Reference Dependence – On Any Given Sunday: Are Taxi Driver's Shift End Decisions Impacted by the NFL?

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Abstract

Within this study, I evaluate supply and demand shocks on level of effort, using NFL games and rain as proxies. In addition, through this paper I resolve opposing findings by Camerer, et al, and Farber. Key findings are: (1) drivers are less likely to end a shift during the time when an NFLgame is ongoing, even though few trips begin or end near the football stadium, (2) Camerer is supported without fixed effects, but findings with fixed effects are inconclusive, and (3) using a discrete choice model with and without fixed effects quits are accurately predicted 29% of the time if 0.50 is used as the threshold for quitting, but 84% if the threshold is raised to 0.525.

INTRODUCTION

A large proportion of the population chooses to work or not work, with pay scales, days worked, work hours and hours of work set by employers, but there are many occupations in which workers determine their own individual level of effort. Doctors, dentists and attorneys, for example, are free to choose how many days a week their practices operate. The basic question is: how do taxi drivers determine when to start and end their shift? Is the decision based on some underlying reference? Do they start at a set time each day and work a certain number of hours before ending their shift (are they "hours" referenced), or do they work until earnings reach a certain amount ("dollars" referenced)? If earnings on a given day are unexpectedly better or worse than expected, how do drivers react?

Camerer, et al (1997) found that drivers exhibit strong reference-dependence with respect to daily wages, Farber (2005) could re-create Camerer, et al findings, but once driver fixed effects were taken into consideration Camerer, et al findings disappeared and drivers instead exhibited strong reference-dependence with respect to shift length. Others have found support for one, the other, or both conclusions. I begin with the base hypothesis that drivers exhibit reference dependence with respect to daily wage and the number of trips taken, but are not reference dependent with respect to shift length. Second, I investigate driver's reaction to unexpected shocks (rain) and positive, expected shocks (NFL games). Finally, a key extension of this analysis would be to include an analysis of app-hail driver reactions. Within the literature review I note scholarly papers using app-hail driver data, but the authors of these have all refused to provide their data for use herein.

Consequently, my null hypotheses are that:

1. Individuals do display negative wage elasticities, as predicted by Camerer, et al, and others.
2. Inclement weather increases the probability that a driver quits for the day on each trip undertaken during a rain event.
3. Large spectator events, such as National Football League games, reduce the probability that a driver quits for the day immediately prior to the event, while the event is ongoing, and for a short time afterwards.

LITERATURE REVIEW

The central assumption in Tversky and Kahneman's (Tversky & Kahneman, 1991) (TK) paper on reference-dependence and risk aversion "is that losses and disadvantages have greater impact on preferences than gains and advantages."[1] Through their own experiments and a review of others, TK demonstrated that losses about a reference point, in terms of disutility, are viewed as being twice as significant as gains, in terms of increased utility. Applying this theory to the case of taxi drivers would imply that negative earnings shocks have a more significant impact on driver choices than positive shocks, suggesting that drivers work longer hours when daily earnings are below a reference point, and might work less when earnings are above that reference point. TK also show that there is diminishing sensitivity to both larger gains and losses, which when applied to taxi drivers implies that on a bad day driver's might quit earlier in the day, choosing to work another day instead. Per TK "Loss aversion appears to be more pronounced…for income than for leisure"[2], suggesting that when income is below target drivers

1 (Tversky & Kahneman, 1991) p. 1039

2 (Tversky & Kahneman, 1991) p. 1054

work longer hours. As predicted by TK "the response to changes is expected to be more intense when the changes are unfavorable (losses) than when they are for the better."[3]

Camerer, et al (Camerer, Babcock, Lowenstein, & Thaler, 1997) found that inexperienced taxi drivers exhibited negative wage elasticities approaching -1 and, using a log-log regression of workhours on wages for each of three datasets, estimated wage elasticities for experienced drivers of -0.503, -0.391 and -0.269. Based on these "strongly negative" wage elasticities Camerer posits that taxi drivers generally use a single day as their decision-making time horizon. Positive wage elasticities, if they existed, would result in intertemporal substitution with drivers working longer hours on good days and taking more leisure time on bad days, consistent with life-cycle labor supply theories. Camerer's findings counter these life-cycle theories. Each of Camerer's datasets included a relatively small number of observations, with the largest relied upon including 1,044 observations for 484 drivers, an average of only 2.2 observations per driver.

