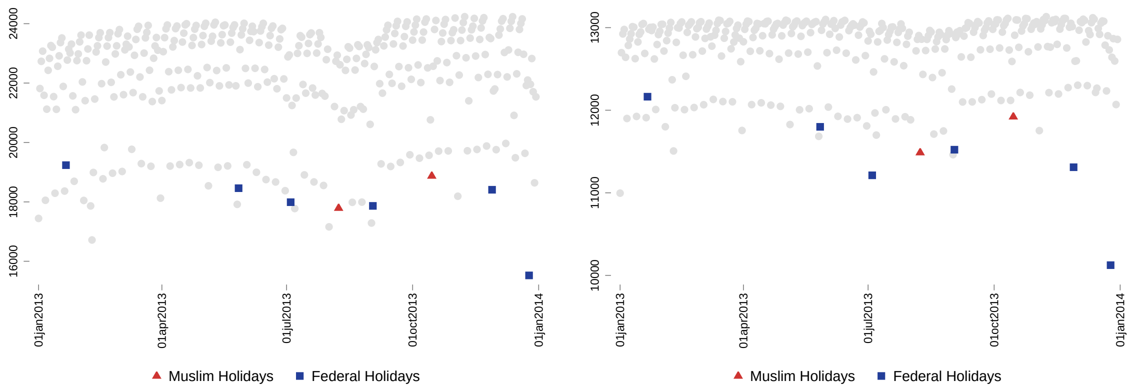
Notes: This figure present the evolution of travel speeds (miles per hour) in New York City by year-quarters.

Figure 2: For-Hire Vehicle Rides 2009–2017



Notes: This figure present the cumulative number of taxi and other for-hire vehicle rides in New York City by year-quarters. Uber data for the fourth quarter of 2014 is missing. The TLC reports data for for-hire vehicles different than taxis since 2015.

Figure 3: Taxi Drivers and Taxis in 2013

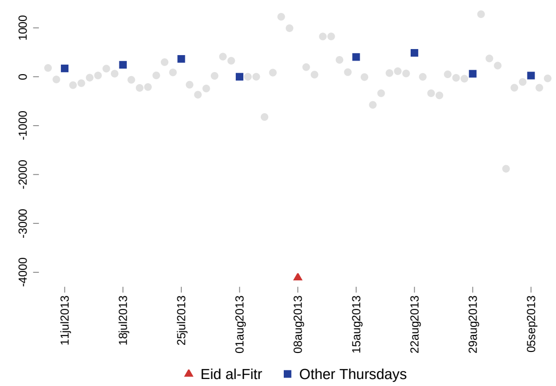


(a) Taxi Drivers

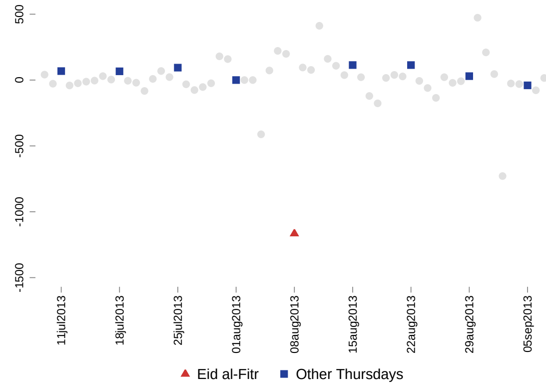
(b) Taxis

Notes: This figure presents the number of taxi drivers who had at least one trip per day and the number of yellow taxis that had at least one ride per day in 2013. Federal holidays include Martin Luther King Jr. Day, Memorial Day, 4th of July, Labor Day, Thanksgiving, and Christmas Day.

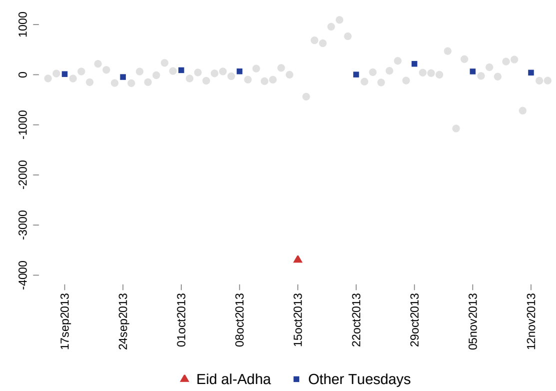
Figure 4: Residualized Number of Drivers and Taxis in 2013



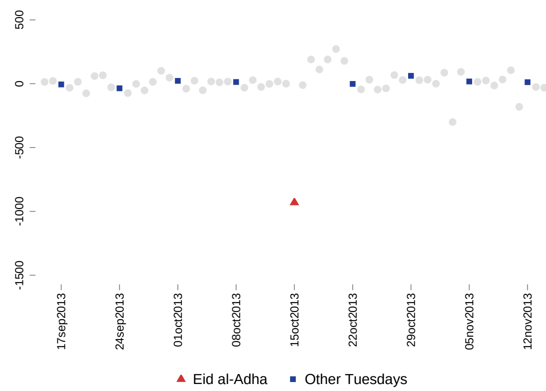
(a) Taxi Drivers - Eid al-Fitr



(b) Taxis - Eid al-Fitr



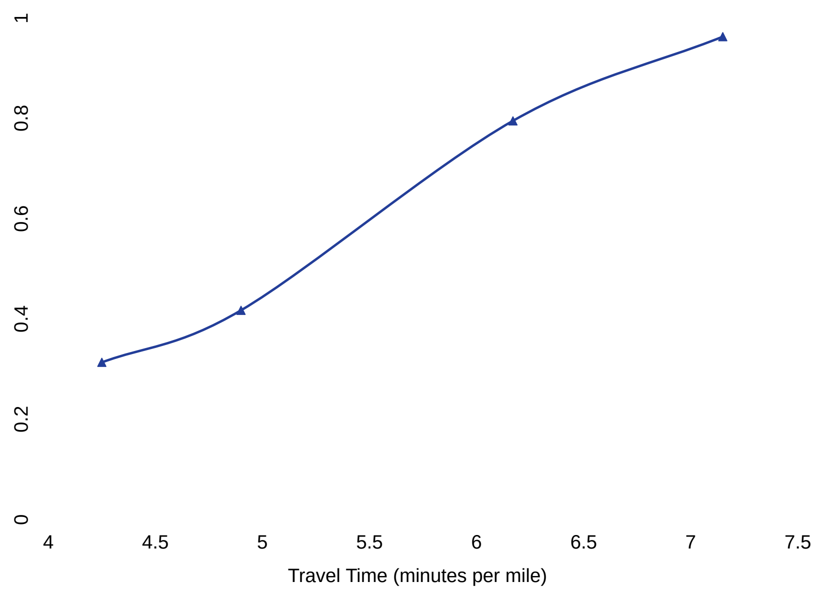
(c) Taxi Drivers - Eid al-Adha



(d) Taxis - Eid al-Adha

Notes: This figure presents the residualized number of taxi drivers who had at least one trip per day and the residualized number of yellow taxis that had at least one ride per day, after controlling for day-of-the-week, week and holiday fixed effects plus meteorological conditions (Equation 1 without Muslim holiday dummies). The graphs present one month before and after each Eid.

Figure 5: Congestion Elasticity for 2009–2013



Notes: This figure presents a back-of-the-envelope calculation of the congestion elasticity in New York City. This elasticity measures the effect of a change in the supply of for-hire vehicles on average travel time in the city measured by minutes per mile. As a reference 4 minutes per mile is equivalent to a travel speed of 15 miles per hour and 7 minutes per mile is equivalent to 8.6 miles per hour.

Table 1: Effects of Muslim Holidays on Daily Active Taxis and Drivers (2009–2013)

	Number of Drivers	Number of Taxis
Eid al-Fitr	-3,336.96***	-1,073.44***
	(985.46)	(347.40)
Eid al-Adha	-3,975.18***	-1,126.10***
	(271.59)	(162.54)
Baseline	21,046.72	12,379.18
N	1,080	

* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Notes: Robust standard errors in parentheses. This table presents the effect of the Muslim holidays on the daily number of active taxis and drivers. The regressions control for day-of-the-week, week and holiday fixed effects plus meteorological conditions.

Table 2: Effects of Muslim Holidays on Congestion

	2009-2017		2009-2013		2014-2017	
	Eid al-Fitr	Eid al-Adha	Eid al-Fitr	Eid al-Adha	Eid al-Fitr	Eid al-Adha
Effect	-0.1758*	-0.4600***	-0.0905	-0.4523***	-0.3026**	-0.4795***
	(0.1038)	(0.0417)	(0.1416)	(0.0443)	(0.1407)	(0.0923)
Baseline	6.21	6.46	6.07	6.26	6.49	6.79
N	799,758,682		490,969,773		308,788,909	

* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Notes: Standard errors clustered by day in parentheses. This table presents the effect of the Muslim holidays on the inverse of speed (minutes per mile) of taxi trips in the city. Baseline values for Eid al-Fitr correspond to the average time per mile in June, July, and August, while the baseline values for Eid al-Adha correspond to the average time per mile in September, October and November. The regressions control for day-of-the-week, week and holiday fixed effects plus meteorological conditions.

Table 3: Effects of Muslim Holidays on Motor Collisions

	Vehicle Collisions	People Injured/Killed		
	Full Sample	Full Sample	No Taxi Involved	Taxis Involved
		Panel a. OLS Estimates		
Eid al-Fitr	7.9773	-0.0090	-0.0106	0.0180
	(17.3972)	(0.0064)	(0.0071)	(0.0406)
Eid al-Adha	8.7038	0.0308***	0.0329***	0.0143
	(18.0156)	(0.0117)	(0.0102)	(0.0493)
		Panel b. Poisson Estimates		
Eid al-Fitr		-0.0091	-0.0108	0.0228
		(0.0061)	(0.0068)	(0.0403)
Eid al-Adha		0.0315***	0.0339***	0.0147
		(0.0120)	(0.0107)	(0.0423)
Baseline	602.82	0.2664	0.2651	0.2367
N	1260	759,550	708,494	51,056

* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Notes: The first column presents robust standard errors in parentheses. In the other columns standard errors are clustered by day. This Table presents the effect of the Muslim holidays on the outcomes detailed by the column headers. The regressions control for day-of-the-week, week and holiday fixed effects plus meteorological conditions.

Table 4: Effects of Muslim Holidays on Traffic Flow

	24 Hours Flow	Flow 1:00-5:59	Flow 6:00-7:59	Flow 8:00-18:59	Flow 19:00-20:59	Flow 21:00-0:59
Eid al-Adha	111.7872	-12.6596	-43.3404	82.4255	34.5000**	50.8617**
	(143.7692)	(19.0227)	(37.9336)	(99.5463)	(17.3376)	(21.9266)
Baseline	7996	255	653	5678	827	583
N			629			

* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Notes: Standard errors clustered by street segment in parentheses. This Table presents the effect of the Muslim holidays (Eid al-Adha) on traffic flow in the periods detailed by the column headers. The regressions use data for the Fridays in October 2012 control and control for street segment fixed effects.

Table 5: Effects of Muslim Holidays on For-Hire Vehicle Trips

	Yellow Taxis 2009-2017	Yellow Taxis 2009-2013	Yellow Taxis 2014-2017	Green Taxis 2013-2017	Uber 2014-2017	Lyft 2015-2017	Other FHV 2015-2017
Eid al-Fitr	-21,800.57**	-28,852.71**	-13,130.37*	-1,796.08*	-3,333.93	-6,238.57*	-2,584.39
	(8,619.85)	(13,731.66)	(6,778.07)	(1,010.28)	(3,575.43)	(3,635.55)	(1,773.57)
Eid al-Adha	-29,361.76***	-37,569.30***	-15,682.88**	-3,867.19***	-8,597.48*	-734.35	2,080.11
	(5,938.73)	(6,214.05)	(6,912.02)	(1,118.21)	(4,589.68)	(2,156.09)	(1,789.97)
Baseline Eid al-Fitr	415,386	459,290	360,505	38,746	150,909	37,989	109,821
Baseline Eid al-Adha	429,482	476,915	370,192	34,951	211,525	46,829	137,272
N	1,944	1,080	864	1,012	776	646	648

* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Notes: Robust standard errors in parentheses. This Table presents the effect of the Muslim holidays on the number of daily trips in different types of for-hire vehicles. The regressions control for day-of-the-week, week and holiday fixed effects plus meteorological conditions.

Table 6: Effects of Muslim Holidays on Other Modes of Transportation

	Number Passengers per Taxi Ride	Taxi Ride Distance	Daily Subway Rides	Bike Rides
Eid al-Fitr	-0.0141*	0.0501**	-18,517.51	726.88
	(0.0084)	(0.0227)	(118,799.05)	(1,589.77)
Eid al-Adha	-0.0199***	0.0989***	3,801.25	-859.14
	(0.0025)	(0.0185)	(77,126.48)	(2,355.71)
Baseline	1.68	2.92	4,906,055	34,525
N	822,959,489	799,758,682	1,244	1,044

* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Notes: Standard errors clustered by day in Columns 1 and 2, and robust standard errors in Columns 3 and 4 (in parentheses). This Table presents the effect of the Muslim holidays on the number of passengers per taxi trip, the distance of the taxi trip, subway rides, and bike rides. The regressions control for day-of-the-week, week and holiday fixed effects plus meteorological conditions.

Table 7: Substitution Effects of Muslim Holidays on Supply Outcomes

	Average Rides per Driver	Average Income per Driver	Shift Duration
Eid al-Fitr	2.80***	35.56***	0.51***
	(0.90)	(11.64)	(0.03)
Eid al-Adha	3.22***	43.94***	0.07***
	(0.75)	(9.08)	(0.02)
Baseline	22.21	280.94	8.71
N	1,080	1,080	4,690,343

* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Notes: Robust standard errors in Columns 1 and 2, and standard errors clustered by day in Column 3 (in parentheses). This Table presents the effect of the Muslim holidays on the daily number of trips per taxi driver, the daily income per driver, and the duration of the drivers' shifts. Shift duration is measured in hours. The regressions control for day-of-the-week, week and holiday fixed effects plus meteorological conditions.

Table 8: Parameters Used in Welfare Calibration

Parameter	Related Variable	Value			Source
Change in travel speed (min per mile)	$\left(\frac{1}{s} - \frac{1}{s'}\right)$		0.4523		Reduced-form
Travel time value ($ per minute)	v_i		1.23		Data calculation
Disutility of waiting for subway	c_s		1.80		Parry and Small (2009)
Average real waiting time (min)	w_i		2.57		Frechette et al. (2018)
Counterfactual waiting times (min)					
If walking is second-best	$\bar{w}$	2.83	3.21	3.68	Data calculation
If transit if second-best	$\bar{w}$	2.83	3.21	12.83	Data calculation
Proportion trips where walking is second-best			0.09		Data calculation
Average distance taxi trip (miles)					
If walking is second-best	m_i		0.83		Data calculation
If transit if second-best	m_i		3.31		Data calculation
Average distance commuting in private cars	m_i		11.33		ACS (2013)
# Commuting trips in private cars			2,003,368		ACS (2013)
# Taxi trips			459,670		Data calculation
Change in taxi trips			-37,569		Reduced-form

Notes: This Table presents the parameters used to quantify the welfare changes defines by Equations 6, 8, and 9. For the counterfactual wait times, the first value represent a 10 percent increase of the real waiting time, the second value a 25 percent increase, and the third value is the maximum wiating time implied by Equations 7 and 10.

Table 9: Welfare Gains and Losses

	Wait Time			
	No change	10% Increase	25% Increase	Maximum
	a. Welfare Change Per Trip ($)			
Private cars	6.29	6.29	6.29	6.29
Taxi (walking is second best)				
Found taxi	0.46	0.15	-0.33	-0.90
Did not find taxi	-1.36	-1.36	-1.36	-1.36
Taxi (transit is second best)				
Found taxi	1.84	1.52	1.05	-10.75
Did not find taxi	-12.59	-12.59	-12.59	-12.59
	b. Daily Welfare Change ($ Millions)			
Private cars	12.6	12.6	12.6	12.6
Taxi (walking is second best)				
Found taxi	0.02	0.01	-0.01	-0.03
Did not find taxi	-0.005	-0.005	-0.005	-0.005
Taxi (transit is second best)				
Found taxi	0.7	0.6	0.4	-4.1
Did not find taxi	-0.4	-0.4	-0.4	-0.4

Notes: This Table present the results of the welfare calibration. Panel (a) presents results at the trip level, and Panel (b) presents daily changes in welfare. The first column presents the welfare change associated with higher travel assuming no change in waiting times. The following columns incorporate the consequences of increasingly higher waiting times. The last column assumes that waiting times increased to the maximum time a person is willing to wait for a taxi.

Appendix

For Online Publication Only

A Eid Dates in 2009–2017

Table A1: Eid Dates in 2009–2017

	Eid al-Fitr		Eid al-Adha	
	Starts the evening of	Ends the evening of	Starts the evening of	Ends the evening of
2009	9/20/2009	9/21/2009	11/26/2009	11/27/2009
2010	9/9/2010	9/10/2010	11/15/2010	11/16/2010
2011	8/30/2011	8/31/2011	11/5/2011	11/6/2011
2012	8/18/2012	8/19/2012	10/25/2012	10/26/2012
2013	8/7/2013	8/8/2013	10/14/2013	10/15/2013
2014	7/28/2014	7/29/2014	10/3/2014	10/4/2014
2015	7/17/2015	7/18/2015	9/23/2015	9/24/2015
2016	7/5/2016	7/6/2016	9/11/2016	9/12/2016
2017	6/24/2017	6/25/2017	8/31/2017	9/1/2017

This table presents the dates of Eid al-Fitr and Eid al-Adha in 2009–2017.

B Data Processing and Speed Calculations

The TLC reports taxi trip data as collected and provided by the two technology companies that supply taximeters in the city. As such, some data issues could if unaccounted bias the estimates. This study detected the following issues:

- One provider did not report data on 8/2/2010, 8/3/2010, 8/4/2010, 10/1/2010, 10/2/2010, 10/3/2010, 8/14/2011, 8/21/2011, 8/1/2013, 8/2/2013, 8/3/2013, 8/4/2013, and 8/11/2013. Estimations that use trip data control for these dates with dummy variables.

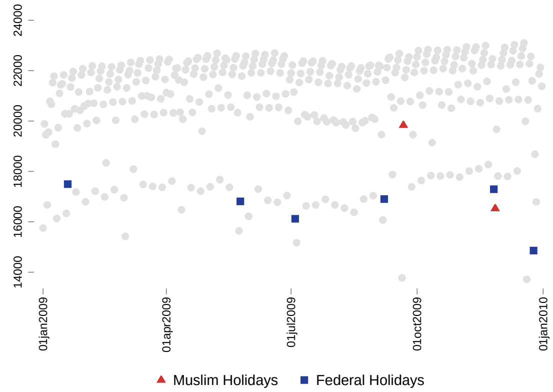
- Registered are duplicated in 9/19/2010. Since the data does not include identifiers, duplicated observations cannot be precisely detected. Estimations that use trip data control for this date with a dummy.

