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ABSTRACT

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In New York City (NYC), it has been a common complaint that it is difficult to find a taxi in the rain. Using all Uber rides in NYC from April to September 2014 and January to June 2015, we show that the number of Uber rides is significantly correlated with whether it rained. The number of Uber rides per hour is about 25 percent higher when it is raining, suggesting that surge pricing encourages an increase in supply. During the same time period, the number of taxi rides per hour increases by only 4 percent in rainy hours. We then show that the number of taxi rides per hour decreased by approximately 8 percent after Uber entered the New York market in May 2011, confirming that Uber is depressing taxi demand. Last, we test whether the total (Uber plus taxi) number of rides in rainy hours increased since May 2011. Our estimates suggest that the total number of rides increased by approximately 9 percent since Uber entered the market and that it is relatively easier to get a ride in rainy than in non-rainy hours in post-Uber years.

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1 Introduction

Standing or walking in the rain is an activity best avoided. In New York City (NYC), when faced with such inclement weather, the demand for personal transportation naturally increases. During such scenarios, taxi drivers spend less time searching for customers and could thus earn a higher wage. Nonetheless, it has been a common complaint that it is difficult to find a taxi in the rain.

In a seminal article, Camerer et al. (1997) present evidence suggesting that taxi drivers have income reference-dependent preferences,[1] so that taxi drivers have a daily income target and stop working once they reached this target. They argue that on rainy days taxi drivers reach their target faster and work less hours. This view, however, has been called into question by Farber (2015). In this recent study, he extends their seminal work and rejects the idea that target earnings behavior explains the difficulty to find taxis when it rains. Instead, Farber (2015) provides evidence that some drivers stop working because of the worsening driving conditions associated with rain; unfavorable working conditions for which there is no compensating differential.

As an alternative service to taxis, Uber entered the NYC market in May 2011 with surge pricing and mobile driver-passenger matching technology. Surge pricing is a pricing scheme implemented by Uber where passengers pay a higher rate for the Uber service during times of high demand; this higher pricing scheme gives incentives to Uber drivers to provide rides in inclement conditions. Uber could thus be a logical response to unmet demand during adverse conditions.

Previous studies on intertemporal substitution of labor supply find mixed evidence of temporal substitution effects. (See Blundell and MaCurdy (1999) for a review of the literature.) Fehr and Goette (2007) conduct a field experiment at a bicycle messenger service in Switzerland in which they vary temporarily the piece rate paid to messengers. They find a large positive elasticity of hours of work, but a negative elasticity of effort per hour. In another experiment, Chang and Gross (2014) document that pear packers in California respond to unexpected overtime by decreasing their effort. In Oettinger (1999), the author studies labor supply of stadium vendors at baseball games and finds that the number of vendors who worked

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[1]See Koszegi and Rabin (2006) for a model of reference-dependent preferences and loss aversion. They build on the work of Kahneman and Tversky (1979) and Tversky and Kahneman (1991) and develop a model where a person's utility depends on a reference point.

in a game is positively related to changes in expected wages. In contrast to earlier studies, we have the unique opportunity of comparing two groups of workers, Uber and taxis in NYC, who are facing different unanticipated wage increases in response to exogenous circumstances. Another key feature of our analysis is that we can test whether the taxi market changed since Uber entered the on-demand transportation network in NYC.

This paper makes four contributions. First, we provide an empirical examination of whether the number of Uber rides increases more than the number of taxi rides when it rains. For this analysis, we rely on all Uber and taxi rides in NYC from April to September 2014 and from January to June 2015 and merge the Uber and taxi data with weather data from the National Weather Service Observatory in Central Park. The results suggest that the number of Uber rides per hour is significantly correlated with whether it rained. More precisely, the number of Uber rides is about 25 percent higher when it is raining, suggesting that surge pricing encourages an increase in supply.[2] This increase in transactions when it rains likely reflects a large increase in both demand and supply. On the other hand, the number of taxi rides per hour increases by only 4 percent in rainy hours during this time period.

Second, we test whether rain increases the number of daily rides. We provide evidence that the number of Uber rides increases by approximately 8 percent during rainy days and that an additional hour of rain increases the number of Uber rides per day by approximately 2.5 percent. On the other hand, there is no evidence that the daily number of taxi rides is related to rain. This is suggestive evidence that Uber drivers do not have a daily target income level and that Uber driver labor supply is best characterized by the neoclassical model.

Third, we use data for all trips taken in NYC taxi cabs before (2009-April 2011) and after (2014-2015) Uber's rise in popularity, and show that the number of taxi rides per hour decreased by approximately 8 percent after Uber entered the New York market in May 2011. This finding is consistent with substitution between Uber and taxis during rainy hours. The results also indicate that the number of taxi rides in both rainy and non-rainy hours have similarly decreased since Uber entered the market.

Finally, we document whether it is easier to find a ride since Uber entered the market. For this exercise, we combine Uber and taxi rides for 2014-2015 and compare the total number of rides post-Uber to the number

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[2]Unfortunately, our data set does not allow us to test whether the increase in labor supply of Uber drivers during rainy hours is due to the extensive or intensive margin.

of taxi rides during the pre-Uber period (2009-April 2011). We find that the total number of rides increased by approximately 9 percent since May 2011 and that it was relatively easier to get a ride in rainy than in non-rainy hours in 2014-2015.

This paper contributes to the literature analyzing labor supply of taxi drivers (Agarwal et al. (2015), Chou (2002), Crawford and Meng (2011), Doran (2014), Farber (2008), Haggag and Paci (2014) and Haggag et al. (forthcoming)). Two relevant papers using NYC data are Farber (2005) and Ashenfelter et al. (2010). Farber (2005) studies the stopping behavior of NYC taxi drivers and finds that the decision to stop working is primarily related to cumulative daily hours. Ashenfelter et al. (2010) also study the labor supply of taxi drivers. They analyze the impact of two permanent fare increases and find an elasticity of labor supply of -0.2 in response to these fare increases.

Our work also contributes to a small economic literature on the Uber platform. Despite its media attention, few research papers analyze the impact of Uber on the labor supply of taxi drivers. The dearth of research on this issue is mainly driven by the lack of publicly available data. In this paper, we rely on Uber data in NYC that were made available through a Freedom of Information request. Two recent papers using different Uber data are Chen and Sheldon (2015) and Cramer and Krueger (2016). In Chen and Sheldon (2015), the authors use a randomly drawn subset of UberX driver-partners in a few American cities.[3] They find that UberX partners are less likely to quit at times with high surge prices. Cramer and Krueger (2016) compare capacity utilization for taxis and UberX drivers in five American cities and provide evidence that taxi drivers drive a smaller fraction of their time with a passenger in their car than UberX drivers.[4]

The paper is structured as follows. In the following section, we provide a description of Uber and surge pricing. In Section 3, we detail the data sets and provide descriptive statistics. Section 4 presents the model specification. Section 5 discusses our findings of the impact of rain on Uber and taxi rides. The last section concludes.

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[3]UberX cars can carry up to four riders and have four doors. The full list of Uber vehicle classes is available here: $http://driveubernyc.com/vehicles/full-list$.

[4]Hall and Krueger (2015) compare Uber's driver-partners labor market demographic to taxi drivers. They find that Uber's driver-partners are more similar to the general workforce than taxi drivers and chauffeurs. In particular, Uber drivers are comparatively more educated and younger.