In a paper published in 2002 Yuan Chou analyses data collected for Singaporean taxi drivers, with findings supporting Camerer's "target income labour supply model". In this study, Chou finds negative wage elasticities ranging between −0.3 to −0.9. Per Chou "a very short planning horizon by workers is required to explain negative wage elasticities. If workers have even a two-day decision-making horizon (say, they have a two-day earnings target), estimated elasticities would be positive for a wide range of plausible specifications."[4] Chou's dataset, compiled from a written survey administered to 150 English-speaking drivers of Singapore's

3 (Tversky & Kahneman, 1991) p. 1055

4 (Chou, 2002) p. 23

largest taxi company, includes 114 self-report responses received, but only 92 were deemed sufficiently complete for use in analyses.

In 2005 the first of three papers by Henry Farber discussing New York City taxi drivers was published (Farber H. S., Is Tomorrow Another Day? The Labor Supply of New York City Cabdrivers, 2005). In this paper, Farber analyzes data gleaned from 584 trip sheets gathered from one taxi cab company that cover a total of 21 drivers. The data represents two separate time periods from June 1999 through May 2000 and June 1999 through May 2001. Farber was unable to obtain meter readouts to verify the accuracy of the trip sheets, as Camerer, et al did, so chose to accept all of the trip sheets for his analyses. Farber points to differences between his model and that of Camerer, et al as being responsible for differences in the findings, indicating that Camerer, et al calculation of average hourly wage as a flaw in Camerer, et al's analysis. As with Camerer, et al, and Chou, findings in Farber's 2005 paper are based on small and somewhat defective datasets. Camerer et al's model is not in the published article, but per Farber is given by the equation:

$$\ln\left(H_{it}\right)=\eta*\ln\left(W_{it}\right)+X_{it}\beta+\varepsilon_{it} \quad \text{(Eq. 1)},$$

where H_{it} represents hours worked by diver *i* on day *t*, η represents the elasticity of labor supply, W_{it} represents average daily wage determined by dividing total daily wage by H_{it}, and X_{it} represents all other factors impacting labor supply. In contrast, Farber's 2005 model is:

$$R_{idc}\left(\tau\right)=\gamma_1 h_t+\gamma_2\psi_t+X_{idc}\beta+\mu_i+\varepsilon_{idct} \quad \text{(Eq. 2)},$$

where i, d, and c index driver, date and hour of the day, h_τ represents cumulative hours worked to that point in a shift, ψ_t measures cumulative income to that point in a shift, X_{idc} represents other factors impacting labor supply and μ_i allows separation of driver fixed effects from other factors within X_{idc}. It is unclear from Camerer, et al, or Farber's review of Camerer, et al's work, what determines driver quit time, but in Farber's model drivers quit for the day when $R_{idc}(\tau) \geq 0$.

In support of Camerer et al, Koszegi & Rabin (Koszegi & Rabin, 2006) (KR) find that "when drivers experience unexpectedly high wages in the morning, for any given afternoon wage they are less likely to continue work. Yet expected wage increases will tend to increase both willingness to show up to work, and to drive in the afternoon once there."[5] "In within-day labor-supply decisions, a worker is less likely to continue work if income earned thus far is unexpectedly high, but more likely to show up as well as continue work if expected income is high."[6] As relates to taxi drivers, KR point out the logical reference point is each driver's average daily wage, tempered by expectations of whether a particular day will be better or worse than average and find that the probability of quitting increases when "wages are unpredictably high."[7]

5 (Koszegi & Rabin, 2006) p. 1136

6 (Koszegi & Rabin, 2006) p. 1133

7 (Koszegi & Rabin, 2006) p. 1151

In his 2008 paper, which counters Camerer, et al (1997), Farber finds that drivers may have a reference wage each day and that there is an increase in the probability of quitting for the day when that wage is earned, but the reference wage level varies significantly from day to day and that most shifts end before the reference wage is reached, implying that drivers are hours focused in the absence of above average wages.[8] Farber assumes "that the decision to stop driving for the day is irreversible."[9] Farber's dataset did not allow for accurate estimation of anticipated positive or negative day-of-the-week, seasonal, weather related and similar shocks, instead noting a "relatively large unexplained within-driver variation in income across shifts."[10]

Taxi drivers are not the only workers that determine their own work hours, and there are several scholarly articles that discuss workers within other industries. A paper by Gerald Oettinger provides an analysis of labor supply elasticities for stadium food and beverage vendors over an entire baseball season[11]. Oettinger notes that Camerer discusses exogenous wage shocks, but that the dataset does not include data on exogenous demand, concluding "it would be desirable to have data on exogenous demand shifters that could be used as instruments for the observed daily wage."[12] As with taxi drivers, changes in daily income could be attributed to shifts in supply and/or demand. Findings included large variations in game-to-game attendance and vendor participation, with both higher for weekend and promotional games and lower for