We can consider very short trips as cases where the traveler changed her mind, and very long trips involve destinations outside the city traveling in highways. Thus, travel speed calculations do not include trips that lasted less than a minute or more than two hours (1.1 percent of the sample) and exclude trips that start or end in areas where taxis are not allowed to pick up a passenger (1.8 percent of the sample). Trip distance also has misreporting issues. Trips with negative distances are excluded (0.2 percent of the sample) and I also delete trips with an average speed greater than 60 miles per hour (0.1 percent of the sample). As a reference, the speed limit in New York highways is 55 miles per hour, and the speed limit in New York City was 30 miles per hour until November 2014 and 25 miles per hour since then.

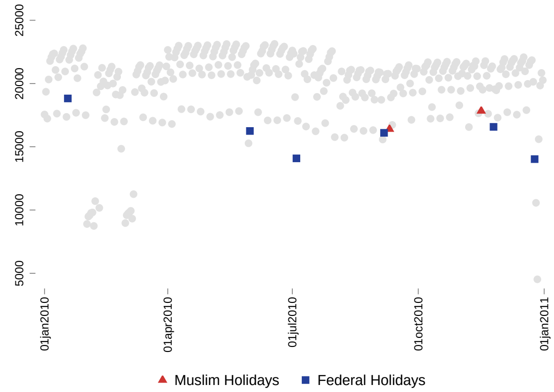
With these adjustments, I calculate the inverse of the average speed of each taxi trip (minutes per mile).

C Driver and Vehicle Patterns over 2009–2013

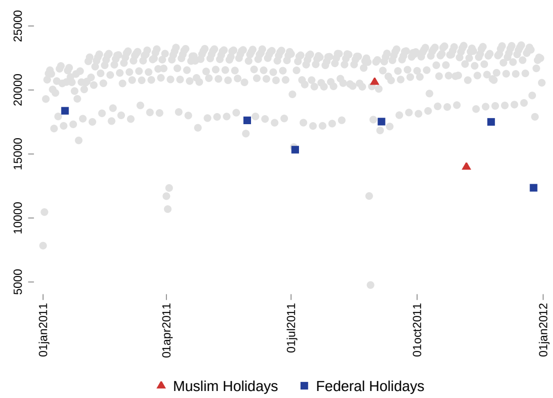
Figure C1: Taxi Drivers in 2009–2013



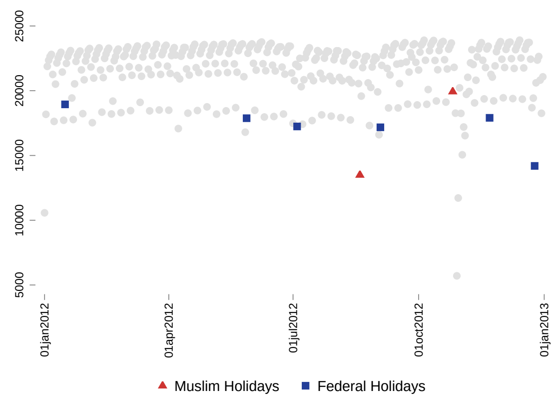
(a) 2009



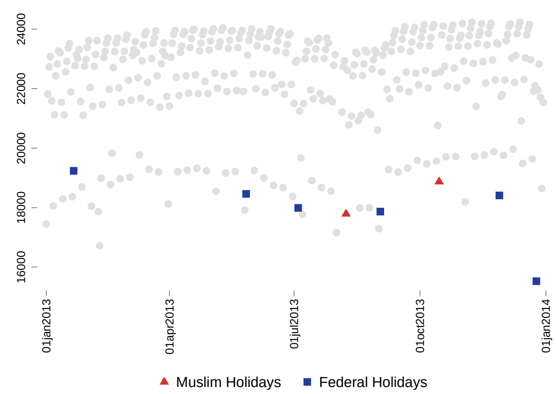
(b) 2010



(c) 2011



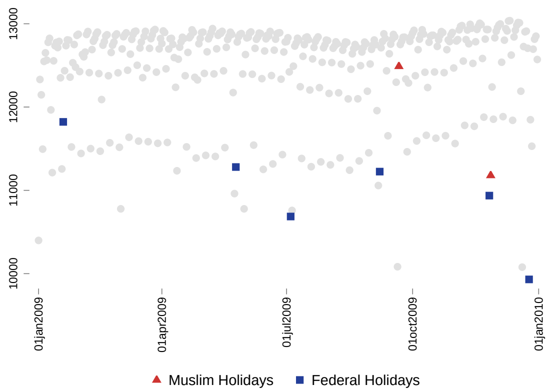
(d) 2012



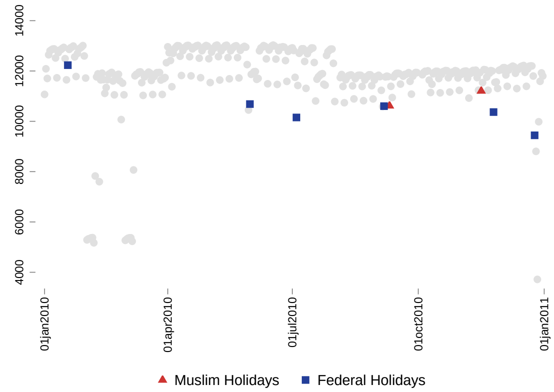
(e) 2013

Notes: This figure present the number of taxi drivers who had at least one trip per day in 2009–2013. Federal holidays include Martin Luther King Jr. Day, Memorial Day, 4 of July, Labor Day, Thanksgiving, and Christmas Day.

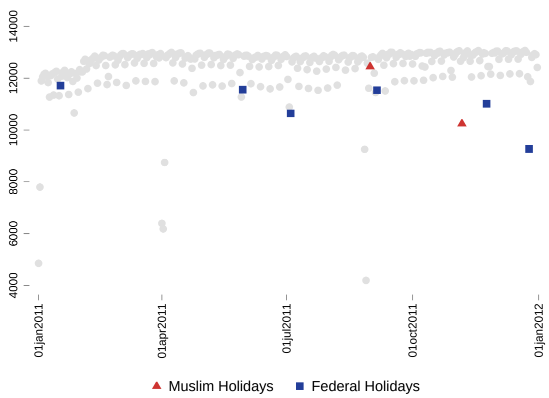
Figure C2: Taxi Vehicles in 2009–2013



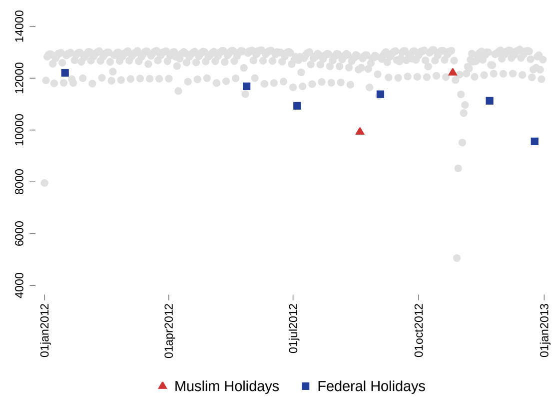
(a) 2009



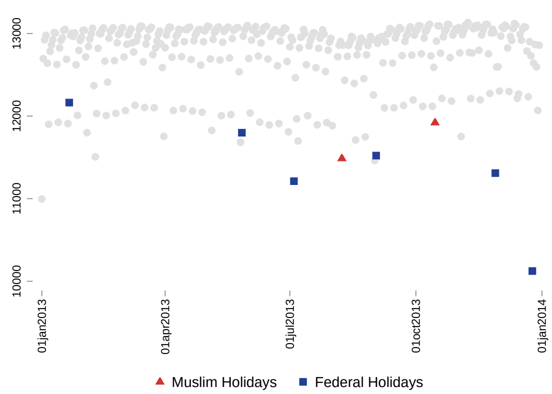
(b) 2010



(c) 2011



(d) 2012

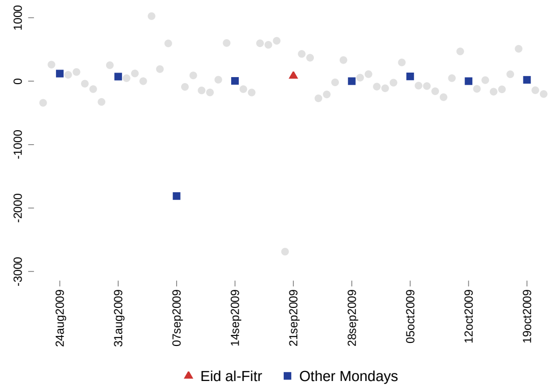


(e) 2013

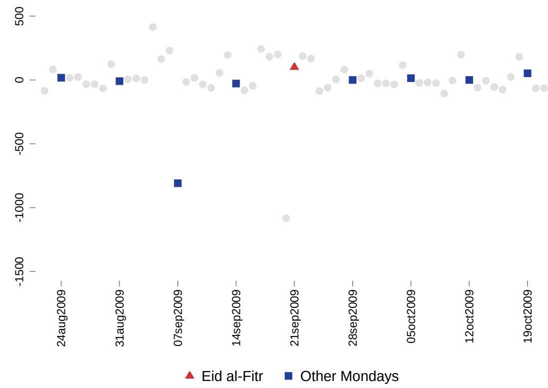
Notes: This figure present the number of yellow taxis who had at least one trip per day in 2009–2013. Federal holidays include Martin Luther King Jr. Day, Memorial Day, 4 of July, Labor Day, Thanksgiving, and Christmas Day.

D Additional Figures on the Effect of Muslim Holidays on the Number of Drivers and For-Hire Vehicles

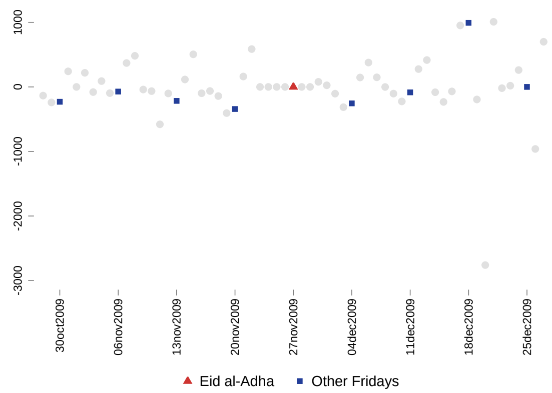
Figure D1: Residualized Number of Drivers and Taxis in 2009



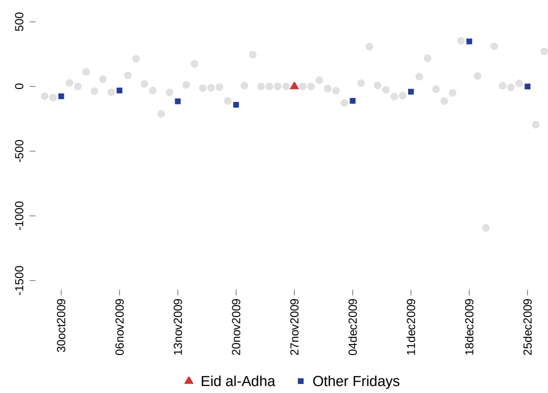
(a) Taxi Drivers - Eid al-Fitr



(b) Taxis - Eid al-Fitr



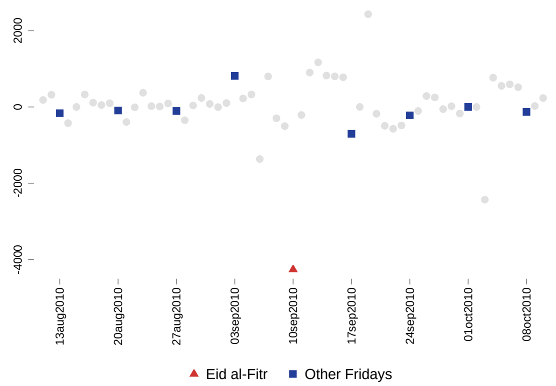
(c) Taxi Drivers - Eid al-Adha



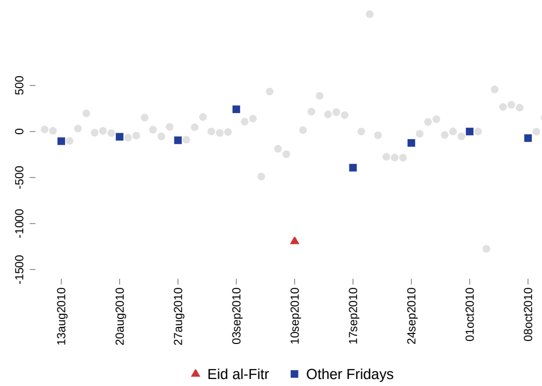
(d) Taxis - Eid al-Adha

Notes: This figure presents the residualized number of taxi drivers who had at least one trip per day and the residualized number of yellow taxis that had at least one ride per day, after controlling for day-of-the-week, week and holiday fixed effects plus meteorological conditions (Equation 1 without Muslim holiday dummies). The graphs present one month before and after each Eid. In 2009, Eid al-Adha coincided with Black Friday, so its effect is not identified.

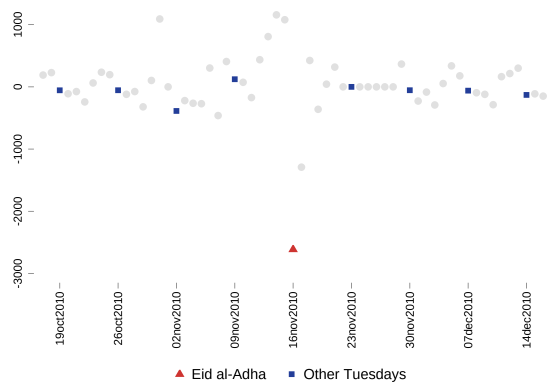
Figure D2: Residualized Number of Drivers and Taxis in 2010



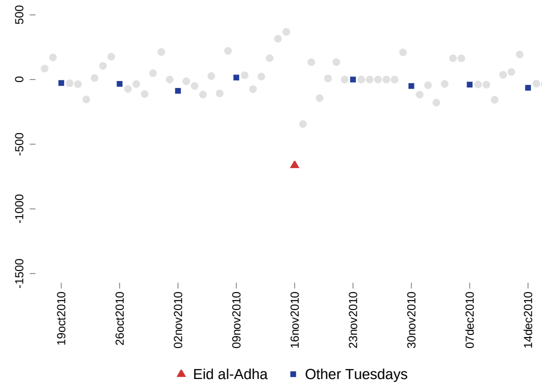
(a) Taxi Drivers - Eid al-Fitr



(b) Taxis - Eid al-Fitr



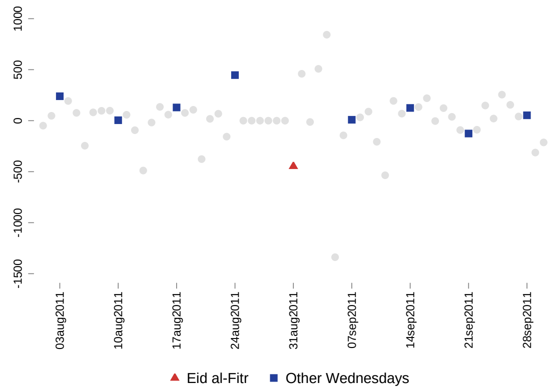
(c) Taxi Drivers - Eid al-Adha



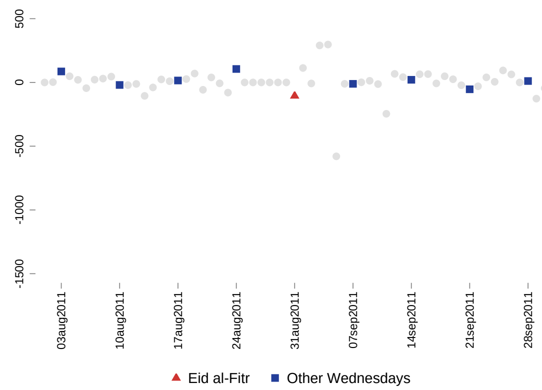
(d) Taxis - Eid al-Adha

Notes: This figure presents the residualized number of taxi drivers who had at least one trip per day and the residualized number of yellow taxis that had at least one ride per day, after controlling for day-of-the-week, week and holiday fixed effects plus meteorological conditions (Equation 1 without Muslim holiday dummies). The graphs present one month before and after each Eid.

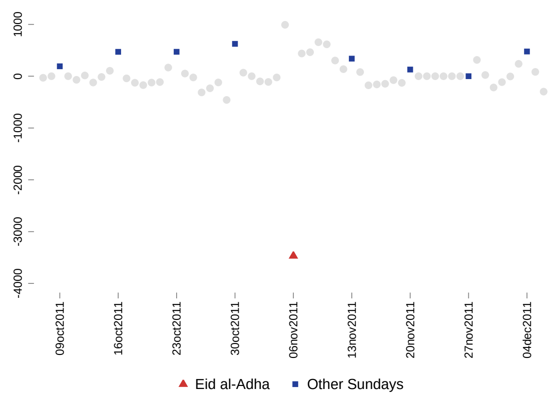
Figure D3: Residualized Number of Drivers and Taxis in 2011



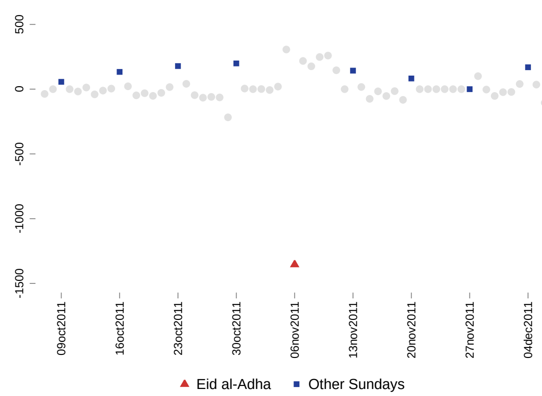
(a) Taxi Drivers - Eid al-Fitr



(b) Taxis - Eid al-Fitr



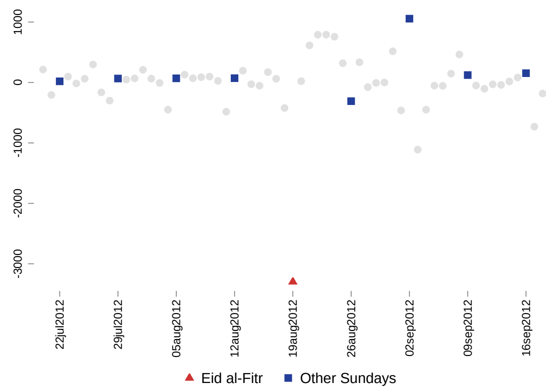
(c) Taxi Drivers - Eid al-Adha



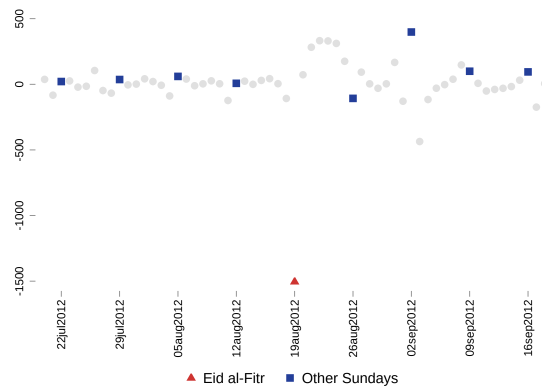
(d) Taxis - Eid al-Adha

Notes: This figure presents the residualized number of taxi drivers who had at least one trip per day and the residualized number of yellow taxis that had at least one ride per day, after controlling for day-of-the-week, week and holiday fixed effects plus meteorological conditions (Equation 1 without Muslim holiday dummies). The graphs present one month before and after each Eid.