2 Conceptual Framework

This section provides insights on how rain might impact the number of Uber and taxi rides in theory. We consider two alternative mechanisms. The first builds on standard neoclassical intertemporal models of labor supply (e.g., Fehr and Goette (2007); Oettinger (1999)) and treats surge pricing as a transitory wage change for Uber drivers. The second is based on models of reference-dependent preferences in which drivers stop working once they reach their target income level (e.g., Camerer et al. (1997); Koszegi and Rabin (2006)).

A key hypothesis in this study is that adverse weather conditions cause an increase in the demand for alternative on-demand sources of transport such as taxis or Uber cars.[5] During rainfall, it is generally considered to be undesirable to be outside (Connolly (2008)). As such, individuals who would generally walk or wait for public transit may wish to utilize taxis or Uber cars. Importantly, we assume that the increase in demand for rides during rainy hours is similar in pre- and post-Uber years.

2.1 Intertemporal Models of Labor

A simple neoclassical intertemporal model of labor predicts that workers respond positively to earnings opportunities. This model implies that unanticipated increases in earnings opportunities such as rain would positively affect labor supply elasticities. In other words, this model predicts that drivers would be working more on high-wage days and less on low-wage days.

A rational choice model with reference-dependent preferences suggests that workers who temporarily earn higher wages will eventually decrease their effort. For instance, cab and Uber drivers who have a reference level of daily income would work more in rainy hours. As they get closer to their daily reference level, the marginal utility of income would be decreasing which in turn would reduce their effort.

The neoclassical model and the model with reference-dependent preferences that exhibit loss aversion around a daily target income level both suggest that rain increases hourly rides. On the other hand, only the former predicts that rain increases daily rides. Using all trips taken in NYC taxis from 2009-2013, Farber (2015) tests whether rain affects earnings, utiliza-

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[5]The New York subway provided significantly more rides than Uber and taxi drivers. Subway and bus ridership statistics are available here: $http : //web.mta.info/nyct/facts/ridership/$.

tion rates and the number of hacks on the streets. He finds that rain has no effect on hourly earnings, but does cause higher utilization of cabs, and in general shorter trips. This is indicative of increased demand for rides when it rains. However, there is also a decreased number of taxis on the streets which is, arguably, due to the disutility experienced by taxi drivers driving in uncomfortable weather conditions. Farber (2015) concludes that these results are "sufficient to reject the hypothesis that target earnings behavior contributes to the difficulty of finding a taxi in the rain [...]"

Unlike taxis, the Uber platform adjusts its prices using a realtime dynamic algorithm (Chen and Sheldon (2015)).[6] The Uber fare rates automatically increase when demand is higher than supply of drivers within a fixed geographic area. Customers are informed of the higher fare before requesting the Uber car. Uber drivers are also aware of surge pricing and have access to maps displaying the locations currently surge pricing.[7] Uber drivers may freely choose when they work and they can drive as long as they like. This is thus an ideal setting for studying intertemporal models of labor (Fehr and Goette (2007)).

As there is no rain surcharge for taxis, taxi drivers do not respond to the increased demand for rides.[8] Uber platforms could then benefit consumers if Uber drivers respond to the unmet demand when it rains. The extra compensation that Uber drivers receive through surge pricing may incentivize them to overcome the disutility of adverse conditions.

2.2 Evaluating the Effect of Rain

We test four hypotheses in what follows. First, we test whether the number of Uber rides increases significantly more than the number of taxi rides in rainy hours. Due to surge pricing, we expect that the number of rides given by Uber drivers increases significantly more than the number of taxi rides in the rain. Such a result would be evidence that the wage increase caused an increase in Uber drivers' labor supply.

Second, we investigate whether rain increases the number of daily rides

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[6]Note that the Uber platform uses a more efficient driver-passenger matching system (Buchholz (2016); Cramer and Krueger (2016)). Another major difference between taxis and Uber is that Uber drivers do not need to purchase one of the city's prized taxi medallions. The cost of a taxi medallion is often hundreds of thousands of dollars.

[7]Surge multipliers are discrete and there is no cap in NYC.

[8]Another possibility is that taxi and Uber drivers have a different aversion to driving in inclement weather. For instance, Hall and Krueger (2015) find that there is a greater representation of younger people among Uber drivers than among taxi drivers. The response to weather conditions could then be due to both surge pricing and drivers' aversion to risk.

for both taxis and Uber. The neoclassical model predicts that rain increases significantly the number of daily rides. On the other hand, if drivers have a daily target income level, then we should find that rainy days are not significantly related to taxi and Uber rides. Note that it is possible that drivers have a weekly or monthly target income level. Unfortunately, the sample size is too small to estimate precisely whether this is the case.

Third, we test whether taxi drivers' supply response to rain changed since Uber entered the market. The lack of rain surcharge for taxis and the increasing presence of Uber drivers when it rains may increase the difficulty of finding customers for taxi drivers. We test this using taxi rides data pre- and post-Uber.

Last, we test whether the total (Uber plus taxi) number of rides increased or decreased since May 2011. We also test whether it was relatively easier to get a ride in rainy than in non-rainy hours in post-Uber years. Note that the presence of Uber does not automatically increase the total number of rides. As mentioned before, there might be a substitution of rides from taxi to Uber and the disutility of adverse conditions for taxi drivers might have changed since May 2011. It thus remains unclear whether the total number of rides in the rain increased proportionally more than the total number of rides in non-rainy hours since Uber entered the market.

3 Data Sources

3.1 Data on Uber and Taxi Rides

This study relies on all trip level data of Uber pickups in NYC from April to September 2014 and January to June 2015. This data set was made available through a Freedom of Information request to the New York Taxi Commission (TLC) made by Carl Bialik of FiveThirtyEight. It is currently available online on a Github repository. This data set includes approximately 18.8 million rides reported from the dispatching bases Uber utilizes in NYC. Uber cars are classified as for-hire vehicles by the TLC.

Individual trip level data for taxi rides are also available for this time frame. TLC has publicly released trip level data for all yellow taxi rides dating back to 2009. This is when the TLC started to require that digital trip records be kept through car GPS devices. For this time period, we calculated the number of rides that occurred hourly for both Uber and taxis. This was done using the time of the pick up.

Figure 1 shows the number of rides per quarter since 2009 for taxis and over the period April to September 2014 and January to June 2015 for Uber. Note that Uber entered the New York market in May 2011. What emerges is that the number of taxi rides is much larger than the number of Uber rides from April to September 2014 and January to June 2015. During the second quarter of 2014, when Uber had been in the market for nearly three years, there were approximately 23 times more taxi rides than Uber rides. But this gap has decreased sharply. During the second quarter of 2015, the most recent quarter in our analysis, there were approximately 5 times more taxi rides than Uber rides. Figure 1 suggests that this decreasing gap is due both to an increase in Uber rides and a decrease in taxi rides.

The differential in rides during rainy hours also decreased during this time period. During the second and third quarters of 2014, there were respectively 3.9 million taxi rides and 236,000 Uber rides during rainy hours (i.e., 16 times more taxi rides than Uber rides). During the first and second quarters, the gap was down to 2.86 million, with 789,000 Uber rides and 3.5 million taxi rides (i.e., less than five times more taxi rides than Uber rides).