8 (Farber H. S., Reference-Dependent Preferences and Labor Supply: The Case of New York City Taxi Drivers, 2008)

9 (Farber H. S., Reference-Dependent Preferences and Labor Supply: The Case of New York City Taxi Drivers, 2008), p. 1072

10 (Farber H. S., Reference-Dependent Preferences and Labor Supply: The Case of New York City Taxi Drivers, 2008), p. 1081

11 (Oettinger, 1999)

12 (Oettinger, 1999), p. 361-362

weekday afternoon games, higher earnings on Saturday nights, significant individual fixed effects (indicating that hard work pays) and opposing team effects.

In their 2011 work Crawford and Meng (Crawford & Meng, 2011) (CM) suggest that labor elasticities near 0 would support a neoclassical position and positive elasticities would be consistent with a classical position. In their conclusion, CM suggest that Camerer, et al's 1997 findings can be reconciled with Farber (2005), and thus with Farber (2008) and Farber (2015).

In a 2014 paper Haggag et al find "drivers benefit from accumulating neighborhood-specific experience, which affects how they search for their next customers"[13]; driver fixed effects can have a significant impact on daily earnings and need to be controlled for (Haggag, McManus, & Paci, 2014) (HMP). HMP base their analyses on a dataset which includes all trips by New York City yellow cab drivers within calendar year 2009, a total of 171 million datapoints, with their focus being 7,869 drivers who worked an average of 179 shifts that year. This dataset appears to be the first large dataset for New York City taxi drivers and is included in the dataset used by Farber (2015) referred to later in this paper. HMP find that new drivers earn significantly less during their first 100 shifts and develop a basis for determining location based fixed effects using drop-off and pick-up points; experienced drivers use their local knowledge (a driver fixed effect) to move from a historically poor pick-up location to a known good pick-up location (location fixed effect). Lease drivers select the shifts they plan to work based on seniority; more experienced drivers tend to drive during shifts expected to be the most productive.

A paper by Agarwal, Diao, Pan and Sing, originally published in 2014 and later revised (Agarwal, Diao, Pan, & Sing, 2015), supports findings by Camerer, et al, and Crawford and Meng, respectively, that taxi drivers display negative wage elasticities and that their actions are

13 (Haggag, McManus, & Paci, 2014) p. 1

significantly correlated with both work hours and earnings reference-dependence. Agarwal, et al, estimate a negative elasticity of labor supply of -0.040 for the overall dataset, but estimate elasticities of -0.423 for high-income shifts and -0.275 for low-income shifts. Agarwal, et al, evaluate a dataset that contains all Singaporean taxi trips during the month of August, 2010, including an average of 15,406 taxis per day and 16,793,501 data points. For their empirical analyses, Agarwal, et al, indicate "we derive the daily income and wage-rate", implying that actual earnings are not included within the data collected.

In his 2015 article Henry Farber provides additional support for his earlier findings that most New York City taxi drivers display strongly positive wage elasticities and that, in general, taxi drivers exhibit strongly reference dependent choices with respect to hours worked, but weak or non-existent reference-dependence with respect to earnings (Farber H. S., 2015). To overcome small dataset issues associated with his 2005 paper, for this article Farber bases his analyses on a random subset from the complete record of all trips taken by taxis issued medallions by the New York Taxi and Limousine Commission from 2009 through 2013; in all Farber uses 116,177,329 trips for 8,802 drivers.

Several papers have discussed the amount of time taxi drivers spend searching for their next fare, and the positive impact driver knowledge has on the average amount of possible trip time lost to searching. In an unpublished paper, Cramer and Krueger find that "UberX drivers have a substantially higher capacity utilization rate than do taxi drivers in every city except New York, where the utilization rates are very similar."[14] On average, over the five cities UberX driver efficiency is between 49% and 61% higher than taxi efficiency. Utilization rates were comparable only in New York, where population density may improve the effectiveness of street hailing. Another paper studying app-hail ride sharing providers by Chen and Sheldon (Chen &

14 (Cramer & Krueker, 2015), p. 7

Sheldon, 2015) finds that Uber partners drive more at times when expected earnings are high and that flexible pricing significantly impacts labor supply.[15] Chen and Sheldon find "significantly and substantially positive supply elasticities", "that increases in the "surge" price of Uber trips significantly decreases the instantaneous stopping rate of drivers", and as a result "drivers appear to dynamically adjust their schedules to drive longer and provide more trips".[16] Chen and Sheldon's findings, that Uber's dynamic pricing system both shifts supply and demand, and that driver's labor elasticities are significantly positive, runs counter to Camerer's findings.