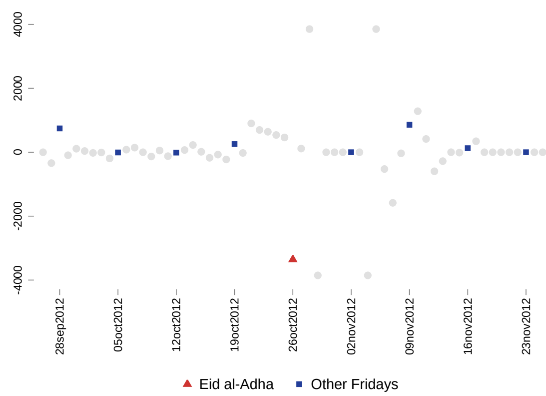
Figure D4: Residualized Number of Drivers and Taxis in 2012



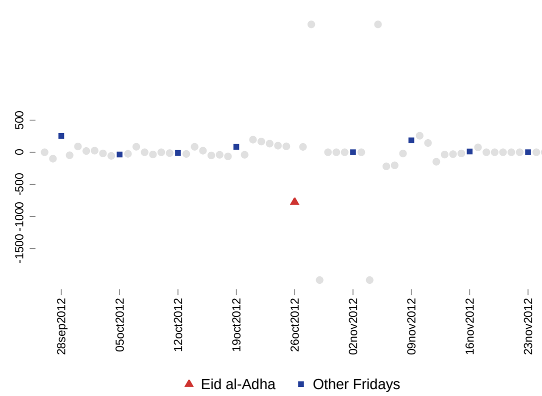
(a) Taxi Drivers - Eid al-Fitr



(b) Taxis - Eid al-Fitr



(c) Taxi Drivers - Eid al-Adha

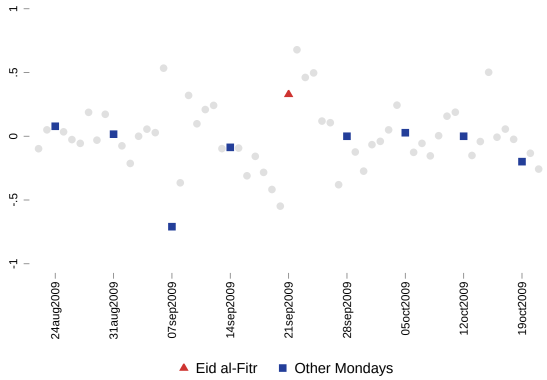


(d) Taxis - Eid al-Adha

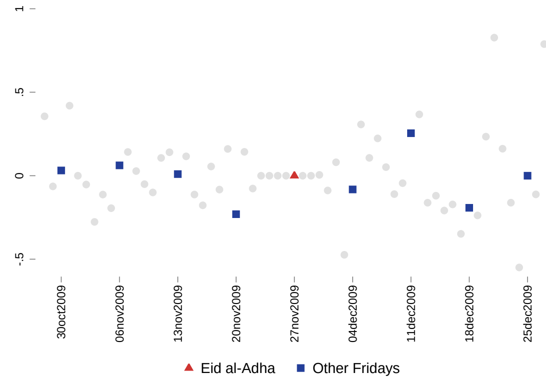
Notes: This figure presents the residualized number of taxi drivers who had at least one trip per day and the residualized number of yellow taxis that had at least one ride per day, after controlling for day-of-the-week, week and holiday fixed effects plus meteorological conditions (Equation 1 without Muslim holiday dummies). The graphs present one month before and after each Eid.

E Additional Tables and Figures on the Effect of Muslim Holidays on Congestion and Collisions

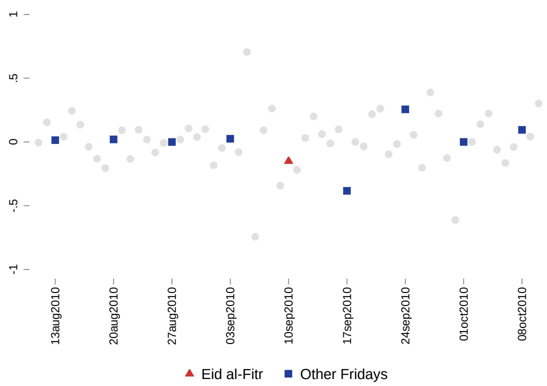
Figure E1: Residualized Time per Mile in 2009–2011



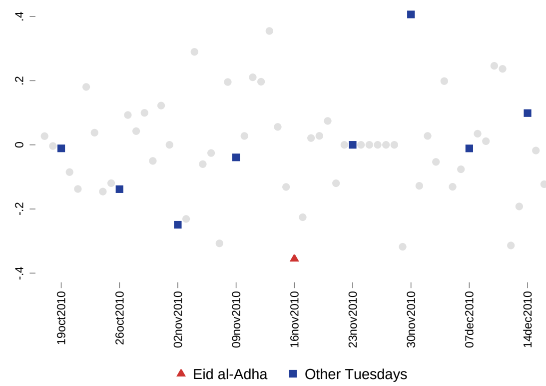
(a) Eid al-Fitr 2009



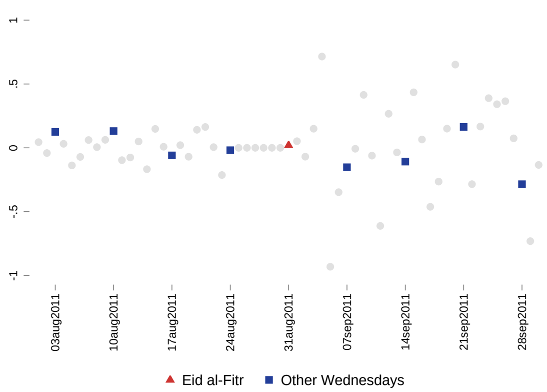
(b) Eid al-Adha 2009



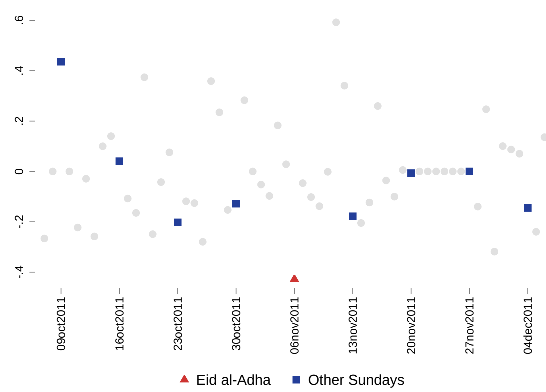
(c) Eid al-Fitr 2010



(d) Eid al-Adha 2010



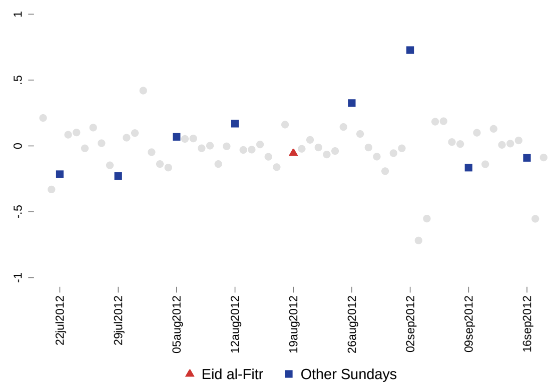
(e) Eid al-Fitr 2011



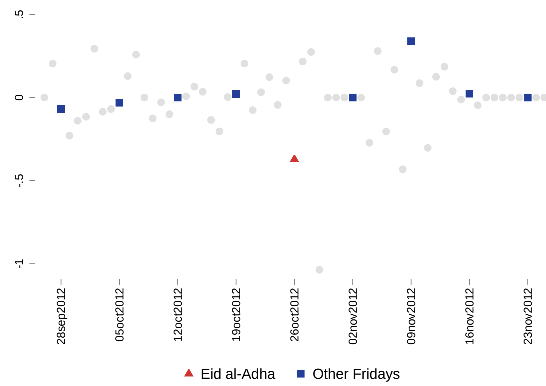
(f) Eid al-Adha 2011

Notes: This figure presents the residualized average time per mile (minutes per mile), after controlling for day-of-the-week, week and holiday fixed effects plus meteorological conditions (Equation 1 without Muslim holiday dummies). The graphs present one month before and after each Eid.

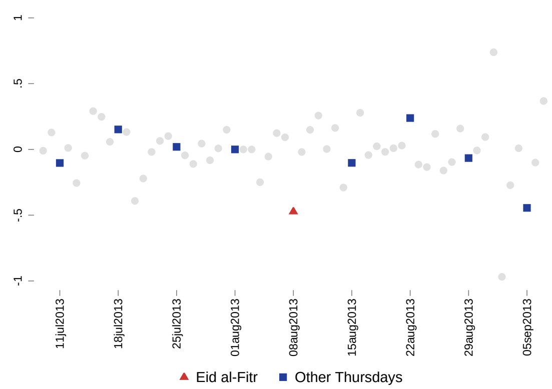
Figure E2: Residualized Time per Mile in 2012–2014



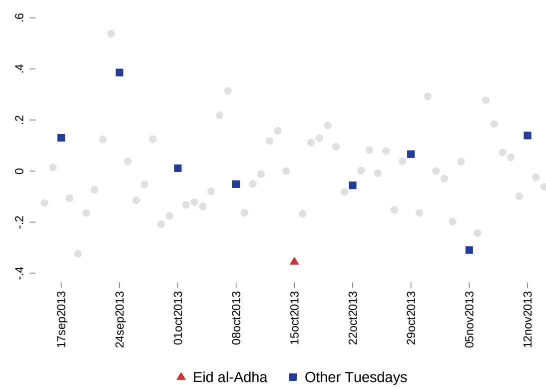
(a) Eid al-Fitr 2012



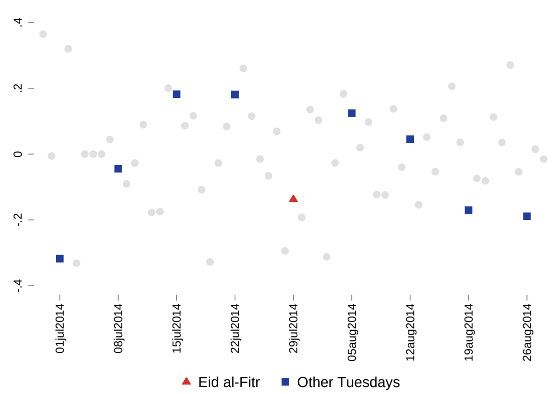
(b) Eid al-Adha 2012



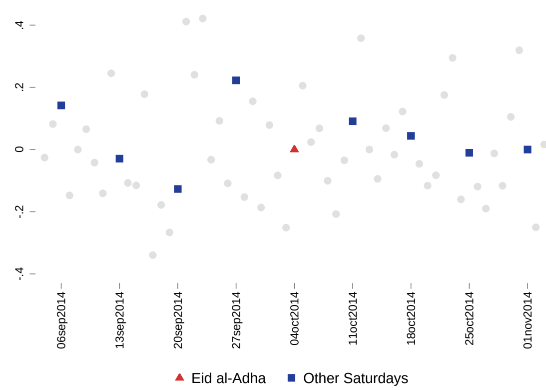
(c) Eid al-Fitr 2013



(d) Eid al-Adha 2013



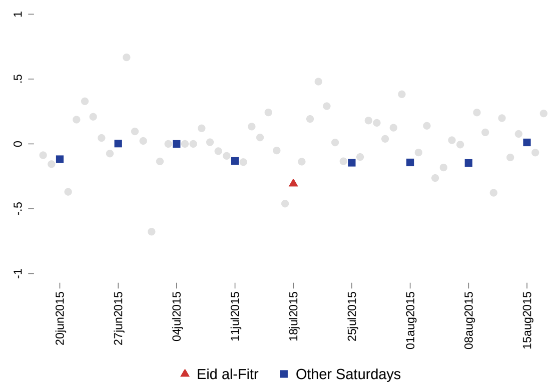
(e) Eid al-Fitr 2014



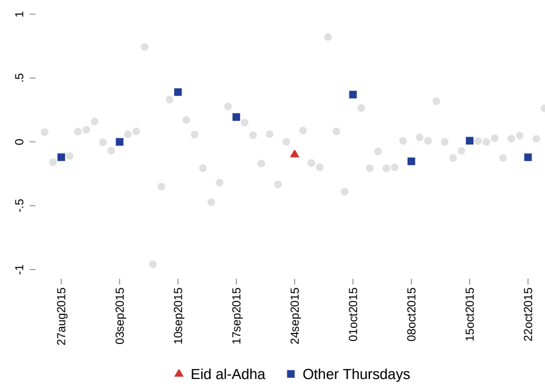
(f) Eid al-Adha 2014

Notes: This figure presents the residualized average time per mile (minutes per mile), after controlling for day-of-the-week, week and holiday fixed effects plus meteorological conditions (Equation 1 without Muslim holiday dummies). The graphs present one month before and after each Eid.

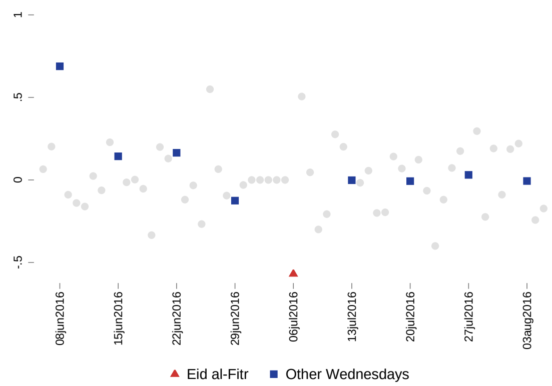
Figure E3: Residualized Time per Mile in 2015–2017



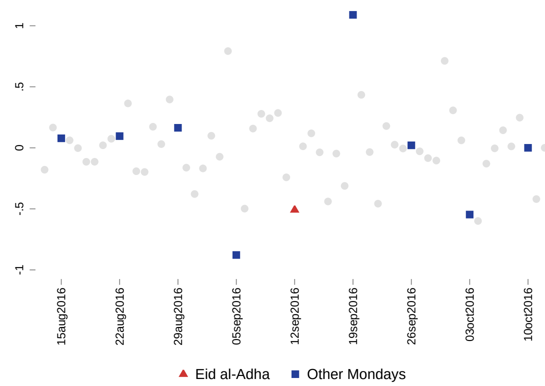
(a) Eid al-Fitr 2015



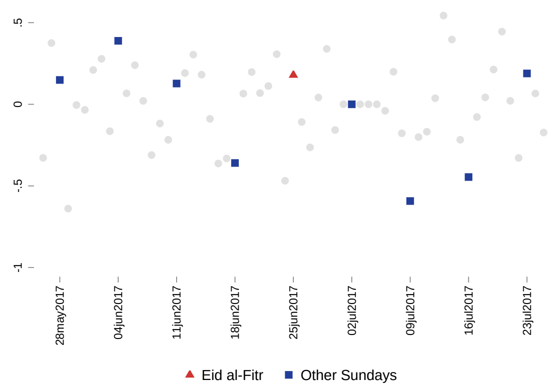
(b) Eid al-Adha 2015



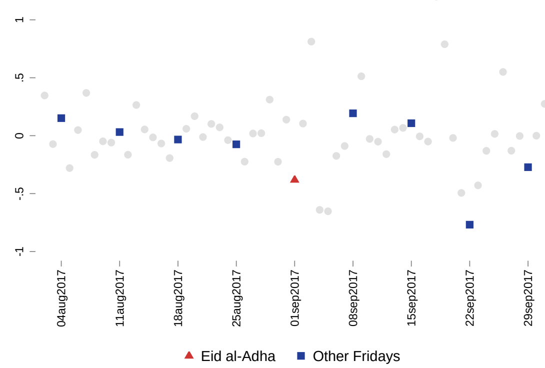
(c) Eid al-Fitr 2016



(d) Eid al-Adha 2016



(e) Eid al-Fitr 2017



(f) Eid al-Adha 2017

Notes: This figure presents the residualized average time per mile (minutes per mile), after controlling for day-of-the-week, week and holiday fixed effects plus meteorological conditions (Equation 1 without Muslim holiday dummies). The graphs present one month before and after each Eid.

Table E1: Effects of Muslim Holidays on Congestion by Region of the City

	Change in Speed	Baseline
Eid al-Fitr: Out Manhattan - Out Manhattan	-0.0055	4.7
	(0.0432)	
Eid al-Fitr: Out Manhattan - In Manhattan	-0.1076*	3.92
	(0.0610)	
Eid al-Fitr: In Manhattan - Out Manhattan	-0.0924**	3.86
	(0.0397)	
Eid al-Fitr: In Manhattan - In Manhattan	-0.1805	6.95
	(0.1255)	
Eid al-Adha: Out Manhattan - Out Manhattan	0.1495	4.7
	(0.1271)	
Eid al-Adha: Out Manhattan - In Manhattan	-0.0836*	3.92
	(0.0486)	
Eid al-Adha: In Manhattan - Out Manhattan	-0.1053***	3.86
	(0.0295)	
Eid al-Adha: In Manhattan - In Manhattan	-0.5254***	6.95
	(0.0493)	
N	799,758,682	

* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Notes: Standard errors clustered by day in parentheses. This table presents the effect of the Muslim holidays on the inverse of speed (minutes per mile) of taxi trips in the city by region. New York is divided into Manhattan and the outer boroughs, and trips are classified into regions depending on the starting and end points. The regressions control for day-of-the-week, week and holiday fixed effects plus meteorological conditions.

Table E2: Robustness: Control for Trip Distance

	Full Sample	
	Eid al-Fitr	Eid al-Adha
Effect	-0.1544	-0.4147***
	(0.1032)	(0.0401)
Baseline	6.21	6.46
N	799,758,682	

* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Notes: Standard errors clustered by day in parentheses. This table test the robustness of the effects on congestion by including the trip distance as an additional control.