For our analysis, two subsets of the taxi data set are used. A first taxi data from April to September 2014 and January to June 2015 (2014-2015 henceforth) is used, as it is a direct comparison to the time frame for which Uber data are available. A second subset, from January 2009-April 2011 (2009-2011 henceforth), is used as well. We rely on this second subset which covers a period before Uber entered the NYC market as a comparison for taxi drivers' response in post-Uber market conditions.[9]

We provide descriptive statistics for Uber and taxi rides per hour in Panel A of Table 1. (See Appendix Table A1 for Uber and taxi rides per day.) The average number of Uber rides per hour is 2,163 over the period 2014-2015. During the same time period, the average number of taxi rides per hour was 18,274. This is a small decrease in comparison to the average number of taxi rides over the period 2009-2011 (19,435). The standard deviation of taxi rides has also decreased in this same time frame. Panels B and C provide the same summary statistics as in Panel A, but for two sub-samples: 1) excluding nighttime observations (1:00 to 5:00am), and 2) excluding winter months (January-March). Unsurprisingly, the average number of rides per hour is higher when we exclude nighttime observations.

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[9]Note that the main results of this research are robust to restricting the sample to the same months in both subsets. In other words, excluding the months of November and December in the second subset yields very similar findings. See Section 4 for the model specification and a list of additional robustness checks.

On the other hand, Panel C shows that the number of Uber and taxi rides is somewhat similar for winter and non-winter months.

Figures 2, 3 and 4 confirm that the fraction of rides is lower for nighttime observations by showing the fraction of rides per hour of day for Uber and taxis (pre- and post-Uber). The fraction of Uber rides from 5 PM to 10 PM (39.2 percent) is slightly larger than the fraction of taxi rides (34.7 percent for pre-Uber and 34.8 percent for post-Uber) while this is the opposite from 8 AM to 1 PM (23.1 percent for Uber, 28.3 percent for taxis pre-Uber and 28.4 percent for taxis post-Uber). Comparing the fraction of taxi rides per hour of the day for the pre- and post-Uber periods, it appears that Uber did not change substantially the fraction of taxi rides in each clock hour.

3.2   Weather Data

The above data sets are combined with weather data from the National Weather Service Observatory in Central Park. This data set was collected using scraping techniques from *www.wunderground.com*. The observatory reports observations at 51 minutes past the hour. As such, when the number of rides per hour were calculated, the number of taxi trips occurring in the half hour preceding and following the weather observation was aggregated into a single observation. For example, for a 10:51 AM weather observation, the number of rides occurring from 10:21:00 AM to 11:20.59 AM would be counted. Each observation reports the weather condition of the time period. Possible conditions include "Clear", "Heavy Rain", "Rain", "Light Rain" or "Partly Cloudy". A full list of weather conditions can be seen in Table 2.

Comparing the number of different weather condition observations from 2009-2011 to 2014-2015, we find that there is a somewhat similar proportion of instances of each condition. There are slightly more frequent instances of rain in 2009-2011 as compared to 2014-2015. There was "Rain" or "Light Rain" in 4.2 percent of the observation in 2014-2015 in comparison to 4.6 percent in 2009-2011. The condition is coded as "Heavy Rain" in 0.3 percent of the observation in both time periods. The number of "Heavy Snow" instances is almost identical across the time periods. It was "Partly Cloudy" or "Mostly Cloudy" for respectively 13.5 percent and 12.8 percent of the observations in 2014-2015 and 2009-2010.

There are also some cases where the observatory does not report the conditions at the 51st minute. The number of observations where this is the case is 28 in 2014-2015. The observatory also has 51 cases of instances

where the reported weather condition was "unknown" in 2014-2015. These observations are removed from the analysis.

4   Identification Strategy

In this section, we describe the main specification and the controls. The objective is to investigate the impact of rain on Uber and taxi rides. To identify this effect, we use trip level data to calculate the number of rides for each of the clock hours in the time period analyzed. Our unit of observation is an hour. As mentioned before, the time period is April to September 2014 and January to June 2015 for the Uber analysis. We then compare this time period to a pre-Uber time period: 2009-April 2011.

In our main specification, we estimate:

$$Y_{hmy} = \alpha + \beta RAIN_{hmy} + \delta_m + \gamma_y + X'_{hmy}\lambda + \varepsilon_{hmy}, \tag{1}$$

where Y_{hmy} is the log of the number of Uber rides (or taxi rides) in hour h, month m and year y. $RAIN_{hmy}$ is a dummy that equals one if it rained in Central Park in hour h and zero otherwise. More precisely, $RAIN_{hmy}$ is equal to one if the conditions were noted as "Heavy Rain", "Rain", "Light Freezing Rain" or "Light Rain". We include month and year fixed effects and X_{hmy} is a vector of other regressors that includes indicators for hour of day by day of week, snow and major holiday.[10] The coefficient of interest here is β.

We check the robustness of our results by removing outliers. First, we check that the association of rain and the number of rides per hour is robust to using a subset of the data set that removes the winter months. The winter months are identified in this research as January, February and March. Second, we exclude nighttime observations since the number of rides is lower during that time of the day. Last, we test the robustness of our findings by excluding from the analysis the more severe weather events "Heavy Rain" and "Light Freezing Rain".

Our econometric model for testing the effect of Uber's rise in popularity

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[10]The dummy for snow is equal to one if the conditions were noted as "Snow", "Heavy Snow" or "Light Snow" and zero otherwise. Major holidays include New Years Day, Martin Luther King Day, Lincoln's Birthday, President's Day, Memorial Day, Independence Day, Labor Day, Columbus Day, Veterans Day, Thanksgiving and Christmas Day.

on the number of taxi rides in rainy hours is as follows:

$$Y_{hmy} = \alpha + \beta RAIN_{hmy} + \theta PostUber_{hmy}$$
$$+ \sigma RAIN_{hmy} \times PostUber_{hmy} + \delta_m + X'_{hmy}\lambda + \varepsilon_{hmy}, \quad (2)$$

where the dependent variable is the log of the number of taxi rides in an hour h, month m and year y. $PostUber$ is a variable that takes the value 1 if the year is after 2011. The interaction of $RAIN$ and $PostUber$ shows the effect of the introduction of Uber's platform in NYC on taxi rides in rainy hours. We include month and year fixed effects and our vector of time dummies (X_{hmy}). We add year fixed effects to the specification in case unobserved time-varying factors correlated with Uber entering the market would explain our results.

The interpretation relies on the identification condition that there are no other time-varying shocks that affect the number of taxi rides. Our analysis of taxi drivers' labor supply pre- and post-Uber should thus be viewed with caution since there were at least two changes in the New York taxi market during the time frame of investigation. First, Green taxi cabs (i.e., Boro taxis), which are able to serve the boroughs of New York and drop passengers off in the Manhattan core, began operating in 2013. Note that these cabs are unable to pick up trips in the south of Manhattan. We thus exclude Green taxi cabs from the analysis. Note that the introduction of Green taxi cabs may also encourage taxi drivers to compete more vigorously. Second, from September 4, 2012 through December 31, 2013 the rate for additional fifths of a mile was increased (Farber (2015)).

5 Results

5.1 Impact of Rain on Hourly Rides Post-Uber

We first estimate the effect of rain on taxi rides per hour. While our time period and dependent variables are different than in Farber (2015) (2009-2013), his results provide a useful benchmark. Farber (2015) finds that there are approximately 7.1 percent less cabs in NYC when it is raining, but that taxi utilization rates (i.e., time with passengers) in the rain are 4.8 percent higher, and trips take 2.4 percent less time. We then test whether the effect of rain is similar for the number of Uber rides. If the demand is unmet in rainy hours, then Uber's surge pricing could encourage an increase in supply.