From the foregoing review, there is yet significant disagreement amongst scholars over what underlies a driver's decision to drive on a particular day, and to quit for the day after making the decision to drive. Further, it is unclear from the literature how drivers react to positive and negative shocks.

Model

$$Pr\left(EndSession_{it}\right)=\frac{\exp\left(z_{it}\right)}{1+\exp\left(z_{it}\right)}$$, where

$$z_{it}=\beta_0+\beta_1\log\left(CUM_{FARE}\right)+\beta_2\log\left(CUM_{SHIFT}\right)+\beta_3\log\left(CUM_{TIME\,W\,FARES}\right)+\beta_4\log\left(CUM_{TRIPS}\right)+\beta_5\log\left(CUM_{DIST}\right.$$

Table 1 – Variables, Description, and Expected Signs

VARIABLE	**DESCRIPTION**	**EXPECTED SIGNS**
DEPENDENT VARIABLE		
QUIT	Binary variable whose value is 0 if the driver accepts a subsequent fare within the same shift, 1 if the fare is the last fare of the shift.	+
INDEPENDENT		

15 (Chen & Sheldon, 2015)

16 (Chen & Sheldon, 2015), p. 2

VARIABLES		
CUM_FARE	Cumulative base fare dollar earnings during the current shift.	+
CUM_SURCHARGE	Cumulative surcharge earnings during the current shift	+
CUM_SHIFT	Cumulative shift duration in hours.	-
CUM_TIME_W_FARE	Cumulative time spent with fares in hours.	-
CUM_TIME_W_FARE * PASSENGERS	Interaction term obtained by multiplying the number of passengers by trip duration, then aggregating that result over a shift.	+
CUM_TRIPS	Cumulative number of trips during the current shift.	+
DIST_W_TRIPS	Cumulative number of miles driven with fares in the car.	-
HOLIDAY	Binary variable indicating whether or not the trip occurs on a major holiday.	-
PRECIP	Cumulative inches of rain during the current shift.	+
NFL_GAMEDAY	Binary variable indicating whether or not the trip occurs on the same day as an NFL game.	-
NFL_GAMEON	Binary variable indicating whether trips ended at Giants Stadium between one hour before schedule game start and half-time or originated at Giants Stadium between half-time and one hour after game end.	-

The variable CUM_FARE represents the sum of base fares earned during the current shift. Tip income for taxi drivers may represent a significant part of a driver's income, but as cash tips are unreported the options are to exclude tips, or include estimated tips based on tips reported and base fare, miles, or some other factor for trips where a tip was reported. Relying on Camerer, et al, and subsequent work, my base hypothesis is that the sign on cumulative earnings, including both fare and surcharge, is positive.

The variable CUM_SHIFT is defined as elapsed time in hours from the time the first trip of a shift originates and the time the last trip of a shift completes.

The binary control variable RAIN is a proxy for a shock to income that may or may not be expected. Assuming drivers make their decision whether to work a particular day or shift in advance of a work day, a control on this variable could be whether the percentage chance of rain in the preceding day's New York Times was greater or less than some value so that RAIN is an unexpected shock if the percentage chance of rain was low and an expected shock if the percentage chance of rain was high. This analysis is left for future work.

The binary control variable NFL_GAMEON is a proxy for an expected positive shock to income, and is calculated to minimize interaction with trips that would have occurred whether the event had occurred or not,. The average length of a regular season NFL game is approximately three hours and fifteen minutes; the exact start and end time of games is recorded by the league, but not published, nor are the exact start and end times of half-time.

Data and Summary Statistics

Dr. Henry Farber has graciously provided a portion of the dataset used by him for his 2015 paper, coincidentally the same data used by Haggag, et al, in their 2014 work. Agarwal, et al, Sheldon & Chen, Cramer & Krueger all refused to provide their data, and Uber and Lyft declined to provide data directly, however some data is available via the internet from Five Thirty-Eight, and other data is published monthly by the New York Taxi and Limousine Commission, but neither of these sources provide sufficient granularity.