Table E3: Effects of Muslim Holidays on Congestion by Time of the Day

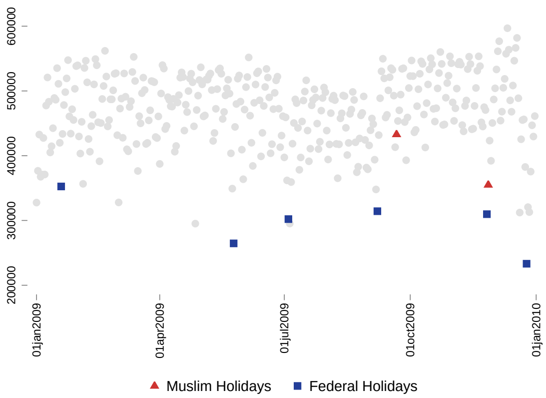
	Full Sample		2009-2013	
	Speed Inverse	Baseline	Speed Inverse	Baseline
Eid al-Fitr: 1:00-5:59	-0.1453***	4.25	-0.1158***	4.25
	(0.0388)		(0.0394)	
Eid al-Fitr: 6:00-7:59	-0.1462**	4.76	-0.1687*	4.66
	(0.0659)		(0.0982)	
Eid al-Fitr: 8:00-18:59	-0.3331**	7.10	-0.2532	6.93
	(0.1642)		(0.2526)	
Eid al-Fitr: 19:00-20:59	-0.0001	6.00	0.1910	5.90
	(0.1945)		(0.1984)	
Eid al-Fitr: 21:00-0:59	0.0700	5.19	0.1096	5.13
	(0.1493)		(0.2142)	
Eid al-Adha: 1:00-5:59	0.0287	4.37	0.0158	4.32
	(0.0483)		(0.0518)	
Eid al-Adha: 6:00-7:59	-0.2005***	5.05	-0.1859***	4.90
	(0.0588)		(0.0577)	
Eid al-Adha: 8:00-18:59	-0.5992***	7.41	-0.6265***	7.15
	(0.0660)		(0.0817)	
Eid al-Adha: 19:00-20:59	-0.5206***	6.33	-0.4463***	6.17
	(0.0777)		(0.0885)	
Eid al-Adha: 21:00-0:59	-0.2105***	5.32	-0.1491*	5.21
	(0.0781)		(0.0826)	
N	799,758,682		490,969,773	

* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

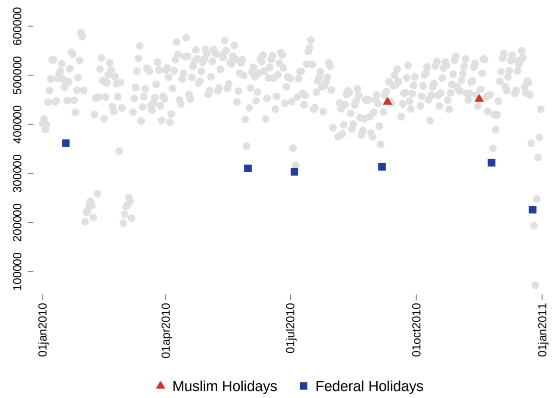
Notes: Standard errors clustered by day in parentheses. This table presents the effect of the Muslim holidays on the inverse of speed (minutes per mile) of taxi trips in the city by time of the day. The hour-ranges match periods with similar speed. The regressions control for day-of-the-week, week and holiday fixed effects plus meteorological conditions.

F Additional Tables and Figures on the Effect of Muslim Holidays on Trips and Substitutting Patterns

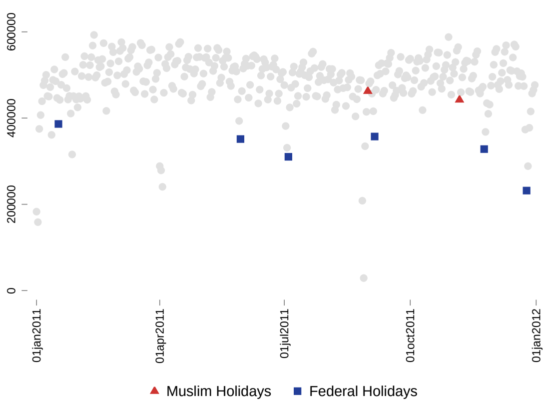
Figure F1: Taxi Rides in 2009–2014



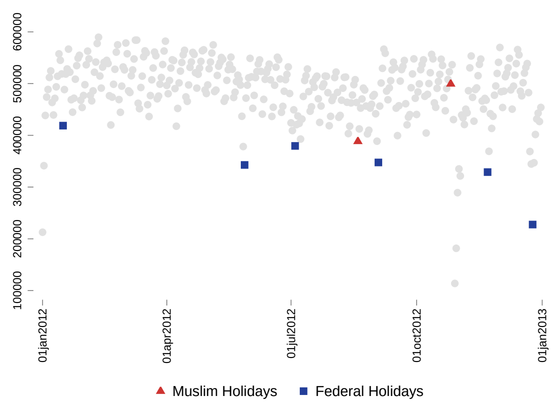
(a) 2009



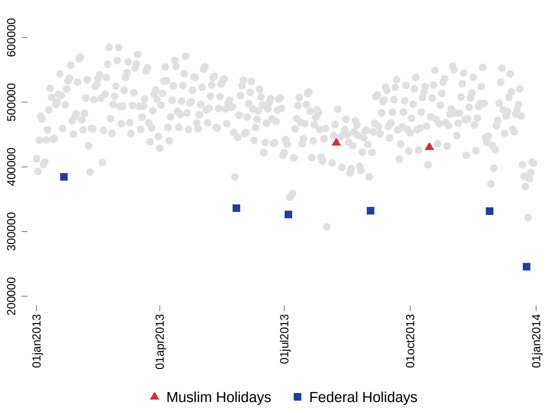
(b) 2010



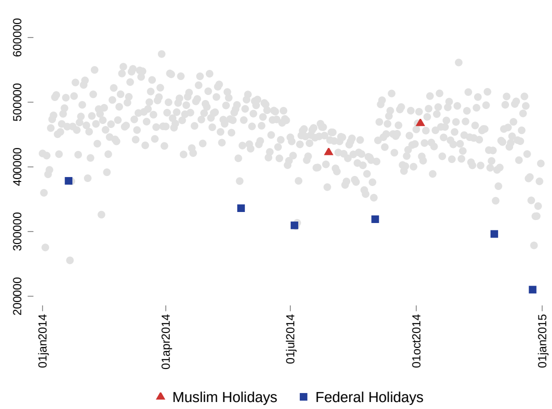
(c) 2011



(d) 2012



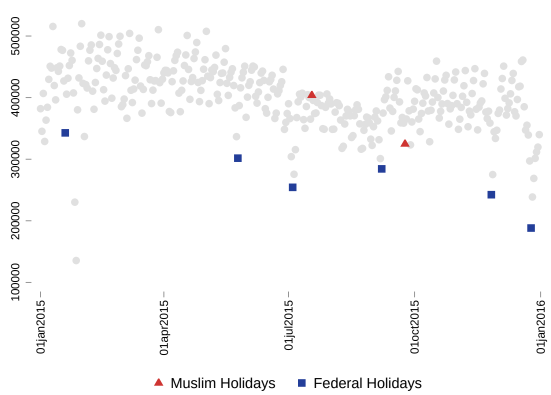
(e) 2013



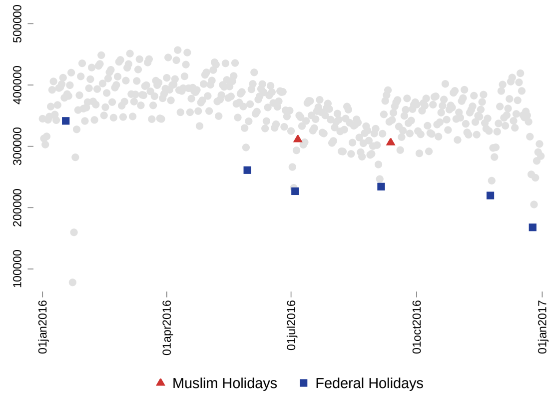
(f) 2013

Notes: This figure present the number of yellow taxis trips per day in 2009–2014. Federal holidays include Martin Luther King Jr. Day, Memorial Day, 4 of July, Labor Day, Thanksgiving, and Christmas Day.

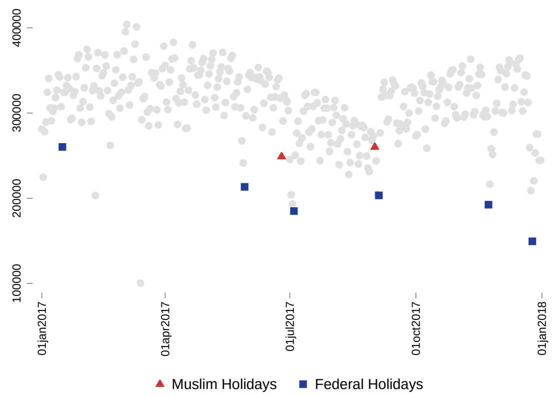
Figure F2: Taxi Rides in 2015–2017



(a) 2009



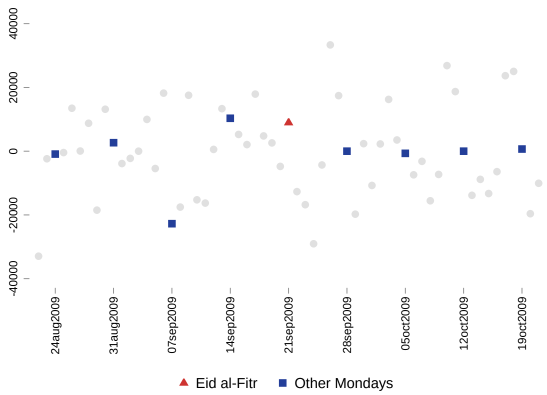
(b) 2010



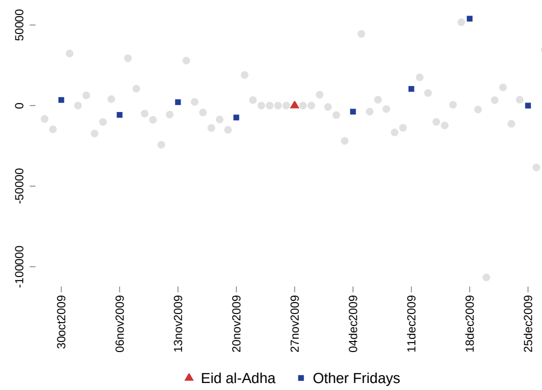
(c) 2011

Notes: This figure present the number of yellow taxis trips per day in 2015–2017. Federal holidays include Martin Luther King Jr. Day, Memorial Day, 4 of July, Labor Day, Thanksgiving, and Christmas Day.

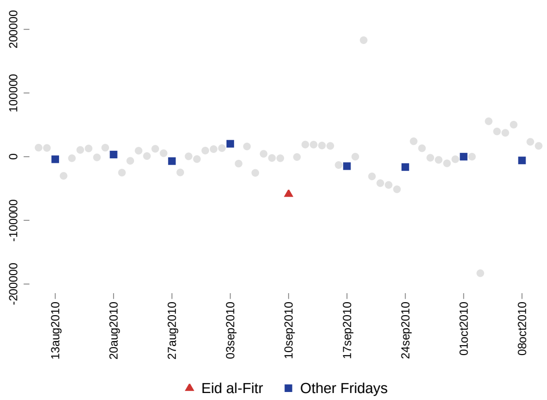
Figure F3: Residualized Yellow Taxi Daily Trips in 2009–2011



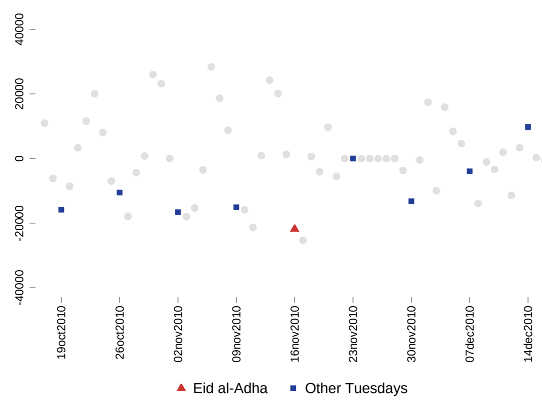
(a) Eid al-Fitr 2009



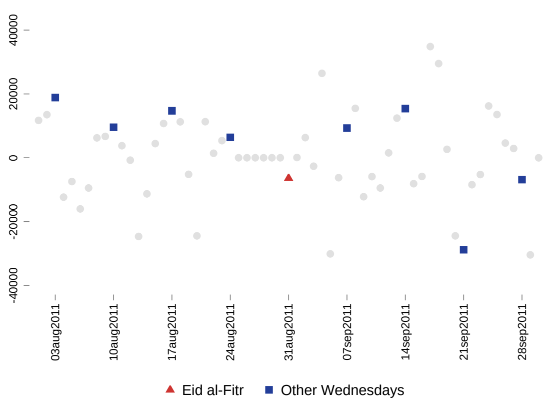
(b) Eid al-Adha 2009



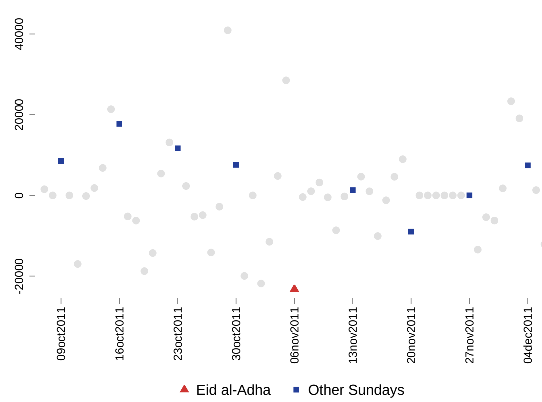
(c) Eid al-Fitr 2010



(d) Eid al-Adha 2010



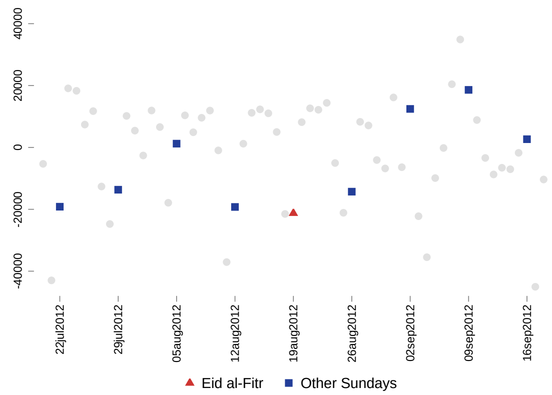
(e) Eid al-Fitr 2011



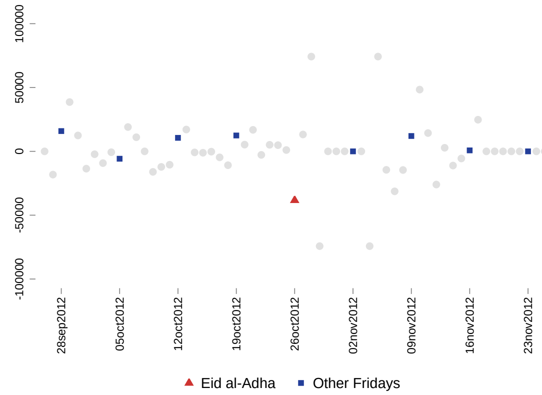
(f) Eid al-Adha 2011

Notes: This figure presents the residualized daily trips on yellow taxis, after controlling for day-of-the-week, week and holiday fixed effects plus meteorological conditions (Equation 1 without Muslim holiday dummies). The graphs present one month before and after each Eid.

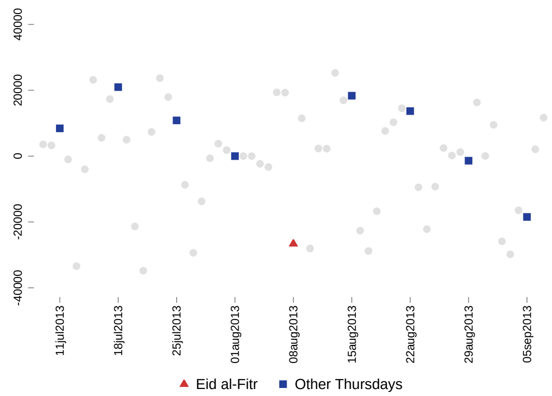
Figure F4: Residualized Yellow Taxi Daily Trips in 2012–2014



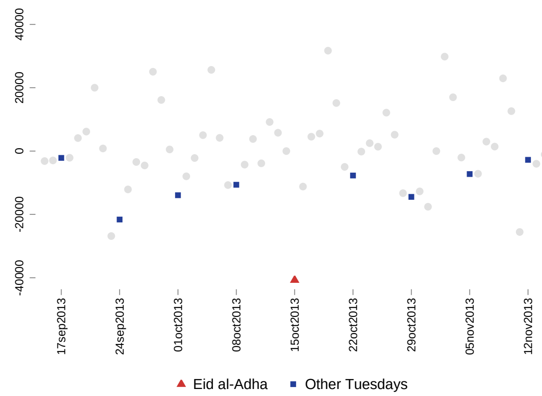
(a) Eid al-Fitr 2012



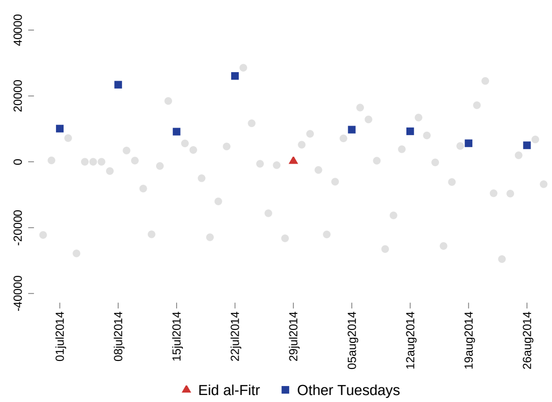
(b) Eid al-Adha 2012



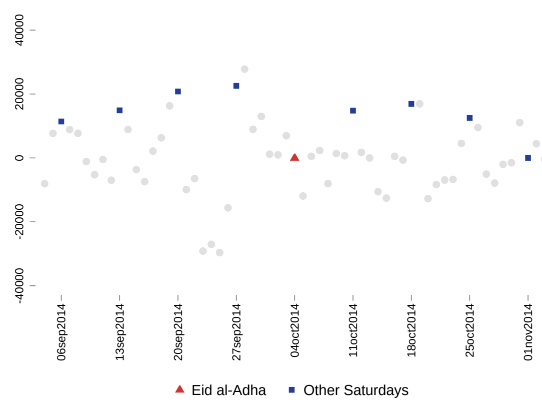
(c) Eid al-Fitr 2013



(d) Eid al-Adha 2013



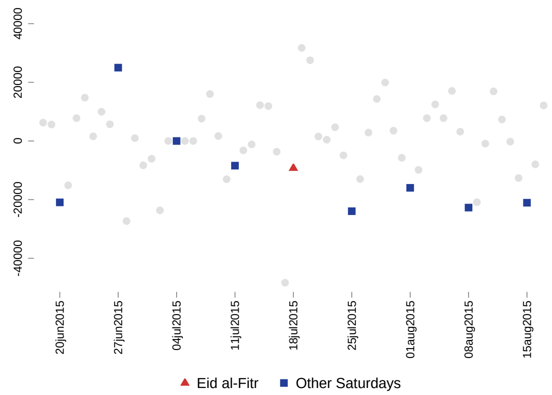
(e) Eid al-Fitr 2014



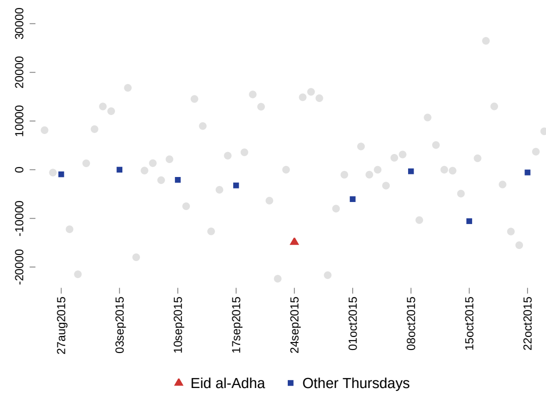
(f) Eid al-Adha 2014

Notes: This figure presents the residualized daily trips on yellow taxis, after controlling for day-of-the-week, week and holiday fixed effects plus meteorological conditions (Equation 1 without Muslim holiday dummies). The graphs present one month before and after each Eid.