Table 3 contains OLS estimates of equation (1) for Uber and taxi rides over the April to September 2014 and January to June 2015 periods (i.e., post-Uber period). The sample size is 8,648 observations (i.e., hours). The dependent variables are, respectively, the log of the number of taxi rides per hour in columns 1-3 and the log of the number of Uber rides per hour in columns 4-6. We report standard errors clustered by hour of day by day of week (168 clusters) in parentheses. What clearly emerges is that rainy hours are associated with a small increase in taxi rides and a large increase in Uber rides. In columns 1 and 4, we do not include any fixed effects and find that Uber rides increase by approximately 21 percent while taxi rides increase by only 3 percent. We include our set of time fixed effects in columns 2 and 5. The number of Uber rides is about 25 percent higher when it is raining and the estimate is significant at the 1 percent level. On the other hand, the number of taxi rides per hour increases by only 4 percent. In columns 3 and 6, we test the robustness of our estimates by excluding nighttime observations. The estimates are slightly larger for both taxi and Uber rides, but the difference is not statistically significantly different from the estimates including nighttime observations.

Table 4 provides additional robustness checks. The structure of the table is similar to Table 3. We exclude respectively hours of heavy rain and light freezing rain in columns 1 and 4 and the months of January, February and March in columns 2 and 5. These specification checks confirm that Uber rides increase by approximately 25 percent in rainy hours while taxi rides increase by only 4 percent.

In columns 3 and 6, we separately test the effect of light rain and heavy rain on rides per hour. The variable *Light Rain* is equal to one if the condition is "Light Rain" and zero otherwise, while the variable *Rain & Heavy Rain* is equal to one if the condition is either "Heavy Rain" or "Rain" and zero otherwise.[11] The estimates are positive and significant for both variables when the dependent variable is the log of the number of Uber rides. The estimated coefficient is larger for *Rain & Heavy Rain* (coeff. 0.380, std. error 0.032) than for *Light Rain* (coeff. 0.207, std. error 0.017) possibly suggesting that light rain does not increase demand as much as heavy rain. The estimates are also positive for taxi rides for both variables.

So far, our results are indicative that surge pricing encourages an overall increase in supply for Uber drivers. Unfortunately, it is impossible to test whether the increase in Uber rides during rainy hours is due to an in-

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[11]Note that coding the variable *Rain & Heavy Rain* equals to one if the condition is "Light Freezing Rain" leads to similar estimates.

crease in hours worked (intensive margin) or an increase in the number of Uber drivers working (extensive margin). Our results for the relationship between rain and taxi rides are consistent with the results of Farber (2015).

5.2   Impact of Rain on Daily Rides Post-Uber

In Table 5, we turn to presenting OLS estimates of the relationship between rain and *daily* rides. The time period is the same as in Table 3 and the dependent variables are, respectively, the log of the number of taxi rides per day in columns 1-3 and the log of the number of Uber rides per day in columns 4-6. Our variable of interest in columns 1, 2, 4 and 5, *Rain Day*, is a dummy that is equal to one if the conditions were noted as "Heavy Rain", "Rain", "Light Freezing Rain" or "Light Rain" at any point during the day and zero otherwise. In columns 3 and 6, we replace *Rain Day* with the variable *Hours of Rain*. *Hours of Rain* is a continuous variable that is equal to the number of hours of rain per day. Note that the average number of hours of rain in a rainy day is 4.01 (std. deviation 3.39). We include week, month and year fixed effects and holiday dummies in columns 2, 3, 5 and 6.

The results suggest that the number of Uber rides increases by approximately 8 percent during rainy days. The estimate is significant at the 10 percent level. We also find that an additional hour of rain increases the number of Uber rides per day by 2.5 percent. On the other hand, there is no evidence that rain increases the number of taxi rides per day. The estimates are small, positive and statistically insignificant. The result that rain increases daily rides provides weak evidence that Uber drivers do not have reference-dependent preferences in which workers have a reference level of daily income. Additional information on utilization rates and length of trips is required to confirm this result.

5.3   Impact of Uber on Taxi Rides

In this subsection, we first investigate whether the estimated effect of rain on taxi rides is similar in the pre-Uber era. We then test whether the number of taxi rides decreased after Uber entered the market.

The time period for the pre-Uber period is from January 2009 to April 2011. Table 6 presents OLS estimates for taxi rides per hour for this time period.[12] Column 1 does not include control variables, while the estimates

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[12]Appendix Table A2 shows OLS estimates for taxi rides per day in the pre-Uber era.

in the remaining columns include our usual time indicators. The number of taxi rides in rainy hours increases by 5 percent. The estimates are significant at the 1 percent level when the controls are included.

We provide robustness checks in columns 3-5. The specifications where we omit nighttime observations, heavy rains and light freezing rain, and winter months yield estimates that range from 4.7 to 6.4 percent, confirming the increased number of transactions in rainy hours for taxis. In column 6, we include the variables *Light Rain* and *Rain & Heavy Rain* in the model. The estimates are statistically significant and suggest that the number of taxi rides increases by 9.1 percent for hours with either rain or heavy rain. The estimated effect for the variable *Light Rain* is also statistically significant with a smaller coefficient of 0.037.

In Table 7, we test explicitly whether the number of taxi rides per hour reacts more to rain in the pre-Uber period than in 2014-2015. (See Appendix Table A3 for the analysis at the day level.) All columns include our time fixed effects. Column 1 first shows the relationship between the number of taxi rides and the variable *PostUber*. Column 1 shows that the number of taxi rides per hour decreased by approximately 8.1 percent in the post-Uber period. This result is in line with descriptive statistics presented before (figure 1) and suggests that the market entry of Uber led to a decrease in taxi rides.

Column 2 adds our dummy variable for rain, but without the interaction with *PostUber*. Over the full period of study, the number of taxi rides in rainy hours increases by roughly 5 percent. Column 3 presents estimates of equation (2) where we include *PostUber*, the dummy for rain and the interaction term. The interaction of *RAIN* and *PostUber* shows the additional effect of Uber entering the market on the variation of taxi rides in rainy hours. A negative estimate could suggest that there is a substitution of taxi rides to Uber rides, and especially so when it rains. A negative effect could also be indicative that that the disutility of driving in the rain for taxi drivers has increased since May 2011. If the increasing number of Uber drivers in rainy hours results in more competition to find passengers, this may decrease the time spent with a passenger and decrease the willingness to work in the rain for taxi drivers.

The interaction term, σ, is negative, but not statistically significant at the 10 percent level. This means that the number of taxi rides in rainy hours has not decreased by more than in non-rainy hours since Uber entered the market. In column 4, we check the robustness of this result by interacting our month fixed effects (δ_m) with the indicator *PostUber*. The interaction

term remains negative and statistically insignificant.

Of note, though, our research focuses on a time period in which Uber was still growing. The analysis of the number of taxi rides pre- and post-Uber could yield very different conclusions when Uber reaches its steady state.