Data provided by Dr. Farber includes two separate datasets, TPEP Fare and TPEP Trip, both attributed to the New York Taxi & Limousine Commission(TLC). The two datasets provided by Dr. Farber include panel and time series data for all TLC licensed cabs for calendar year 2009. As noted in the literature review above, TPEP Fare includes encrypted cab medallion and driver permit numbers, which are constant throughout all the datasets, vendor name, base fare, surcharges, tolls, MTA tax, method of payment, and tips, but only for tips paid by credit card. TPEP Trip includes latitude and longitude coordinates for the start and end of each trip, and the number of miles driven. Each of the twenty-four files contains data for one calendar month. For purposes of this work I have elected to rely upon the six consecutive months running from July 1, 2009 through December 31, 2009.

In 2009 taxi drivers licensed by the TLC earned fare income based on a formula of \$2.50 for the first 1/5th of a mile, plus \$0.40 per additional 1/5th of a mile when traveling at or above 12 miles per hour, plus \$0.40 per minute when traveling at less than 12 miles per hour. In addition, a \$1.00 surcharge was added for weekday trips starting between 4 PM and 8 PM, and a surcharge of \$0.50 was added for trips starting between 8 PM and 6 AM. Thus, a driver's daily income is a function of the number of trips, each trip's distance, the duration of each trip, the day of the week and the time of day when the trip starts.

The purpose of the TPEP program is to automate and perfect data collection, and while the program accurately collects the bulk of trip and fare data, the data collected is neither perfectly accurate or ideal. Details on data cleaning process are available upon request, but collectively, ignoring imperfect and less than ideal data results in removal of 2,064,832 observations, or about 2% of the original data.

Following a path like Farber's 2015 methodology, trip data was merged with data on rainfall in Central Park[17]. The weather data is such that greater granularity could be achieved by generating minute length intervals, but rain being imminent may be as impactful as rain falling, so Farber's one-hour interval is adopted, allowing better comparison of findings.

17 Source: National Oceanographic and Atmospheric Administration U.S. Local Climatological Data for station WBAN:94728

Within Table 2 below are presented the matrix of correlation coefficients between the variables analyzed within this study. Quit is positively correlated with *trip_no, shift_no*, *fare_amt, surcharge, NFL_gameday, holiday*, and with all cumulative shift variables. Quit is negatively correlated with *trip_pickup_date_and_time, trip_dropoff_date_and_time, day_of_week, day_of_year, hours_since_last_trip, precipitation, shift_start*, and *shift_end*. Cumulative fare is highly positively correlated with *trip_no*, cumulative shift length, *cum_time_w_fare*, and cumulative distance driven during the shift with passengers in the vehicle, and are positively correlated with *precip.*