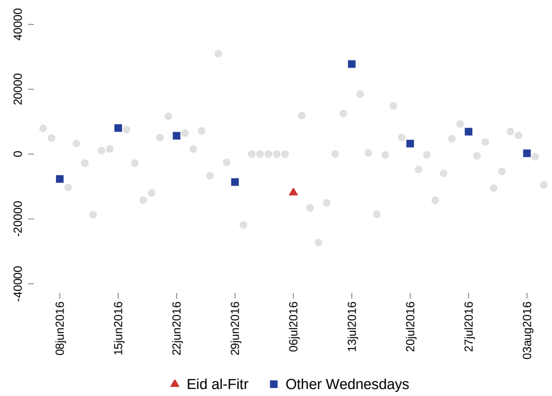
Figure F5: Residualized Yellow Taxi Daily Trips in 2015–2017



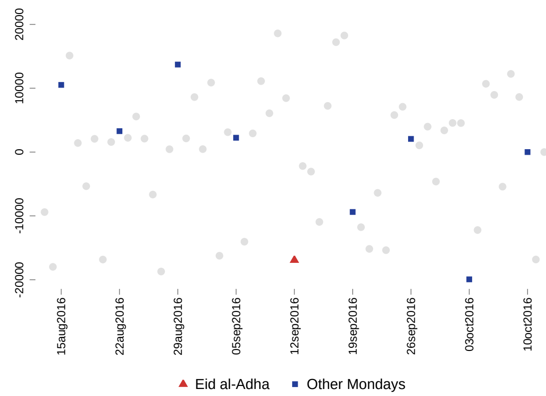
(a) Eid al-Fitr 2015



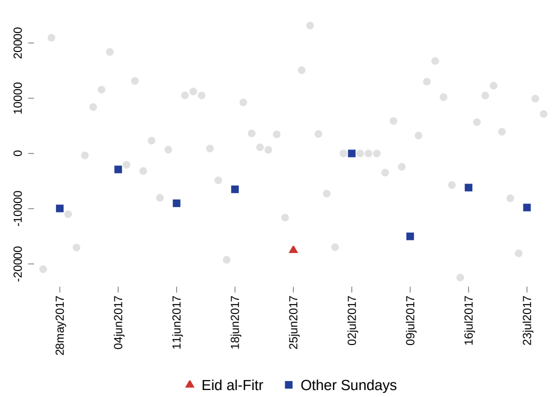
(b) Eid al-Adha 2015



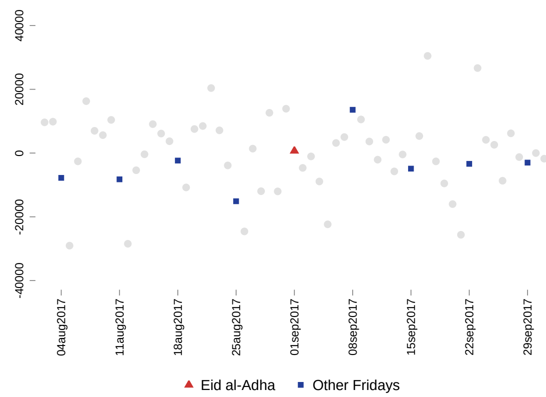
(c) Eid al-Fitr 2016



(d) Eid al-Adha 2016



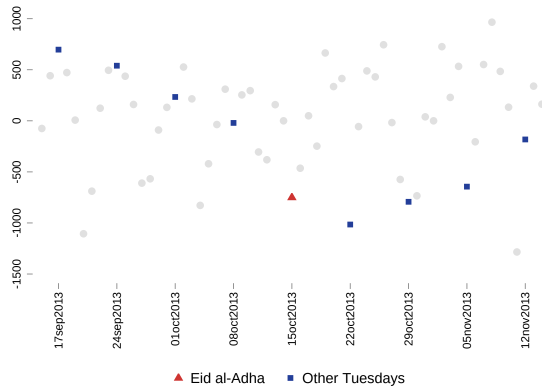
(e) Eid al-Fitr 2017



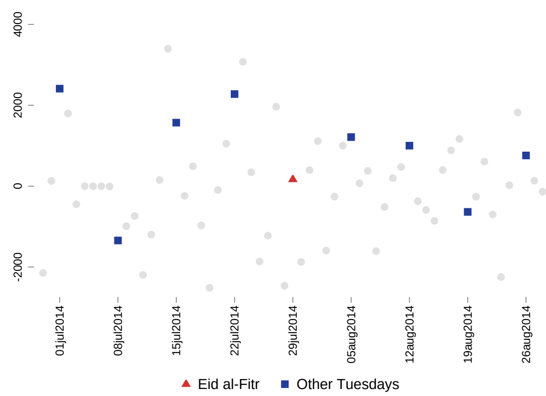
(f) Eid al-Adha 2017

Notes: This figure presents the residualized daily trips on yellow taxis, after controlling for day-of-the-week, week and holiday fixed effects plus meteorological conditions (Equation 1 without Muslim holiday dummies). The graphs present one month before and after each Eid.

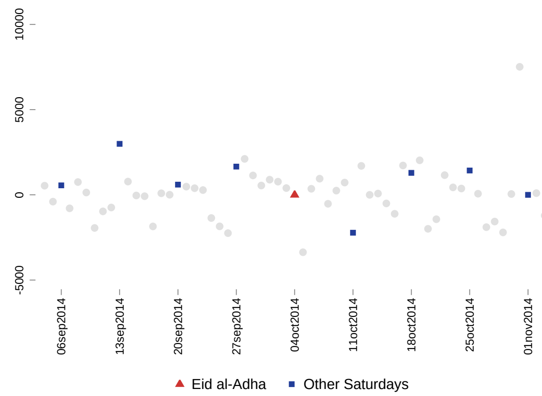
Figure F6: Residualized Green Taxi Daily Trips in 2013–2015



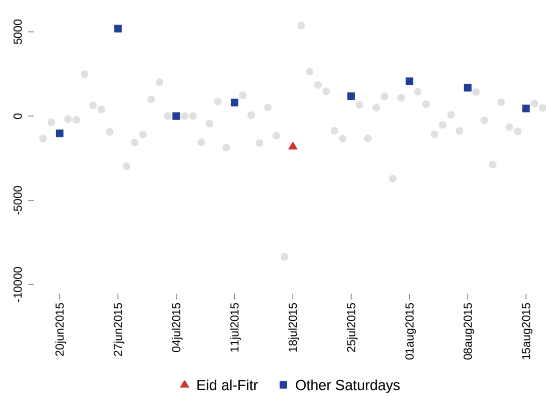
(a) Eid al-Adha 2013



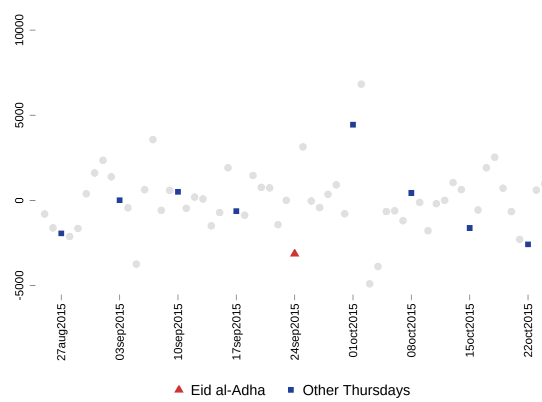
(b) Eid al-Fitr 2014



(c) Eid al-Adha 2014



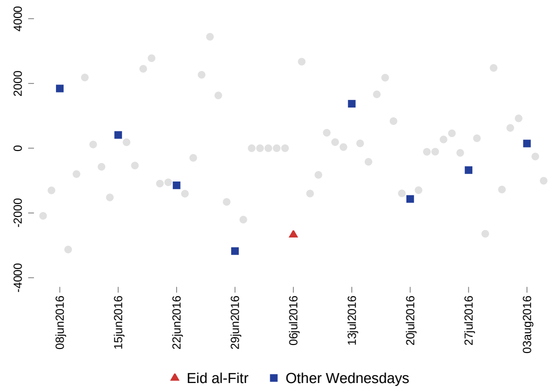
(d) Eid al-Fitr 2015



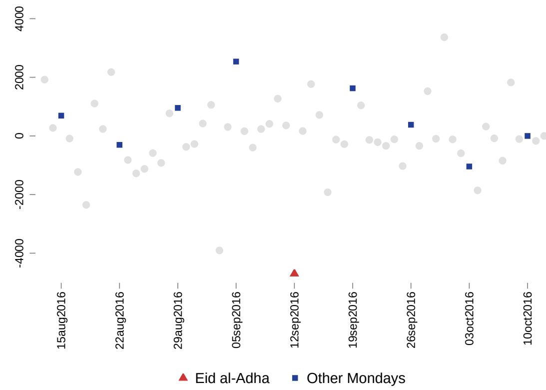
(e) Eid al-Adha 2015

Notes: This figure presents the residualized daily trips on green taxis, after controlling for day-of-the-week, week and holiday fixed effects plus meteorological conditions (Equation 1 without Muslim holiday dummies). The graphs present one month before and after each Eid.

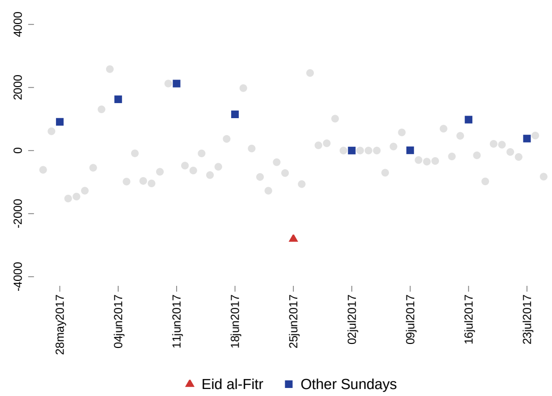
Figure F7: Residualized Green Taxi Daily Trips in 2016–2017



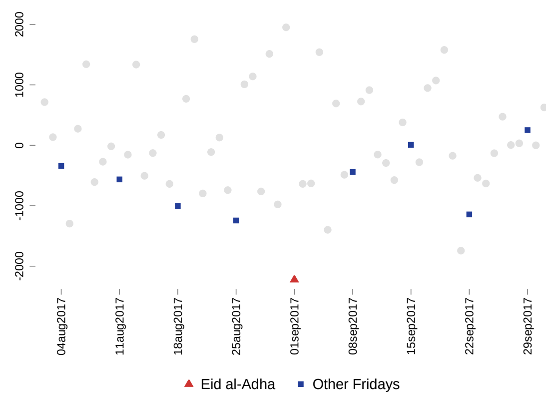
(a) Eid al-Fitr 2016



(b) Eid al-Adha 2016



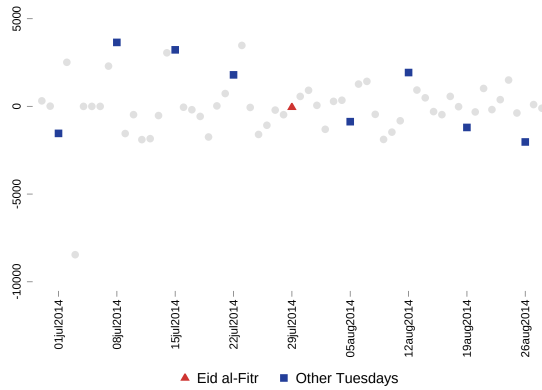
(c) Eid al-Fitr 2017



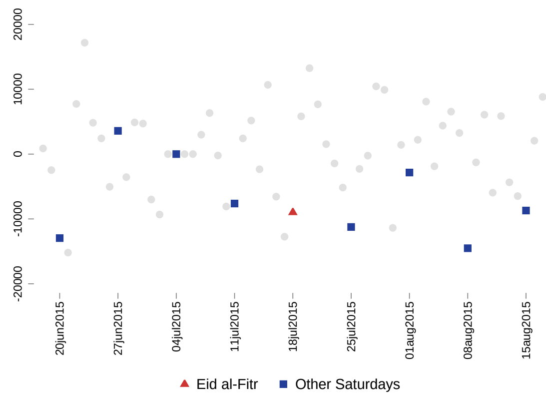
(d) Eid al-Adha 2017

Notes: This figure presents the residualized daily trips on green taxis, after controlling for day-of-the-week, week and holiday fixed effects plus meteorological conditions (Equation 1 without Muslim holiday dummies). The graphs present one month before and after each Eid.

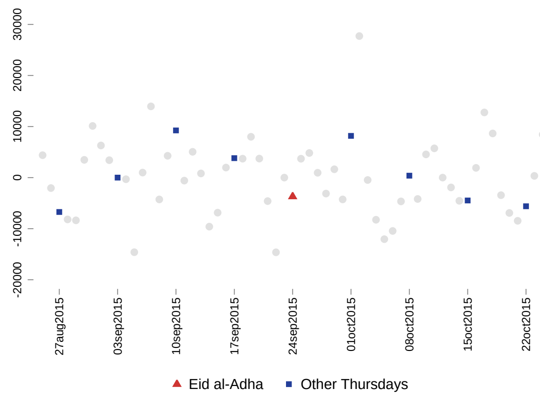
Figure F8: Residualized Uber Daily Trips in 2014–2015



(a) Eid al-Fitr 2014



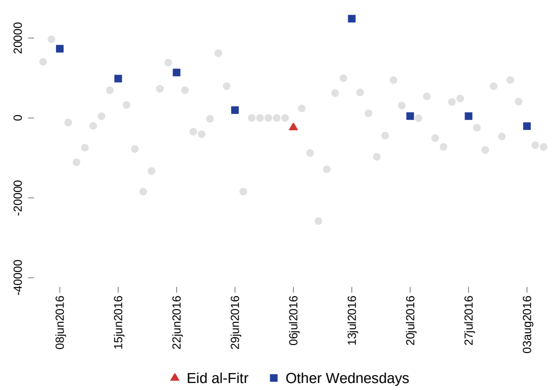
(b) Eid al-Fitr 2015



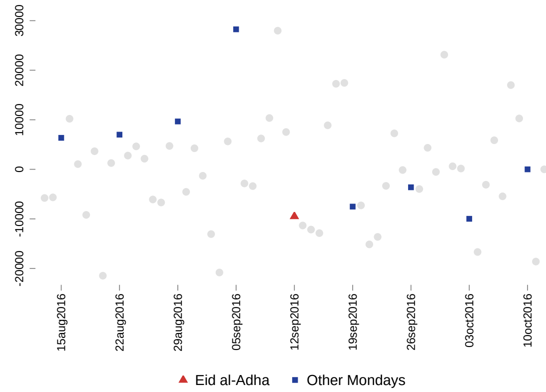
(c) Eid al-Adha 2015

Notes: This figure presents the residualized daily trips on Uber, after controlling for day-of-the-week, week and holiday fixed effects plus meteorological conditions (Equation 1 without Muslim holiday dummies). The graphs present one month before and after each Eid.

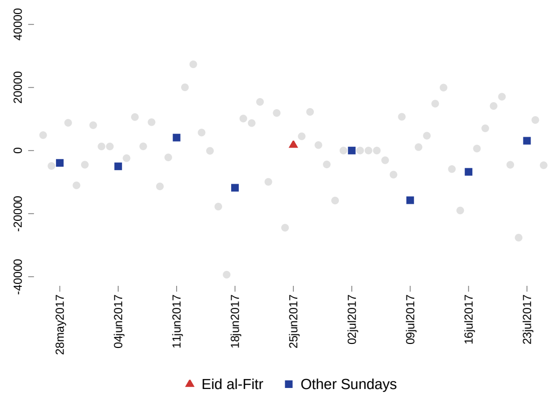
Figure F9: Residualized Uber Daily Trips in 2016–2017



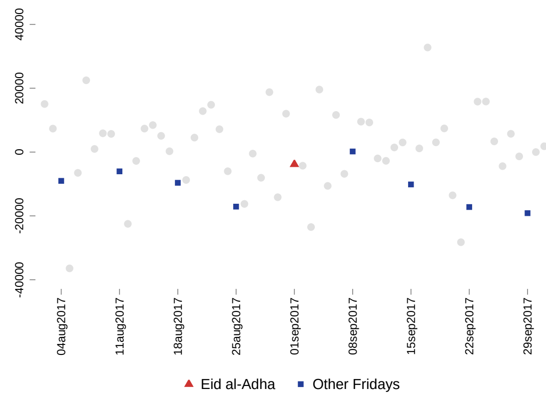
(a) Eid al-Fitr 2016



(b) Eid al-Adha 2016



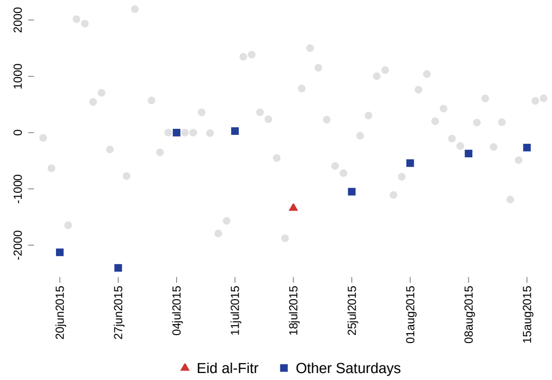
(c) Eid al-Fitr 2017



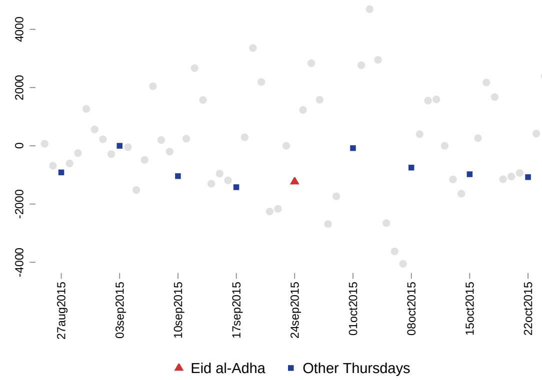
(d) Eid al-Adha 2017

Notes: This figure presents the residualized daily trips on Uber, after controlling for day-of-the-week, week and holiday fixed effects plus meteorological conditions (Equation 1 without Muslim holiday dummies). The graphs present one month before and after each Eid.