5.4   Impact of Uber on Total (Uber and Taxi) Rides

Turning now to a different dependent variable, Table 8 shows the effect of Uber entering NYC's market on the total number of rides (i.e. Uber plus taxi rides) per hour. (See Appendix Table A4 for the analysis at the day level.) The layout is the same as in Table 7. The coefficients on the *PostUber* variable indicate that the total number of rides per hour is 8 to 9 percent higher in the time period 2014-2015. As shown before, this result is due to the large increase in Uber rides and the small decrease in taxi rides.

The coefficient estimates for the rain dummy indicate that over the full period of study total rides increases by approximately 5.7 percent when it rains. Then, the next row shows the coefficient estimates for the interaction of the variables *RAIN* and *PostUber*. A positive coefficient is expected if the increased number of transactions in the rain is relatively larger than the increased number of rides in non-rainy hours since May 2011. The estimated coefficient is positive and statistically significant at the 10 percent level, suggesting that, since Uber entered the market, it is relatively easier to get a ride in rainy than in non-rainy hours. More precisely, we find that the number of total rides in rainy hours increased by an additional 1.2 percent in post-Uber years.

In column 4, we check whether this result is robust by interacting our month dummies and the indicator *PostUber*. We find that the coefficient is slightly larger, suggesting that the result presented in column 3 is robust. In column 5, we test whether the effect is larger for interaction of the variables *Rain & Heavy Rain* and *PostUber*. The estimate is positive and statistically significant (coeff. 0.021, std. error 0.012).

Our findings suggest that Uber has made it easier to get a ride, and especially so in the rain. The results are consistent with a substitution from taxi rides to Uber rides and suggest that surge pricing encourages an overall increase in supply for Uber drivers.

6 Conclusion

Using all Uber rides in NYC from April to September 2014 and January to June 2015, we investigated the effect of rain on the labor supply of Uber drivers and found that the number of Uber rides per hour increases by approximately 25 percent when it is raining. During the same time period, the number of taxi rides per hour increases significantly less than the number of Uber rides in rainy hours. We also provided some evidence that during rainy days, the number of rides increases by about 8 percent for Uber. On the other hand, the number of taxi rides per day is not related to rain. That rain would have a different effect on taxi and Uber rides is in line with a neoclassical intertemporal model of labor, given that only Uber rides are subject to rain surge pricing.

Looking at the impact of Uber on taxi rides, we found that the number of taxi rides per hour decreased by 8 percent after Uber entered the New York market in May 2011. This result is consistent with a substitution from taxis to Uber cars.

We then checked whether it was easier to find a ride in the rain after the entry of Uber in May 2011. We first compared the total (Uber plus taxi) number of rides in a post-Uber period to the number of taxi rides in a pre-Uber period and found that the total number of rides increased by approximately 9 percent in post-Uber years. We then tested whether it was relatively easier to get a ride in rainy than in non-rainy hours in 2014-2015. Our results indicated that the total number of rides increased by proportionally more in rainy hours.

The results have important implications for the ongoing debate on whether Uber is depressing taxi demand and whether Uber increases consumers' welfare. In particular, they highlight that Uber is substituting for taxi cabs in NYC and that surge pricing seems effective in increasing labor supply. Future research could study in more details whether Uber driver labor supply is best characterized by standard neoclassical intertemporal models of labor supply or models of reference-dependent preferences using hourly data on occupancy and number of hacks.