Table 2 - Matrix of Correlation Coefficients

Variables	car_no	driver_no	car_drive	shift_no	trip_no	passen~t	trip_dist	start_lon	start_lat	end_lon	end_lat	trip_date
car_no	1											
driver_no	-0.0001	1										
car_driver	0.9999	0	1									
shift_no	-0.0007	-0.0007	-0.0007	1								
trip_no	-0.0014	0.0008	-0.0014	-0.03	1							
passenger_count	-0.0057	-0.0029	-0.0056	0.0209	0.0236	1						
trip_distance	-0.0002	-0.0007	-0.0002	0.0149	-0.054	0.0175	1					
start_lon	0.0004	-0.002	0.0004	0.0362	-0.0883	-0.0065	0.3108	1				
start_lat	-0.0017	-0.0018	-0.0018	0.0123	-0.0117	-0.013	-0.1527	0.4236	1			
end_lon	-0.0003	-0.0012	-0.0003	0.0195	-0.0162	-0.0083	0.2634	0.6176	0.3927	1		
end_lat	-0.0018	-0.0018	-0.0018	0.0152	-0.0116	-0.0088	-0.13	0.3665	0.616	0.4655	1	
trip_pick_date	0.0009	-0.0003	0.0009	0.5679	0.0292	0.0007	-0.0083	0.0096	0.0196	0.0077	0.0167	1
trip_pickup_date_and_time	0.0009	-0.0003	0.0009	0.568	0.029	0.0008	-0.0085	0.0097	0.0197	0.0075	0.0168	1
trip_dropoff_date_and_time	0.0009	-0.0003	0.0009	0.568	0.029	0.0008	-0.0084	0.0097	0.0197	0.0075	0.0168	1
trip_time	0.0006	-0.0007	0.0006	0.0311	-0.0573	0.0232	0.7816	0.2079	-0.0937	0.1708	-0.1127	0.0162
day_of_week	0.0007	-0.0016	0.0007	0.0143	-0.0073	0.0117	-0.024	-0.017	-0.0032	-0.0127	-0.0079	-0.0123
day_of_year	0.0009	-0.0003	0.0009	0.5679	0.0292	0.0007	-0.0083	0.0096	0.0196	0.0077	0.0167	1
fare_amt	0.0003	-0.0007	0.0003	0.0198	-0.06	0.0172	0.9509	0.287	-0.14	0.2299	-0.1349	0.0013
surcharge	-0.0007	-0.0027	-0.0007	0.1338	0.0771	0.0883	-0.0283	-0.0138	0.0011	0.004	0.0065	0.1624
hours_since_last_tripp	-0.0002	0.0006	-0.0002	-0.0293	-0.0664	-0.005	0.0198	0.0189	-0.004	0.0085	-0.0009	0.0175
trip_id	1	0	1	-0.0007	-0.0014	-0.0057	-0.0002	0.0004	-0.0017	-0.0003	-0.0018	0.0009
NFL_gameday	-0.001	0.0005	-0.001	0.0334	0.0689	0.0182	0.022	-0.0004	-0.0119	0.0048	-0.007	0.11
NFL_gameon	-0.0006	0.0007	-0.0006	0.0145	0.0094	0.0103	0.012	0.0068	0.0003	0.0009	-0.0009	0.0509
near_fid_end	0.0007	-0.0001	0.0007	-0.0054	0.0011	-0.0005	-0.1126	-0.1648	-0.2434	-0.41	-0.5291	-0.005
near_dist_end	-0.0004	-0.0011	-0.0004	0.0224	-0.0016	-0.0068	0.1815	0.4896	0.4345	0.6388	0.4256	0.0123
near_fid_start	0.0006	0.0004	0.0006	-0.0172	0.0575	-0.0012	-0.1789	-0.4338	-0.3837	-0.2074	-0.2418	-0.0091
near_dist_start	0.0002	-0.001	0.0002	0.0309	-0.0457	-0.0056	0.1672	0.6981	0.4424	0.4901	0.4008	0.0123
holiday	0	0.0003	0	-0.0035	-0.0222	0.0137	0.0122	0.0025	-0.002	0.0056	-0.0007	0.0032
precip	0	0	0	0.0137	0.027	0.0105	-0.0138	-0.0048	0.0003	-0.0034	0.0003	0.0267
shift_start	0.0009	-0.0003	0.0009	0.5681	0.0266	0.0007	-0.0085	0.0098	0.0198	0.0075	0.0169	1
shift_end	0.0009	-0.0003	0.0009	0.5679	0.0276	0.0008	-0.0085	0.0098	0.0198	0.0075	0.0169	1
trip_speed	-0.001	-0.0005	-0.001	-0.0223	-0.0009	-0.0008	0.6515	0.2098	-0.0992	0.2228	-0.047	-0.0389
quit	0.0002	-0.0002	0.0002	0.0079	0.1829	0.001	0.1148	0.0251	-0.0219	0.0853	-0.026	-0.0044
cum_shift	-0.0019	0.0016	-0.0019	-0.038	0.8833	0.0285	0.0358	-0.0308	-0.0319	0.0127	-0.0204	-0.0048
cum_fare	-0.0011	0.0007	-0.0011	-0.0127	0.9284	0.0299	0.0671	-0.0364	-0.042	0.0156	-0.0317	0.034
cum_dist	-0.0012	0.0007	-0.0012	-0.0138	0.8251	0.0345	0.1445	0.0005	-0.0575	0.0385	-0.0405	0.0173
cum_time_w_fare	-0.0008	0.0004	-0.0008	0.0052	0.9289	0.0314	0.0348	-0.0492	-0.0317	0.0086	-0.0243	0.051
cum surcharge	-0.0009	-0.0026	-0.0009	0.1008	0.4075	0.0815	0.0035	-0.0467	-0.0355	0.0032	-0.0252	0.1543