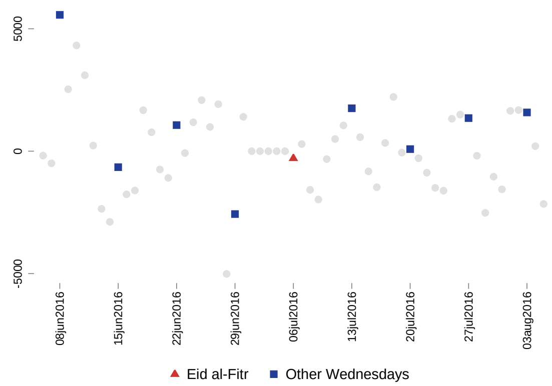
Figure F10: Residualized Lyft Daily Trips in 2015–2017



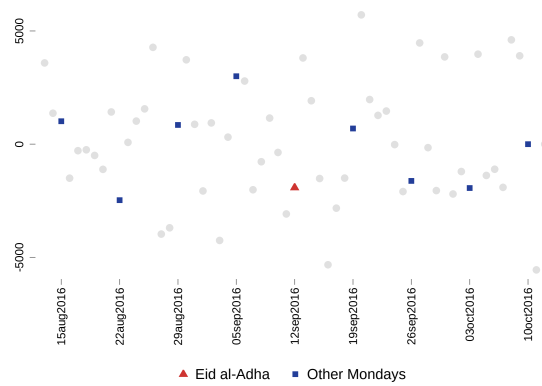
(a) Eid al-Fitr 2015



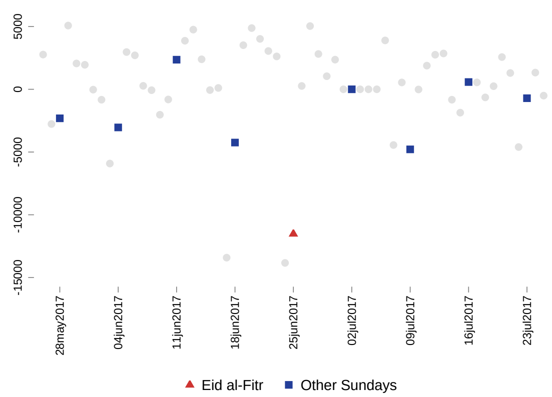
(b) Eid al-Adha 2015



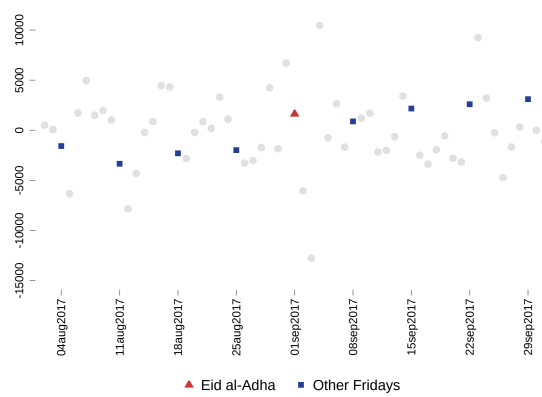
(c) Eid al-Fitr 2016



(d) Eid al-Adha 2016



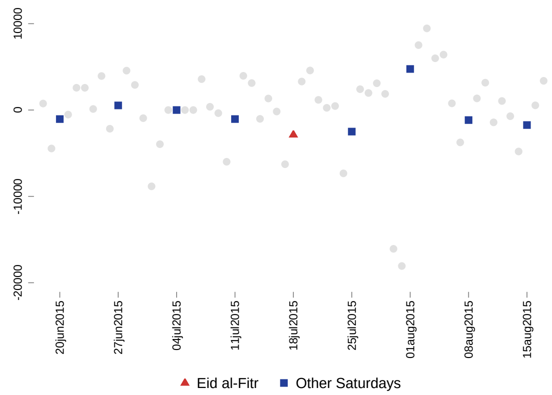
(e) Eid al-Fitr 2017



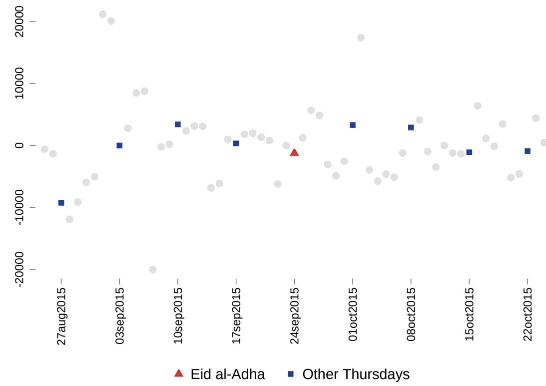
(f) Eid al-Adha 2017

Notes: This figure presents the residualized daily trips on Lyft, after controlling for day-of-the-week, week and holiday fixed effects plus meteorological conditions (Equation 1 without Muslim holiday dummies). The graphs present one month before and after each Eid.

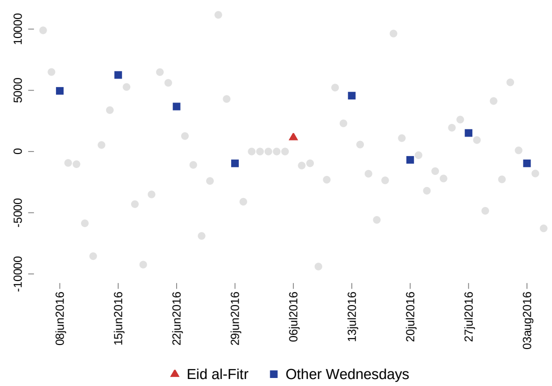
Figure F11: Residualized Other For-Hire Daily Trips in 2015–2017



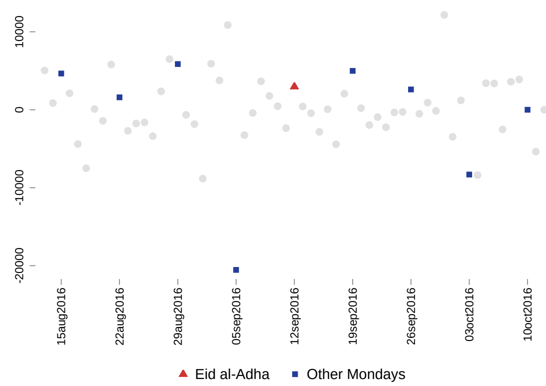
(a) Eid al-Fitr 2015



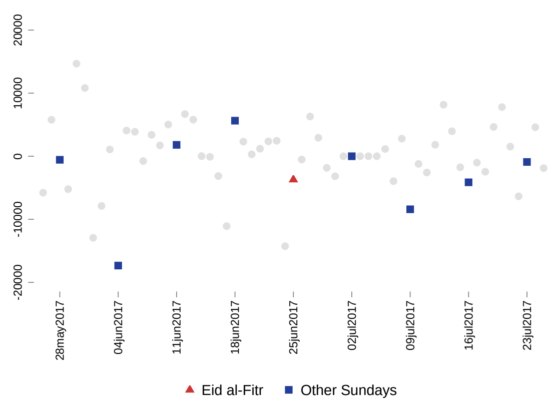
(b) Eid al-Adha 2015



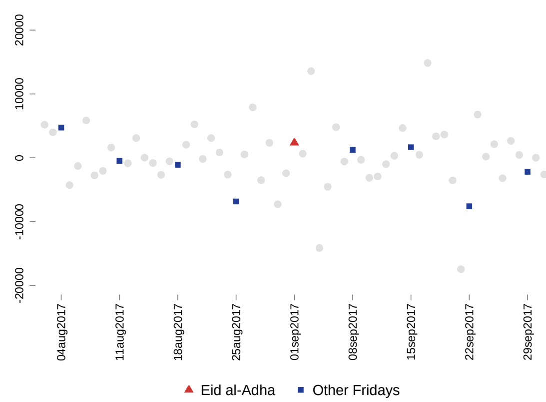
(c) Eid al-Fitr 2016



(d) Eid al-Adha 2016



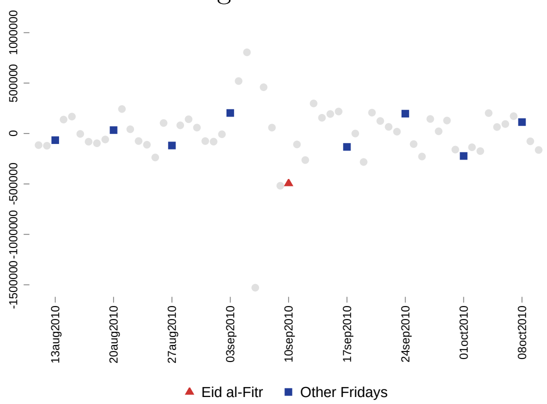
(e) Eid al-Fitr 2017



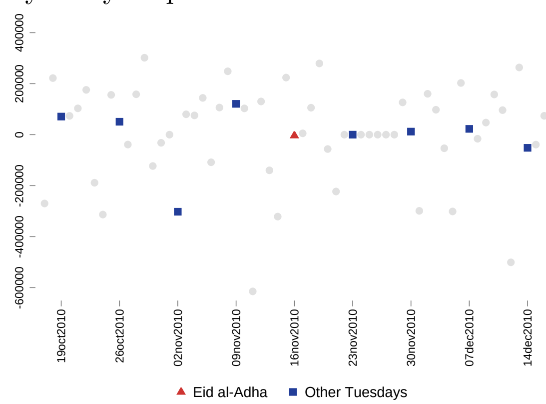
(f) Eid al-Adha 2017

Notes: This figure presents the residualized daily trips on other for-hire vehicles, after controlling for day-of-the-week, week and holiday fixed effects plus meteorological conditions (Equation 1 without Muslim holiday dummies). The graphs present one month before and after each Eid.

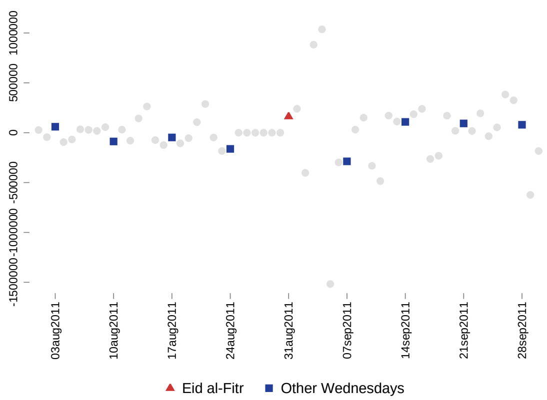
Figure F12: Residualized Subway Daily Trips in 2010–2011



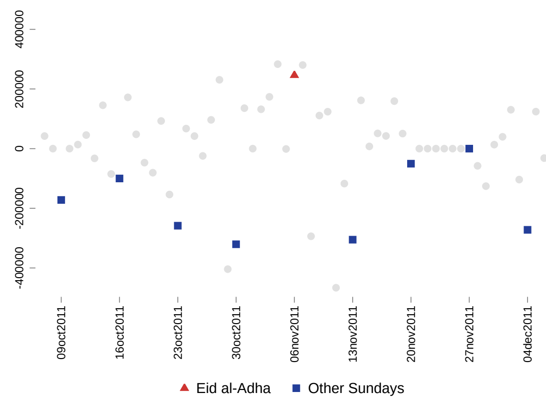
(a) Eid al-Fitr 2010



(b) Eid al-Adha 2010



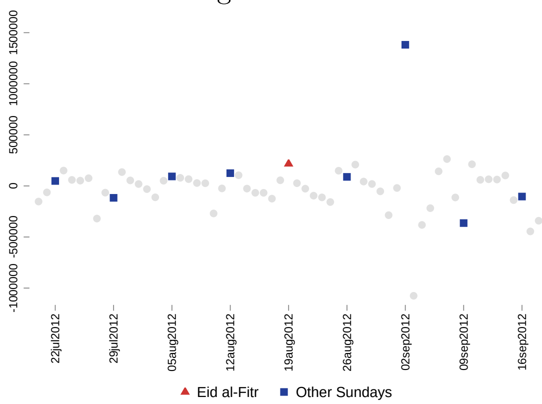
(c) Eid al-Fitr 2011



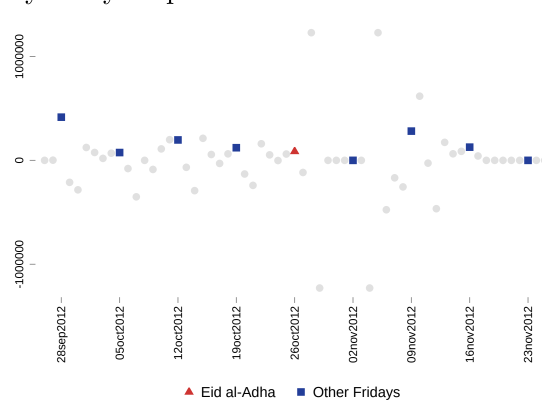
(d) Eid al-Adha 2011

Notes: This figure presents the residualized daily trips on subway, after controlling for day-of-the-week, week and holiday fixed effects plus meteorological conditions (Equation 1 without Muslim holiday dummies). The graphs present one month before and after each Eid.

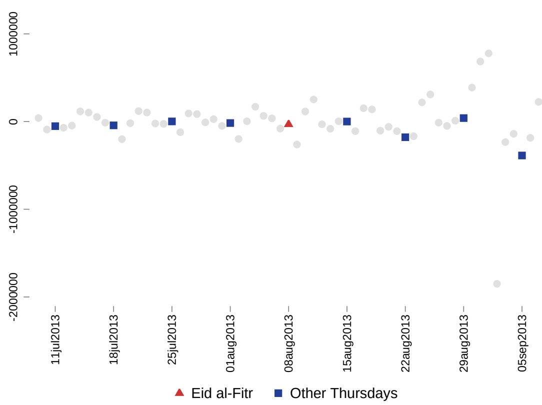
Figure F13: Residualized Subway Daily Trips in 2012–2014



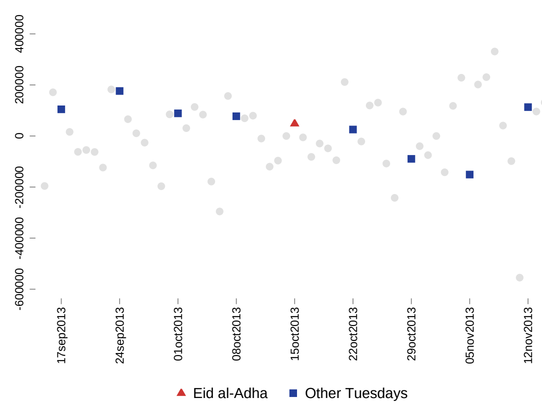
(a) Eid al-Fitr 2012



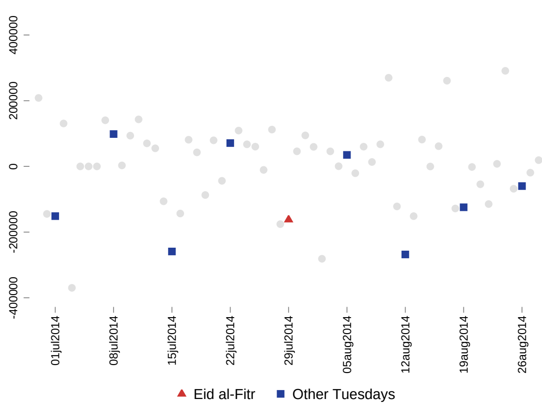
(b) Eid al-Adha 2012



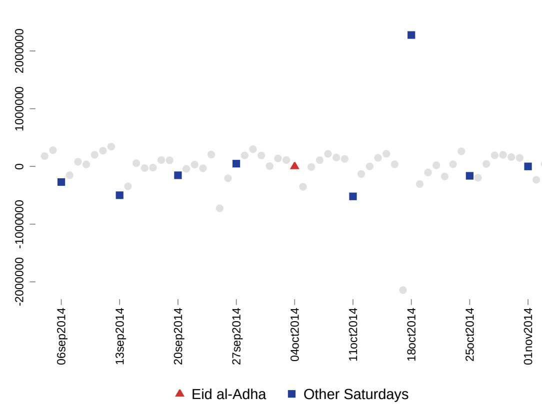
(c) Eid al-Fitr 2013



(d) Eid al-Adha 2013



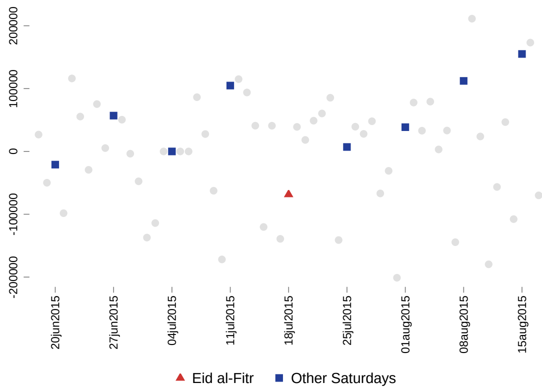
(e) Eid al-Fitr 2014



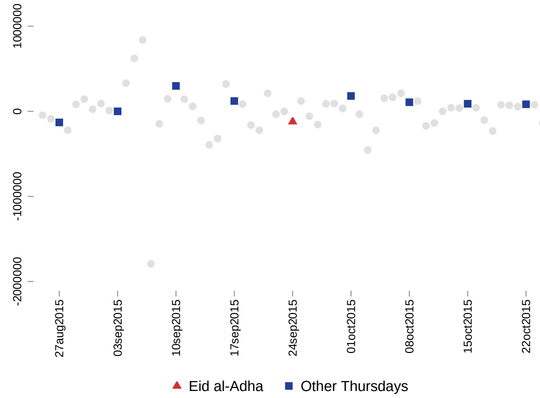
(f) Eid al-Adha 2014

Notes: This figure presents the residualized daily trips on subways, after controlling for day-of-the-week, week and holiday fixed effects plus meteorological conditions (Equation 1 without Muslim holiday dummies). The graphs present one month before and after each Eid.