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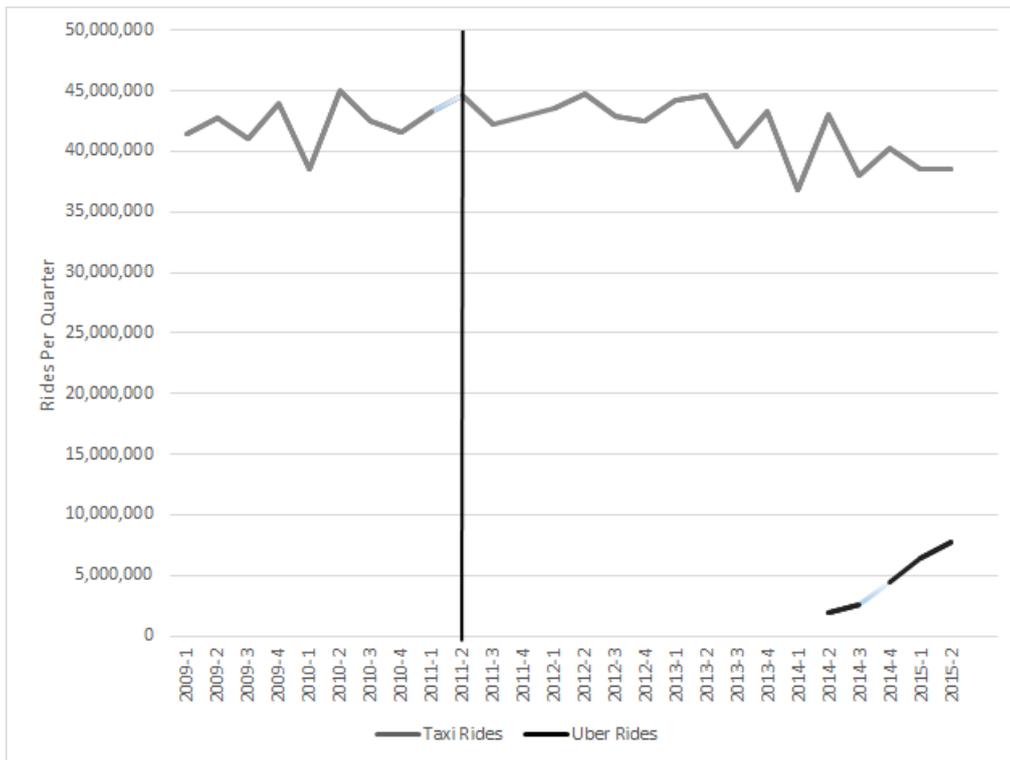
Figure 1: Number of Uber and taxi rides per month. Uber entered the market in May 2011.
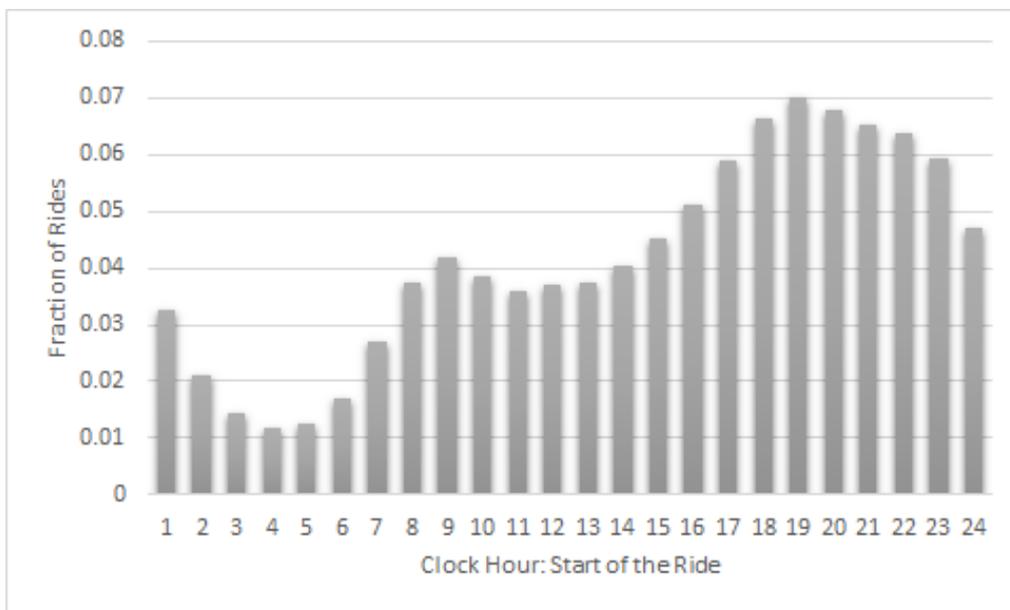
Figure 2: Fraction of Uber rides per hour of day. The time period is April-September 2014 and January-June 2015.
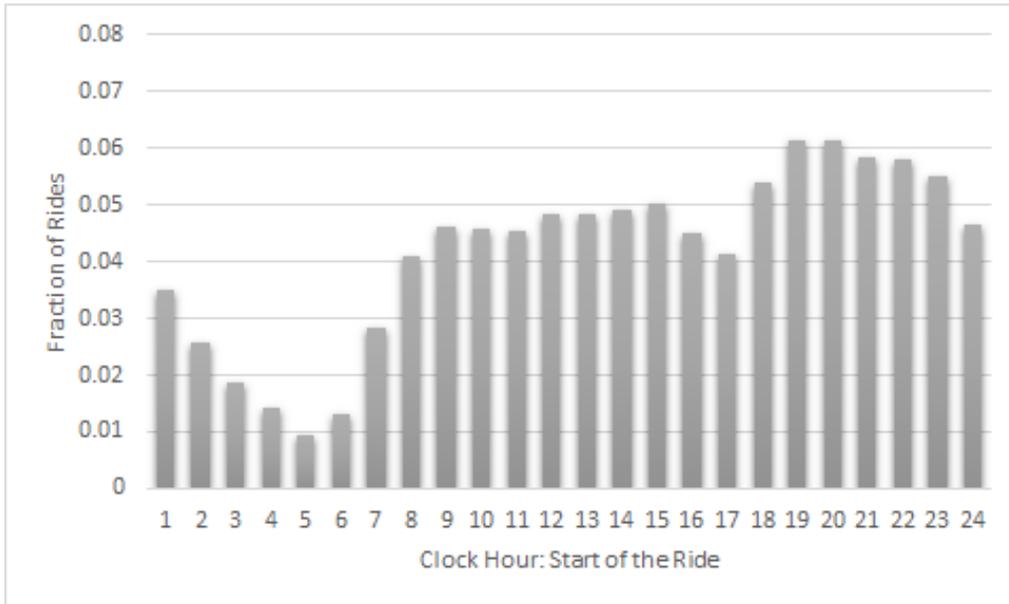
Figure 3: Fraction of taxi rides per hour of day. The time period is April-September 2014 and January-June 2015 (post-Uber).
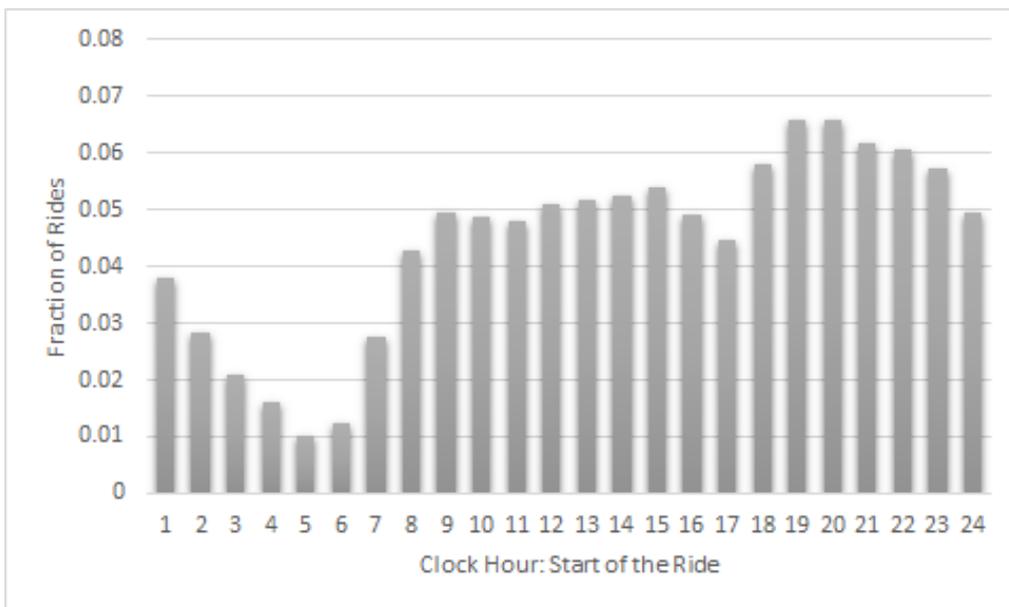

Figure 4: Fraction of taxi rides per hour of day. The time period is January 2009-April 2011 (pre-Uber).

7 Tables

Table 1: Summary Statistics (per Hour).

	Mean	Std. Dev.	Max	Min	Obs.
Panel A					
Uber Rides	2,163	1,770	10,806	18	8,648
Taxi Rides (Post-Uber)	18,274	8,013	34,983	520	8,648
Taxi Rides (Pre-Uber)	19,435	9,151	53,022	209	18,039
Panel B	Dropped Night (1:00 - 5:00 AM)				
Uber Rides	2,520	1,775	10,806	18	6,851
Taxi Rides (Post-Uber)	21,197	5,668	34,983	520	6,851
Taxi Rides (Pre-Uber)	22,551	6,996	53,022	426	14,266
Panel C	Dropped Winter (January - March)				
Uber Rides	1,883	1,689	10,806	43	6,497
Taxi Rides (Post-Uber)	18,394	7,949	34,983	1,948	6,497
Taxi Rides (Pre-Uber)	19,566	8,997	53,022	209	11,165

Note: Authors' calculations. We report rides per hour. See Data section for more details. The time period pre-Uber is 2009-April 2011 The period post-Uber is April-September 2014 and January-June 2015. Panel B excludes from the sample rides from 1:00 to 5:00 AM. Panel C excludes from the sample the months of January, February and March.

Table 2: Weather Data

	Post-Uber Period	Pre-Uber Period
Heavy Rain	22 (0.3%)	51 (0.3%)
Rain	69 (0.8%)	175 (1.0%)
Light Rain	295 (3.4%)	644 (3.6%)
Light Freezing Rain	8 (0.1%)	20 (0.1%)
Heavy Snow	6 (0.1%)	19 (0.1%)
Snow	32 (0.4%)	63 (0.4%)
Light Snow	76 (0.9%)	178 (1.0%)
Clear	4,522 (52.2%)	9,459 (52.4%)
Scattered Clouds	362 (4.2%)	738 (4.1%)
Partly Cloudy	468 (5.4%)	1,056 (5.6%)
Mostly Cloudy	697 (8.1%)	1,293 (7.2%)
Light Freezing Fog	0 (0.0%)	6 (0.0%)
Overcast	1,872 (21.6%)	4,116 (22.8%)
Fog	4 (0.1%)	6 (0.0%)
Haze	213 (2.5%)	215 (1.2%)
Mist	2 (0.0%)	0 (0.0%)
Total	8,648 (100%)	18,039 (100%)

Note: Data from the National Weather Service Observatory in Central Park. The time pre-Uber period is 2009-April 2011. The post-Uber period is April-September 2014 and January-June 2015.