Variables	trip_p..	t~ropo~e	trip_time	day_of~k	day_of~r	fare_amt	surcharge	hours_~p	trip_id	NFL_ga~y	NFL_game	near_f_e
trip_pickup_date_and_time	1											
trip_dropoff_date_and_time	1	1										
trip_time	0.0164	0.0165	1									
day_of_week	-0.0122	-0.0122	0.0183	1								
day_of_year	1	1	0.0162	-0.0123	1							
fare_amt	0.0012	0.0013	0.852	-0.0114	0.0013	1						
surcharge	0.1637	0.1637	-0.0146	0.001	0.1624	-0.0372	1					
hours_since_last_tripp	0.0174	0.0174	0.0114	-0.0051	0.0175	0.0183	0.0053	1				
trip_id	0.0009	0.0009	0.0006	0.0007	0.0009	0.0003	-0.0007	-0.0002	1			
NFL_gameday	0.1097	0.1097	-0.0125	-0.3739	0.11	0.0113	-0.0592	0.0039	-0.001	1		
NFL_gameon	0.0513	0.0513	0.0063	-0.18	0.0509	0.0108	-0.0548	0.0009	-0.0006	0.5025	1	
near_fid_end	-0.0049	-0.0049	-0.0453	0.0061	-0.005	-0.0856	-0.0045	-0.0045	0.0007	-0.0062	-0.0017	1
near_dist_end	0.0123	0.0123	0.1141	-0.0046	0.0123	0.1754	0.0215	0.0034	-0.0004	0.0048	0.0034	-0.1779
near_fid_start	-0.0091	-0.0091	-0.1157	0.0128	-0.0091	-0.164	0.0106	-0.0149	0.0006	-0.0028	-0.0051	0.2762
near_dist_start	0.0123	0.0123	0.1131	-0.0008	0.0123	0.1548	-0.0006	0.0098	0.0002	0.0015	0.0038	-0.134
holiday	0.0032	0.0032	-0.0199	0.0468	0.0032	0.0025	-0.0276	0.0012	0	-0.038	-0.0194	-0.008
precip	0.0267	0.0267	0.0203	0.1154	0.0267	-0.0049	-0.0242	-0.0015	0	0.0143	-0.0118	0.0009
shift_start	1	1	0.0164	-0.0121	1	0.0012	0.1636	0.0176	0.0009	0.1095	0.0513	-0.0049
shift_end	1	1	0.0164	-0.012	1	0.0012	0.1636	0.0175	0.0009	0.1096	0.0513	-0.0049
trip_speed	-0.0395	-0.0395	0.1708	-0.0631	-0.0389	0.5151	-0.0071	0.021	-0.001	0.0615	0.0109	-0.144
quit	-0.0048	-0.0048	0.077	-0.0102	-0.0044	0.1067	0.0335	-0.0071	0.0002	0.005	-0.0044	-0.0411
cum_shift	-0.0051	-0.005	0.0287	-0.0227	-0.0048	0.0324	0.0621	-0.0662	-0.0019	0.0594	0.0081	-0.009
cum_fare	0.0338	0.0338	0.0452	-0.0116	0.034	0.0649	0.0935	-0.0658	-0.0011	0.0802	0.0133	-0.0083
cum_dist	0.017	0.017	0.08	-0.0298	0.0173	0.1222	0.0786	-0.0611	-0.0012	0.0927	0.0232	-0.0183
cum_time_w_fare	0.0509	0.0509	0.0611	0.0127	0.051	0.0382	0.1314	-0.0651	-0.0008	0.0622	-0.0005	-0.0024
cum_surcharge	0.1546	0.1546	-0.0465	0.0663	0.1543	-0.0212	0.5927	-0.0266	-0.0009	-0.053	-0.0572	0.0002

Variables	near_d_e	near_f_s	near_d_s	holiday	precip	shift_star	shift_end	trip_s~d	quit	cum_sh~t	cum_fare	cum_dist
near_dist_end	1											
near_fid_start	-0.1615	1										
near_dist_start	0.7427	-0.251	1									
holiday	0.0024	-0.0061	0.0019	1								
precip	-0.0008	0.0033	-0.0004	-0.0188	1							
shift_start	0.0122	-0.0092	0.0124	0.0032	0.0267	1						
shift_end	0.0122	-0.0092	0.0123	0.0031	0.0267	1	1					
trip_speed	0.146	-0.1337	0.1157	0.0555	-0.0514	-0.0396	-0.0396	1				
quit	0.0457	-0.0143	0.0168	0.011	-0.0015	-0.0054	-0.0057	0.1107	1			
cum_shift	0.0148	0.0215	-0.0152	0.0001	0.0163	-0.0078	-0.0066	0.0403	0.2282	1		
cum_fare	0.0209	0.0296	-0.017	-0.0214	0.0213	0.0312	0.0323	0.0708	0.2114	0.9362	1	
cum_dist	0.0334	0.0072	0.0037	-0.0064	0.0112	0.0145	0.0155	0.1538	0.2172	0.8983	0.9624	1
cum_time_w_fare	0.0181	0.0398	-0.0215	-0.0396	0.0323	0.0484	0.0495	0.0053	0.1987	0.9186	0.9743	0.9069
cum_surcharge	0.0198	0.0348	-0.0158	-0.0212	-0.0135	0.1537	0.154	0.0953	0.084	0.3199	0.3909	0.3541