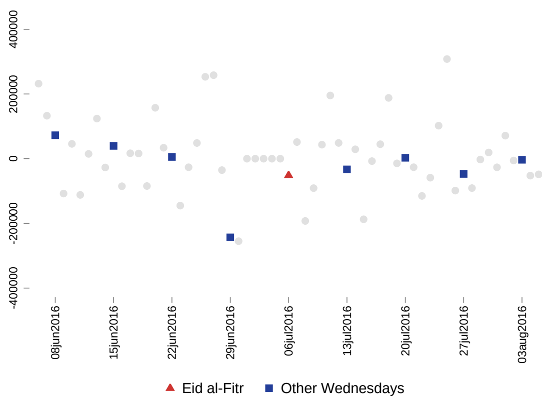
Figure F14: Residualized Subways Daily Trips in 2015–2017



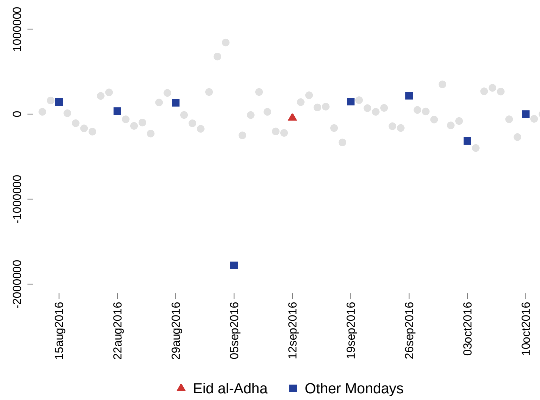
(a) Eid al-Fitr 2015



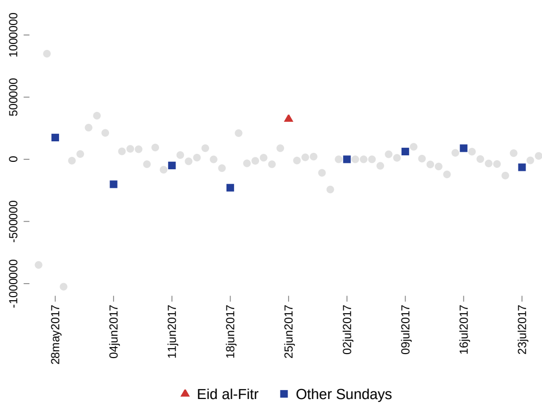
(b) Eid al-Adha 2015



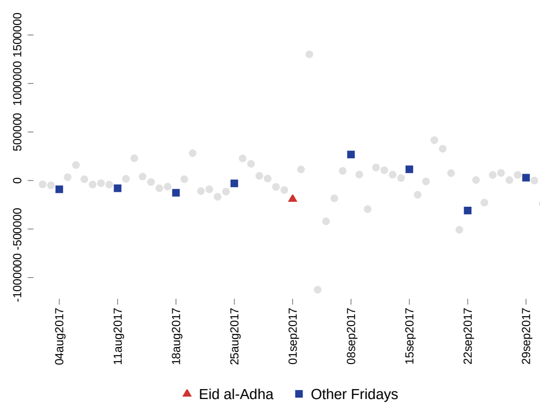
(c) Eid al-Fitr 2016



(d) Eid al-Adha 2016



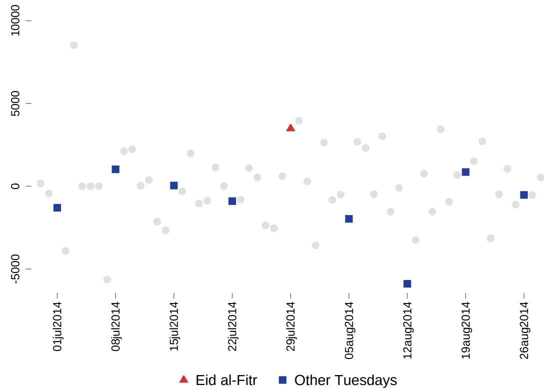
(e) Eid al-Fitr 2017



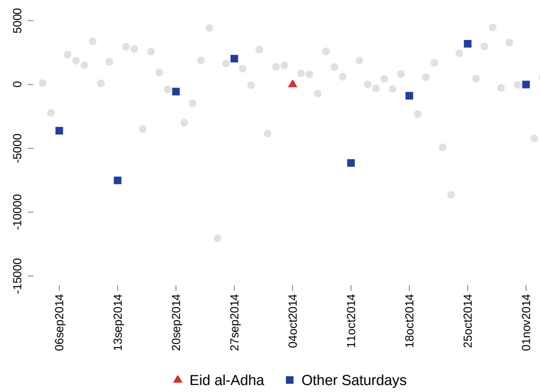
(f) Eid al-Adha 2017

Notes: This figure presents the residualized daily trips on subway, after controlling for day-of-the-week, week and holiday fixed effects plus meteorological conditions (Equation 1 without Muslim holiday dummies). The graphs present one month before and after each Eid.

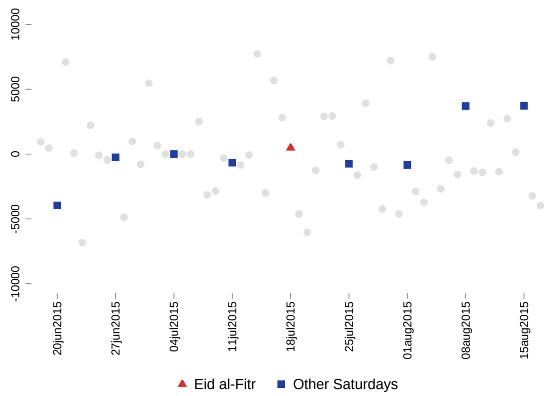
Figure F15: Residualized Bike Daily Trips in 2014–2015



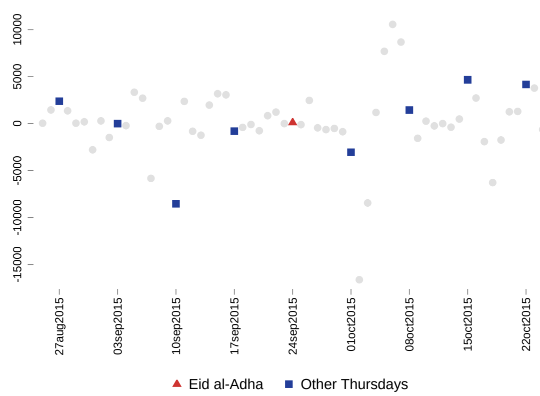
(a) Eid al-Fitr 2014



(b) Eid al-Adha 2014



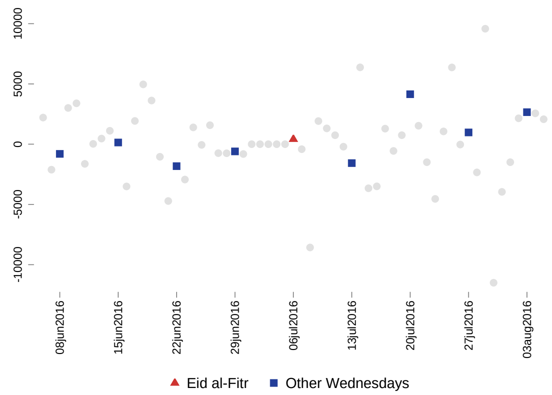
(c) Eid al-Fitr 2015



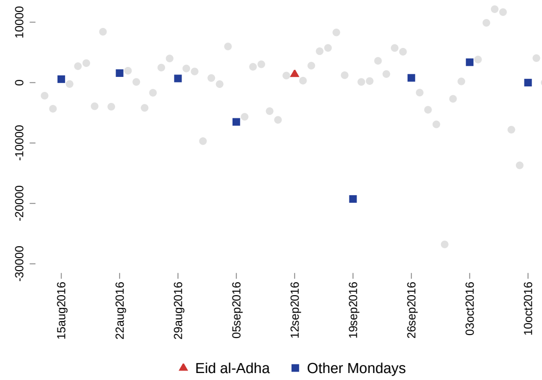
(d) Eid al-Adha 2015

Notes: This figure presents the residualized daily trips on bikes, after controlling for day-of-the-week, week and holiday fixed effects plus meteorological conditions (Equation 1 without Muslim holiday dummies). The graphs present one month before and after each Eid.

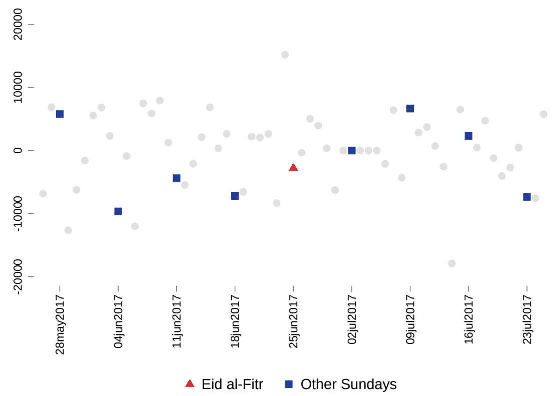
Figure F16: Residualized Bike Daily Trips in 2016–2017



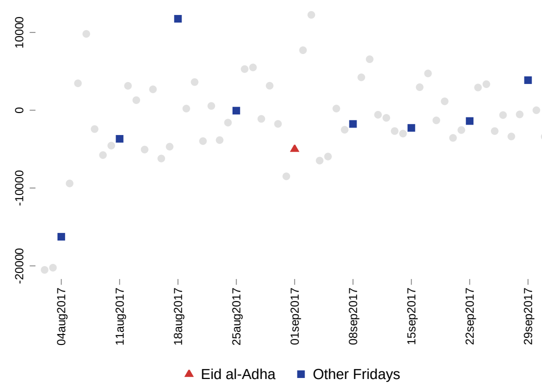
(a) Eid al-Fitr 2016



(b) Eid al-Adha 2016



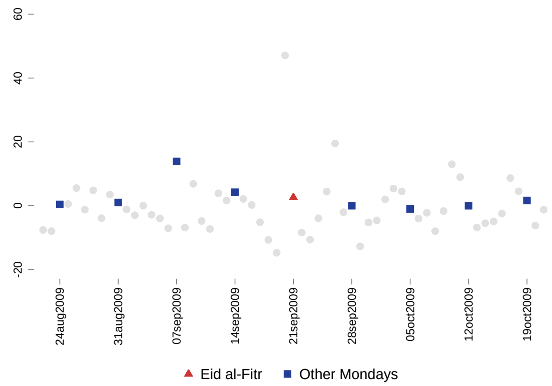
(c) Eid al-Fitr 2017



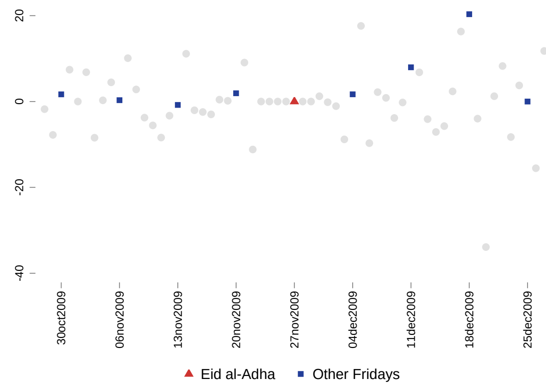
(d) Eid al-Adha 2017

Notes: This figure presents the residualized daily trips on bikes, after controlling for day-of-the-week, week and holiday fixed effects plus meteorological conditions (Equation 1 without Muslim holiday dummies). The graphs present one month before and after each Eid.

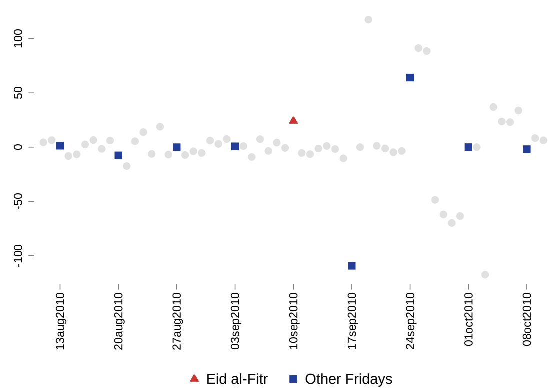
Figure F17: Residualized Average Daily Income per Driver in 2009–2011



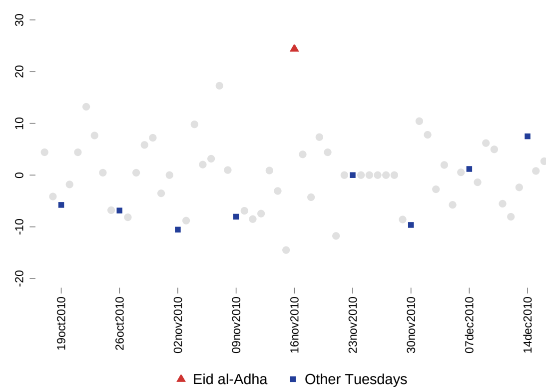
(a) Eid al-Fitr 2009



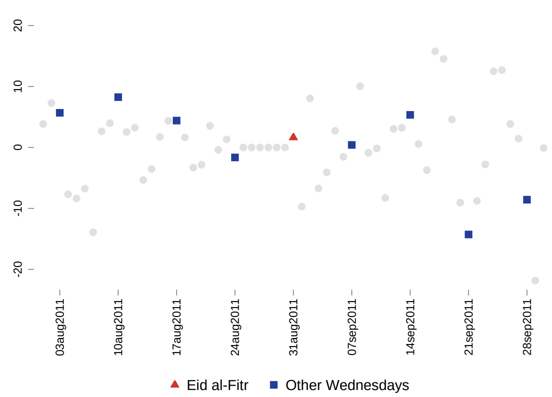
(b) Eid al-Adha 2009



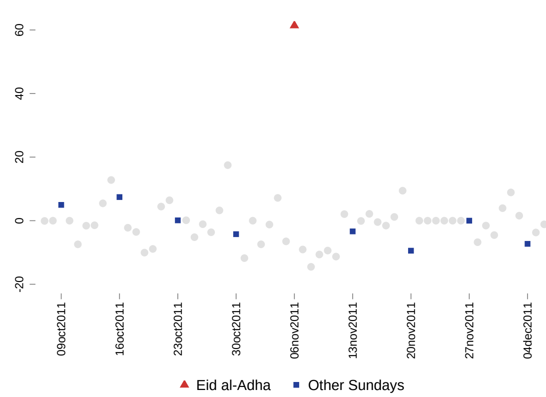
(c) Eid al-Fitr 2010



(d) Eid al-Adha 2010



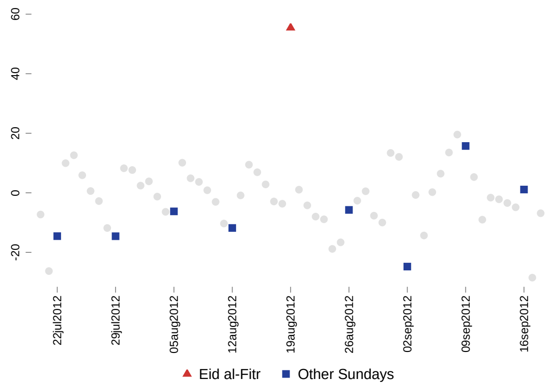
(e) Eid al-Fitr 2011



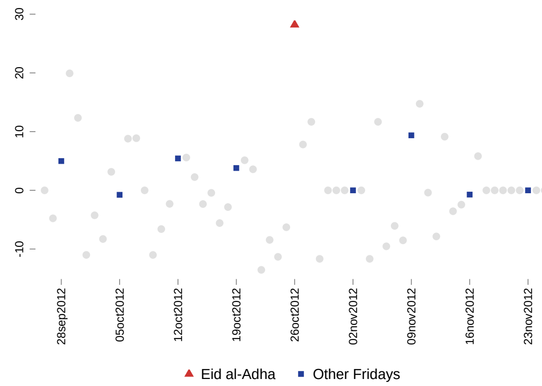
(f) Eid al-Adha 2011

Notes: This figure presents the residualized average daily income per driver, after controlling for day-of-the-week, week and holiday fixed effects plus meteorological conditions (Equation 1 without Muslim holiday dummies). The graphs present one month before and after each Eid.

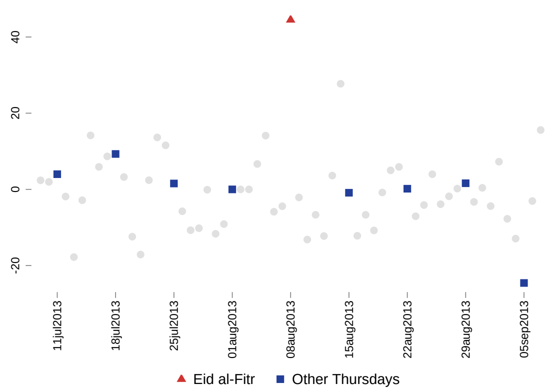
Figure F18: Residualized Average Daily Income per Driver in 2012–2013



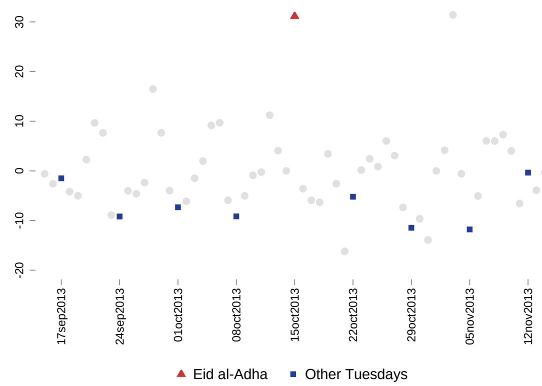
(a) Eid al-Fitr 2012



(b) Eid al-Adha 2012



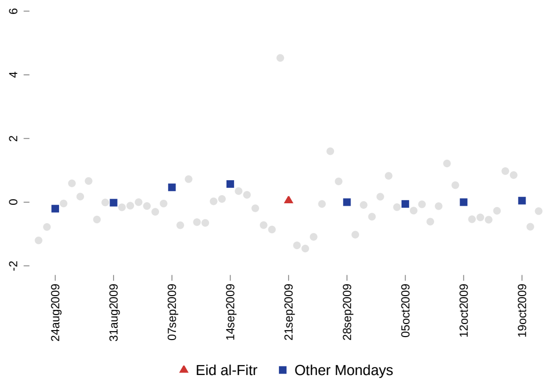
(c) Eid al-Fitr 2013



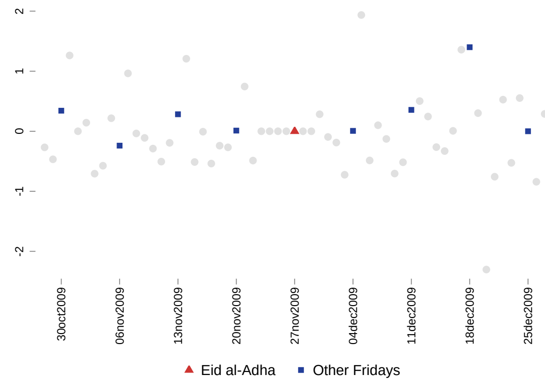
(d) Eid al-Adha 2013

Notes: This figure presents the residualized average daily income per driver, after controlling for day-of-the-week, week and holiday fixed effects plus meteorological conditions (Equation 1 without Muslim holiday dummies). The graphs present one month before and after each Eid.