Table 3: Effect of Rain on Taxi and Uber Rides per Hour: Post-Uber.

Natural log of	Taxi Rides	Taxi Rides	Taxi Rides Exclude Night	Uber Rides	Uber Rides	Uber Rides Exclude Night
	(1)	(2)	(3)	(4)	(5)	(6)
Rain	0.033	0.038	0.046	0.208	0.245	0.275
	(0.032)	(0.005)	(0.006)	(0.056)	(0.015)	(0.016)
Control Variables						
Hour × Day FE		✓	✓		✓	✓
Week FE		✓	✓		✓	✓
Month & Year FE		✓	✓		✓	✓
Holiday & Snow FE		✓	✓		✓	✓
Observations	8,648	8,648	6,851	8,648	8,648	6,851
R-Squared	0.000	0.955	0.859	0.007	0.931	0.917

Note: The unit of observation is an hour. The dependent variables are respectively the natural log of the number of taxi rides (col. 1-3) and the natural log of the number of Uber rides (col. 4-6). The time period is April-September 2014 and January-June 2015. *Rain* is a dummy that is equal to one if the conditions were noted as "Heavy Rain", "Rain", "Light Freezing Rain" or "Light Rain" and zero otherwise. Columns 3 and 6 exclude from the sample rides from 1:00 to 5:00 AM. Standard errors clustered by hour of day by day of week (168 clusters) are in parentheses.

Table 4: Robustness Checks for the Period Post-Uber (per Hour).

Natural log of	Taxi Rides Exclude Heavy Rain	Taxi Rides Exclude Winter	Taxi Rides	Uber Rides Exclude Heavy Rain	Uber Rides Exclude Winter	Uber Rides
	(1)	(2)	(3)	(4)	(5)	(6)
Rain	0.042	0.041		0.237	0.265	
	(0.006)	(0.005)		(0.015)	(0.018)	
Light Rain			0.032			0.207
			(0.006)			(0.017)
Rain & Heavy Rain			0.073			0.380
			(0.010)			(0.032)
Control Variables						
Hour × Day FE	✓	✓	✓	✓	✓	✓
Week FE	✓	✓	✓	✓	✓	✓
Month & Year FE	✓	✓	✓	✓	✓	✓
Holiday & Snow FE	✓	✓	✓	✓	✓	✓
Observations	8,618	6,497	8,648	8,618	6,497	8,648
R-Squared	0.955	0.978	0.955	0.931	0.944	0.931

Note: The unit of observation is an hour. The dependent variables are respectively the natural log of the number of taxi rides (col. 1-3) and the natural log of the number of Uber rides (col. 4-6). *Rain* is a dummy that is equal to one if the conditions were noted as "Heavy Rain", "Rain", "Light Freezing Rain" or "Light Rain" and zero otherwise. *Light Rain* is a dummy that is equal to one if the condition was noted as "Light Rain" and zero otherwise. *Rain & Heavy Rain* is a dummy that is equal to one if the conditions were noted as "Heavy Rain" or "Rain" and zero otherwise. Columns 1 and 4 exclude hours of "Heavy Rain" and "Light Freezing Rain". Columns 2 and 5 exclude from the sample the months of January, February and March. The time period is April-September 2014 and January-June 2015. Standard errors clustered by hour of day by day of week (168 clusters) are in parentheses.

Table 5: Effect of Rain on Taxi and Uber Rides per Day: Post-Uber.

Natural log of	Taxi Rides (1)	Taxi Rides (2)	Taxi Rides (3)	Uber Rides (4)	Uber Rides (5)	Uber Rides (6)
Rain Day	0.0186 (0.0164)	0.0100 (0.0142)		-0.0024 (0.1026)	0.0766 (0.0465)	
Hours of Rain			0.0018 (0.0021)			0.0247 (0.0053)
Control Variables						
Week FE		✓	✓		✓	✓
Month & Year FE		✓	✓		✓	✓
Holiday & Snow FE		✓	✓		✓	✓
Observations	366	366	366	366	366	366
R-Squared	0.003	0.344	0.344	0.000	0.810	0.814

Note: The unit of observation is a day. The dependent variables are respectively the natural log of the number of taxi rides (col. 1-3) and the natural log of the number of Uber rides (col. 4-6). The time period is April-September 2014 and January-June 2015. *Rain Day* is a dummy that is equal to one if the conditions were noted as "Heavy Rain", "Rain", "Light Freezing Rain" or "Light Rain" at any point during the day and zero otherwise. *Hours of Rain* is a variable that is equal to the number of hours in which the conditions were noted as "Heavy Rain", "Rain", "Light Freezing Rain" or "Light Rain". Robust standard errors are in parentheses.

Table 6: Effect of Rain on Taxi Rides per Hour: Pre-Uber.

Natural log of	Taxi Rides (1)	Taxi Rides (2)	Taxi Rides Exclude Night (3)	Taxi Rides Exclude Heavy Rain (4)	Taxi Rides Exclude Winter (5)	Taxi Rides (6)
Rain	0.050 (0.021)	0.049 (0.006)	0.064 (0.006)	0.047 (0.006)	0.053 (0.006)	
Light Rain						0.037 (0.006)
Rain & Heavy Rain						0.091 (0.008)
Control Variables						
Hour × Day FE		✓	✓	✓	✓	✓
Week FE		✓	✓	✓	✓	✓
Month and Year FE		✓	✓	✓	✓	✓
Holiday & Snow FE		✓	✓	✓	✓	✓
Observations	18,039	18,039	14,226	17,968	11,615	18,039
R-Squared	0.000	0.923	0.813	0.927	0.939	0.927

Note: The unit of observation is an hour. The dependent variable is the natural log of the number of taxi rides. The time period is 2009-April 2011. *Rain* is a dummy that is equal to one if the conditions were noted as "Heavy Rain", "Rain", "Light Freezing Rain" or "Light Rain" and zero otherwise. *Light Rain* is a dummy that is equal to one if the condition was noted as "Light Rain" and zero otherwise. *Rain & Heavy Rain* is a dummy that is equal to one if the conditions were noted as "Heavy Rain" or "Rain" and zero otherwise. Column 3 excludes from the sample rides from 1:00 to 5:00 AM. Column 4 excludes hours of "Heavy Rain" and "Light Freezing Rain". Column 5 excludes from the sample the months of January, February and March. Standard errors clustered by hour of day by day of week (168 clusters) are in parentheses.

Table 7: Effect of Rain on Taxi Rides per Hour: Pre- and Post-Uber.