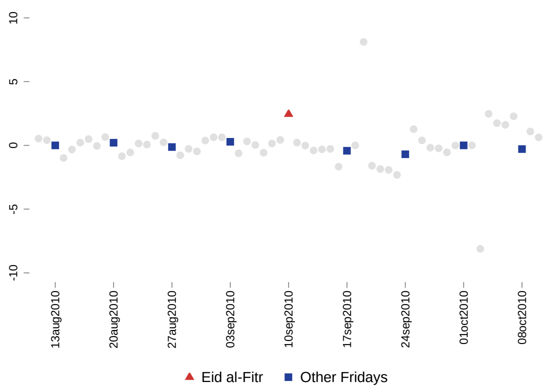
Figure F19: Residualized Average Daily Trips per Driver in 2009–2011



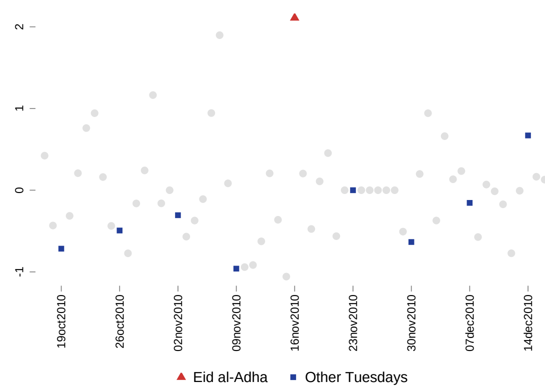
(a) Eid al-Fitr 2009



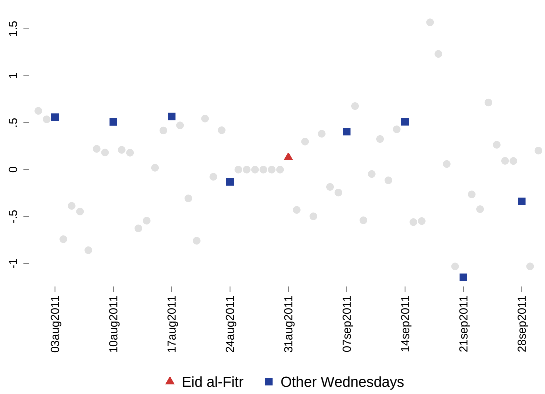
(b) Eid al-Adha 2009



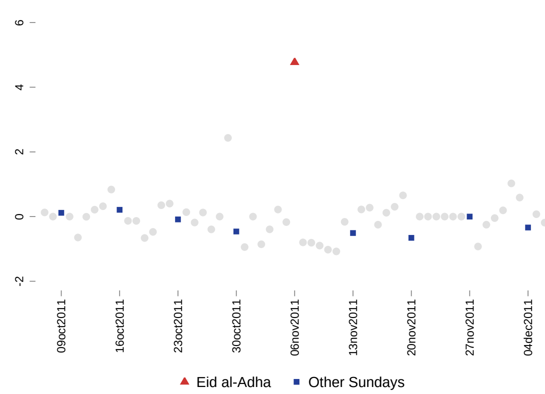
(c) Eid al-Fitr 2010



(d) Eid al-Adha 2010



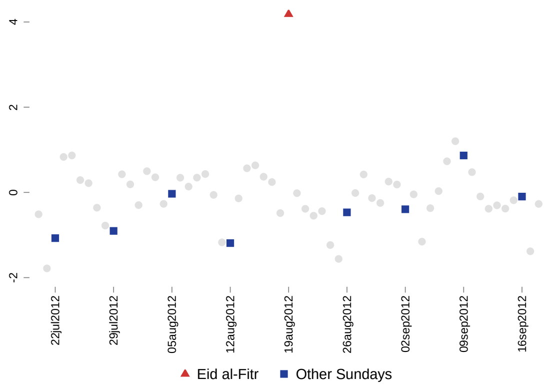
(e) Eid al-Fitr 2011



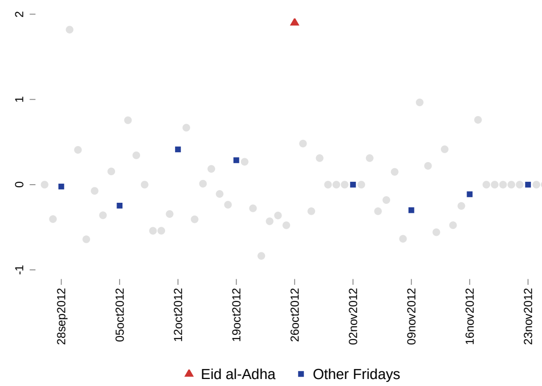
(f) Eid al-Adha 2011

Notes: This figure presents the residualized average daily trips per driver, after controlling for day-of-the-week, week and holiday fixed effects plus meteorological conditions (Equation 1 without Muslim holiday dummies). The graphs present one month before and after each Eid.

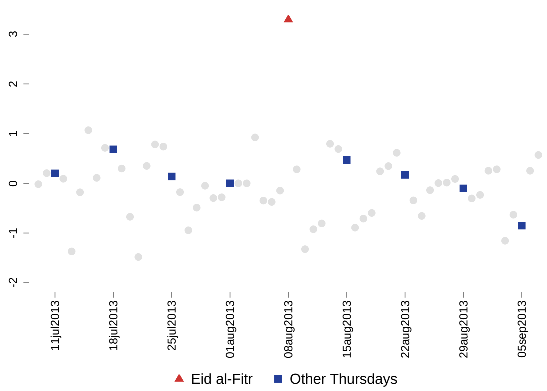
Figure F20: Residualized Average Daily Trips per Driver in 2012–2013



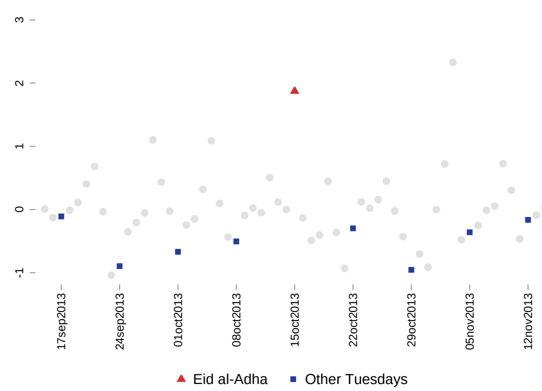
(a) Eid al-Fitr 2012



(b) Eid al-Adha 2012



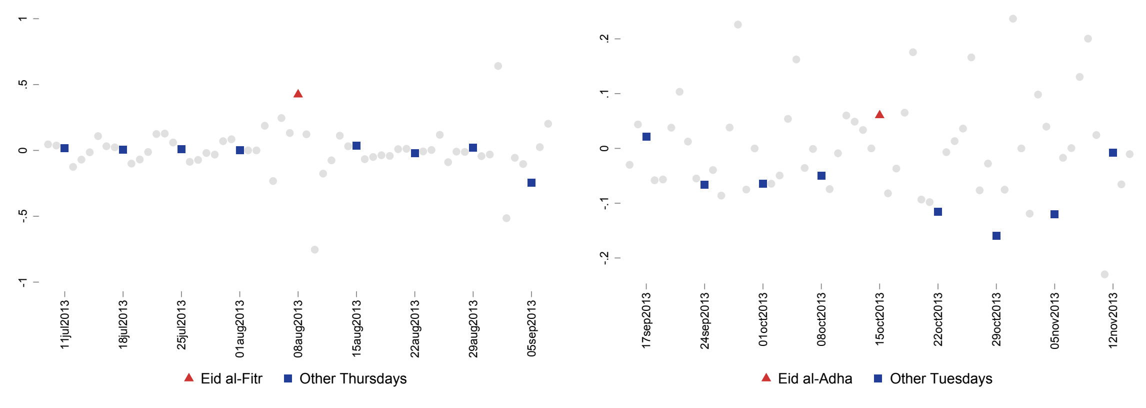
(c) Eid al-Fitr 2013



(d) Eid al-Adha 2013

Notes: This figure presents the residualized average daily trips per driver, after controlling for day-of-the-week, week and holiday fixed effects plus meteorological conditions (Equation 1 without Muslim holiday dummies). The graphs present one month before and after each Eid.

Figure F21: Residualized Drivers' Shift Duration in 2013



(a) Eid al-Fitr 2013 (b) Eid al-Adha 2013

Notes: This figure presents the residualized average shift duration, after controlling for day-of-the-week, week and holiday fixed effects plus meteorological conditions (Equation 1 without Muslim holiday dummies). The graphs present one month before and after each Eid.

Table F1: Effects of Muslim Holidays on Trip Distant by Quantiles

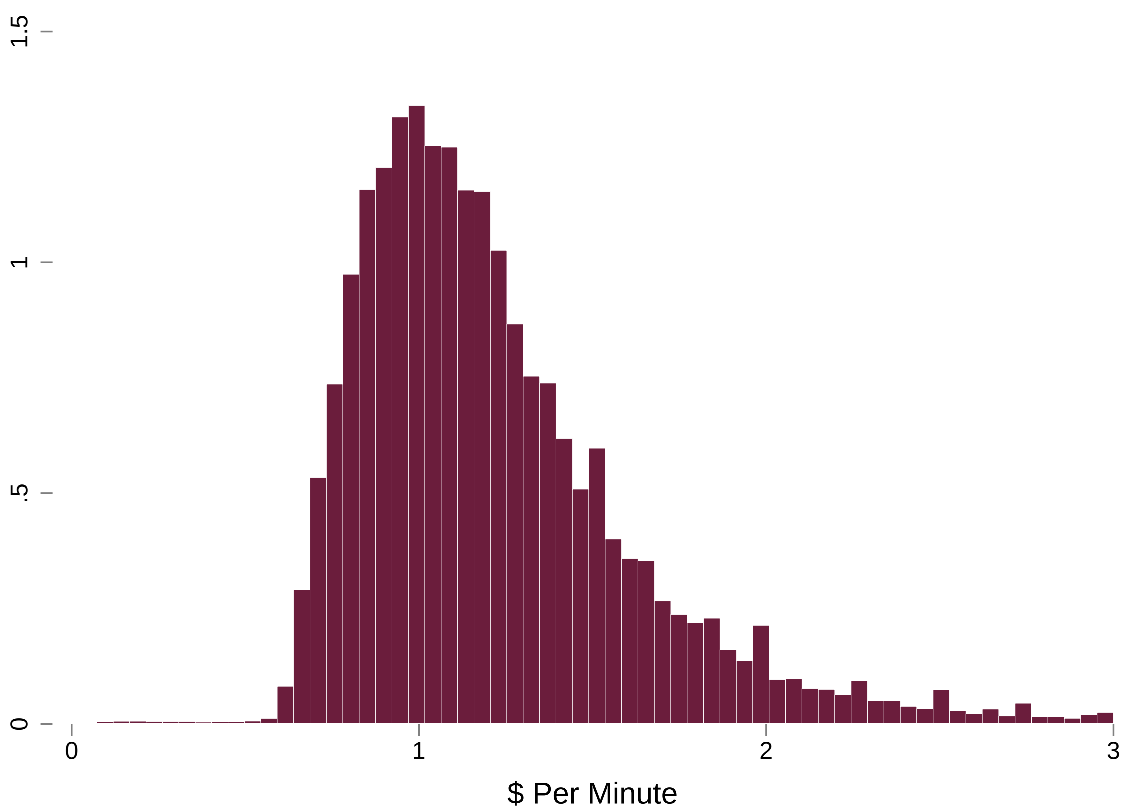
	Travel Distance Greater Than:				
	0.69 miles	1.00 miles	1.69 miles	2.82 miles	4.70 miles
Eid al-Fitr	0.0009	0.0048*	0.0037*	0.0033	0.0022
	(0.0015)	(0.0025)	(0.0022)	(0.0023)	(0.0018)
	[0.001]	[0.006]	[0.007]	[0.013]	[0.022]
Eid al-Adha	0.0034***	0.0066***	0.0102***	0.0098***	0.0052***
	(0.0012)	(0.0021)	(0.0025)	(0.0017)	(0.0008)
	[0.004]	[0.009]	[0.020]	[0.039]	[0.053]
Baseline	0.899	0.746	0.501	0.250	0.098
N	753,921,622	753,921,622	753,921,622	753,921,622	753,921,622

* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Notes: Standard errors clustered by day in parentheses. Randomization inference p-values in brackets. This table presents the effect of the Muslim holidays on taxi trip distance by quantile. In each column, the dependent variable is a dummy that takes 1 if the trip traveled more miles than indicated in the column header. The table presents effects on the 10%, 25%, 50%, 75% and 90% unconditional quantiles of the distance distribution. The regressions control for day-of-the-week, week and holiday fixed effects plus meteorological conditions. the sample excludes trips to the airports.

G Welfare Calculations

Figure G1: Value of Commuting Time



Notes: This figure presents the distribution of the value of commuting time calculated as the total amount paid divided by the duration of the taxi trip.

I follow a revealed preference approach to obtain a measure of the value of travel time. By definition, v_i should be greater or equal than the amount paid by taxi riders. To approximate v_i for a representative agent, I use the average total amount paid per minute in the sample of taxi rides.

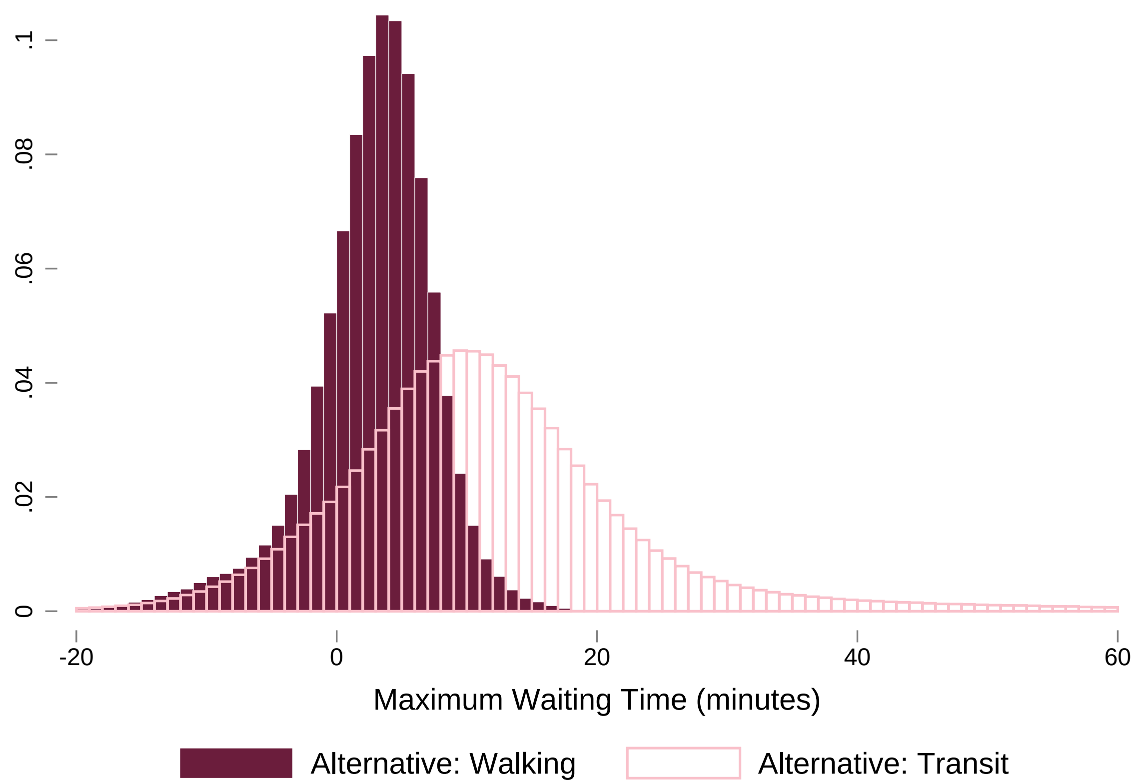
After approximating the value of commuting time, I can recover the maximum waiting time ($\bar{w}$) from the data using Equations 7 and 10. By definition, $\bar{w}$ is the waiting time that makes these equations equal to zero. To perform this calculation, first we have to determine what is the second-best alternative (walking or transit) for each trip and then calculate the counterfactual travel time ($\frac{m_i}{s_p}$ or $\frac{m_i}{s_s}$), access and egress time for transit (a_s), and transit waiting time (w_{is}). To obtain these values, I use an open source trip planner whose code can be downloaded from `http://www.opentripplanner.org/`. Among other cities and states, the state of New York uses this trip planner to provide travel times in the state. I downloaded from the MTA travel time data for the New York City and calibrated the trip planner with this data.[26]

The trip planner assumes that for destinations up to 1.25 miles away, walking is the best alternative. Otherwise, it plots a trip using transit. This application automatically calculates all the times listed above. It also calculates the number of transfers between subway and buses, which we need to determine the total payment of using transit. In New York City a subway or bus trip costs $2.75. Due to the massive number of taxi trips, I ran the trip planner on a subsample consisting on the day in the two previous and two following weeks of a Muslim holiday. For example, in 2013, Eid al-Adha was on a Tuesday. To calculate the maximum waiting time, I take the Tuesdays in the two previous and two following weeks to Eid al-Adha. This sampling procedure accounts for seasonal patterns that might affect waiting times and yields a sample of 2.4 million trips to calculate the maximum wait time.

Appendix Figure G2 plots the distribution of the maximum waiting time by type of second-best alternative. As a consequence of using the total amount paid per minute in the sample as a measure of the value of travel time, the distributions include negative waiting times (21.8 percent of the distribution for walking and 12.5 percent for transit). These times correspond to individuals whose value of travel time is substantially larger than the total amount paid. To calculate the average maximum waiting time, I replace negative values with zeros to attenuate a downward bias in these measures. This adjustment yields a maximum waiting time of 3.68 minutes when the second-best alternative is walking and 12.83 minutes when the second-best alternative is transit as reported in Table 8 in the main text.

[26]Many cities in the world generate this travel data in standard GTFS format, which is then used by trip planner applications including Google Maps.

Figure G2: Distribution of the Maximum Waiting Time



Notes: This figure presents the distribution of the maximum waiting time in the city.