Natural log of	Taxi Rides (1)	Taxi Rides (2)	Taxi Rides (3)	Taxi Rides (4)	Taxi Rides (5)
Post-Uber	-0.081	-0.081	-0.080	-0.085	-0.080
	(0.007)	(0.007)	(0.007)	(0.014)	(0.007)
Rain		0.050	0.053	0.052	
		(0.005)	(0.006)	(0.006)	
Rain × Post-Uber			-0.010	-0.011	
			(0.007)	(0.007)	
Light Rain					0.042
					(0.006)
Light Rain × Post-Uber					-0.010
					(0.009)
Rain & Heavy Rain					0.091
					(0.008)
Rain & Heavy Rain × Post-Uber					-0.006
					(0.013)
Control Variables					
Hour × Day FE	✓	✓	✓	✓	✓
Week, Month & Year FE	✓	✓	✓	✓	✓
Month × Post-Uber				✓	
Holiday & Snow FE	✓	✓	✓	✓	✓
Observations	26,687	26,687	26,687	26,687	26,687
R-Squared	0.929	0.929	0.929	0.931	0.929

Note: The unit of observation is an hour. The dependent variable is the natural log of the number of taxi rides. The time period is 2009-April 2011, April-September 2014 and January-June 2015. *Rain* is a dummy that is equal to one if the conditions were noted as "Heavy Rain", "Rain", "Light Freezing Rain" or "Light Rain" and zero otherwise. *Light Rain* is a dummy that is equal to one if the condition was noted as "Light Rain" and zero otherwise. *Rain & Heavy Rain* is a dummy that is equal to one if the conditions were noted as "Heavy Rain" or "Rain" and zero otherwise. *Post Uber* is a dummy that is equal to one for the period April-September 2014 and January-June 2015 and zero otherwise. Standard errors clustered by hour of day by day of week (168 clusters) are in parentheses.

Table 8: Effect of Rain on Total (Taxi and Uber) Rides per Hour: Pre- and Post-Uber.

Natural log of	Total Rides (1)	Total Rides (2)	Total Rides (3)	Total Rides (4)	Total Rides (5)
Post-Uber	0.090 (0.007)	0.091 (0.007)	0.090 (0.007)	0.054 (0.014)	0.091 (0.007)
Rain		0.057 (0.005)	0.053 (0.006)	0.053 (0.006)	
Rain × Post-Uber			0.012 (0.007)	0.012 (0.007)	
Light Rain					0.041 (0.006)
Light Rain × Post-Uber					0.009 (0.009)
Rain & Heavy Rain					0.092 (0.008)
Rain & Heavy Rain × Post-Uber					0.021 (0.012)
Control Variables					
Hour × Day FE	✓	✓	✓	✓	✓
Week, Month & Year FE	✓	✓	✓	✓	✓
Month × Post-Uber				✓	
Holiday & Snow FE	✓	✓	✓	✓	✓
Observations	26,687	26,687	26,687	26,687	26,687
R-Squared	0.929	0.930	0.930	0.930	0.930

Note: The unit of observation is an hour. The dependent variable is the natural log of the number of total (taxi plus Uber) rides. The time period is 2009-April 2011, April-September 2014 and January-June 2015. *Rain* is a dummy that is equal to one if the conditions were noted as "Heavy Rain", "Rain", "Light Freezing Rain" or "Light Rain" and zero otherwise. *Light Rain* is a dummy that is equal to one if the condition was noted as "Light Rain" and zero otherwise. *Rain & Heavy Rain* is a dummy that is equal to one if the conditions were noted as "Heavy Rain" or "Rain" and zero otherwise. *Post Uber* is a dummy that is equal to one for the period April-September 2014 and January-June 2015 and zero otherwise. Standard errors clustered by hour of day by day of week (168 clusters) are in parentheses.

Appendix

Table A1: Summary Statistics (per Day).

	Mean	Std. Dev.	Max	Min	Obs.
Panel A					
Uber Rides	51,105	30,024	136,819	46	366
Taxi Rides (Post-Uber)	434,041	54,663	547,097	73,506	366
Taxi Rides (Pre-Uber)	462,508	78,436	835,489	73,432	758
Panel B	Dropped Winter (January - March)				
Uber Rides	44,485	30,607	136,819	1,680	275
Taxi Rides (Post-Uber)	436,044	53,942	547,097	73,506	275
Taxi Rides (Pre-Uber)	465,687	75,010	835,489	73,432	488

Note: Authors' calculations. We report rides per day. See Data section for more details. The time period pre-Uber is 2009-April 2011 The period post-Uber is April-September 2014 and January-June 2015. Panel B excludes from the sample the months of January, February and March.

Table A2: Effect of Rain on Taxi Rides per Day: Pre-Uber.

Natural log of	Taxi Rides (1)	Taxi Rides (2)	Taxi Rides (3)
Rain Day	0.0209	-0.0128	
	(0.0146)	(0.0133)	
Hours of Rain			0.0008
			(0.0016)
Control Variables			
Week FE		✓	✓
Month & Year FE		✓	✓
Holiday & Snow FE		✓	✓
Observations	758	758	758
R-Squared	0.002	0.335	0.334

Note: The unit of observation is a day. The dependent variable is the natural log of the number of taxi rides. The time period is 2009-April 2011. *Rain Day* is a dummy that is equal to one if the conditions were noted as "Heavy Rain", "Rain", "Light Freezing Rain" or "Light Rain" at any point during the day and zero otherwise. *Hours of Rain* is a variable that is equal to the number of hours in which the conditions were noted as "Heavy Rain", "Rain", "Light Freezing Rain" or "Light Rain". Robust standard errors are in parentheses.

Table A3: Effect of Rain on Taxi Rides per Day: Pre- and Post-Uber.

Natural log of	Taxi Rides (1)	Taxi Rides (2)	Taxi Rides (3)	Taxi Rides (4)
Post-Uber	-0.083	-0.083	-0.087	-0.090
	(0.013)	(0.013)	(0.015)	(0.049)
Rain Day		0.001	-0.003	-0.008
		(0.010)	(0.013)	(0.013)
Rain Day × Post-Uber			0.014	0.025
			(0.020)	(0.019)
Control Variables				
Week, Month & Year FE	✓	✓	✓	✓
Month × Post-Uber				✓
Holiday & Snow FE	✓	✓	✓	✓
Observations	1,124	1,124	1,124	1,124
R-Squared	0.275	0.275	0.276	0.308

Note: The unit of observation is a day. The dependent variable is the natural log of the number of taxi rides. The time period is 2009-April 2011, April-September 2014 and January-June 2015. *Rain Day* is a dummy that is equal to one if the conditions were noted as "Heavy Rain", "Rain", "Light Freezing Rain" or "Light Rain" at any point during the day and zero otherwise. *Post Uber* is a dummy that is equal to one for the period April-September 2014 and January-June 2015 and zero otherwise. Robust standard errors are in parentheses.

Table A4: Effect of Rain on Total (Taxi and Uber) Rides per Day: Pre- and Post-Uber.

Natural log of	Total Rides (1)	Total Rides (2)	Total Rides (3)	Total Rides (4)
Post-Uber	0.088	0.089	0.082	0.051
	(0.014)	(0.013)	(0.016)	(0.049)
Rain Day		0.004	-0.004	-0.008
		(0.010)	(0.013)	(0.013)
Rain Day × Post-Uber			0.023	0.033
			(0.020)	(0.020)
Control Variables				
Week, Month & Year FE	✓	✓	✓	✓
Month × Post-Uber				✓
Holiday & Snow FE	✓	✓	✓	✓
Observations	1,124	1,124	1,124	1,124
R-Squared	0.285	0.285	0.286	0.310

Note: The unit of observation is an hour. The dependent variable is the natural log of the number of total (taxi plus Uber) rides. The time period is 2009-April 2011, April-September 2014 and January-June 2015. *Rain Day* is a dummy that is equal to one if the conditions were noted as "Heavy Rain", "Rain", "Light Freezing Rain" or "Light Rain" at any point during the day and zero otherwise. *Post Uber* is a dummy that is equal to one for the period April-September 2014 and January-June 2015 and zero otherwise. Robust standard errors are in parentheses.