Variables	cum_ti~e	cum_su~e
cum_time_w_fare	1	
cum_surcharge	0.4149	1

Within Table 2 are presented descriptive statistics for both the original TLC variables, and calculated variables. During the last six months of 2009 there were 13403 TLC licensed taxis operating in New York, and 36,057 licensed drivers. The variable *car_driver* captures the unique combinations of *car_no* and *driver_no* observed within the data, and is used to capture driver fixed effects within the data. Many drivers adopt a split-shift schedule, working for a few hours, taking a break (defined here as being four hours or longer), and then working for a few more hours. During the six-month period covered by the data utilized there are 184 days, but the highest number of shifts, calculated using the four-hour break criteria, is 548; some drivers drive three or more split-shifts each day.

Unlike taxis in most other cities, taxis in New York are not dispatched to a residence or place of business; instead prospective fares hail a cab by waving their hand or waiting at fixed taxi stands. In many cities, this arrangement would be ineffective, but in New York it has the effect of improving driver efficiency – drivers spend more of their day with fares in their taxi than they would in other cities using a dispatch system. Drivers spend a good part of their day looking for their next fare, and might have 4 or more trips every hour. As the heat map in Figure 1 shows, the bulk of trips originate within a very small area.

Figure 1 - Taxi Pick-up Heat Map - 12/2009

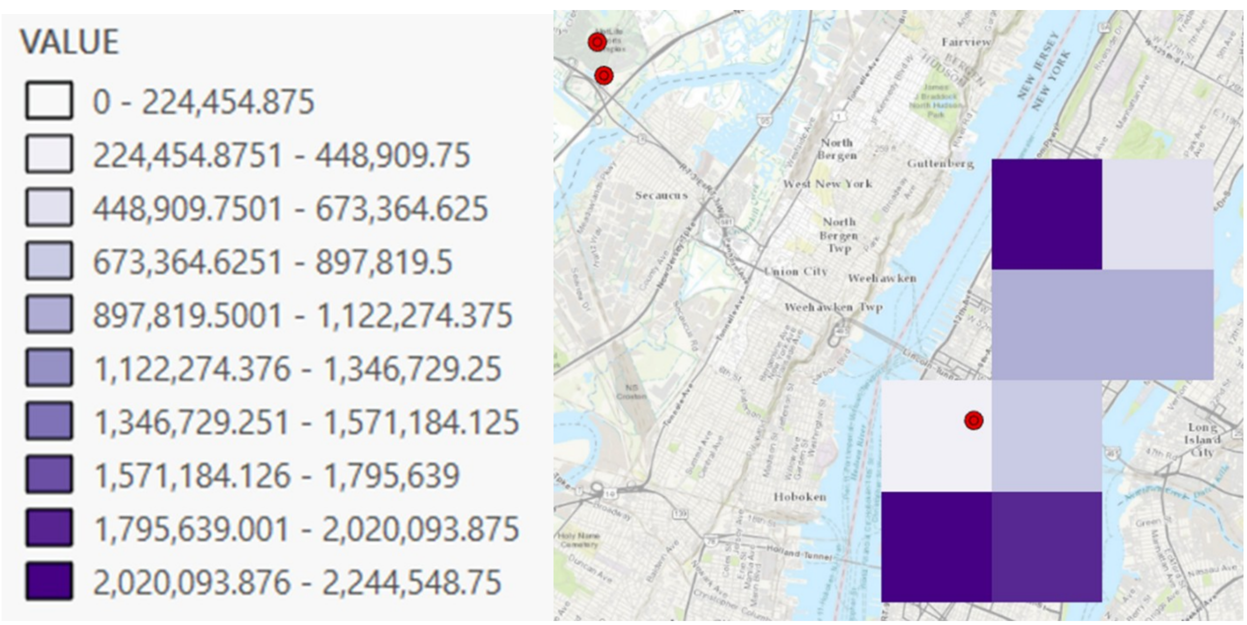


Table 3 - Descriptive Statistics

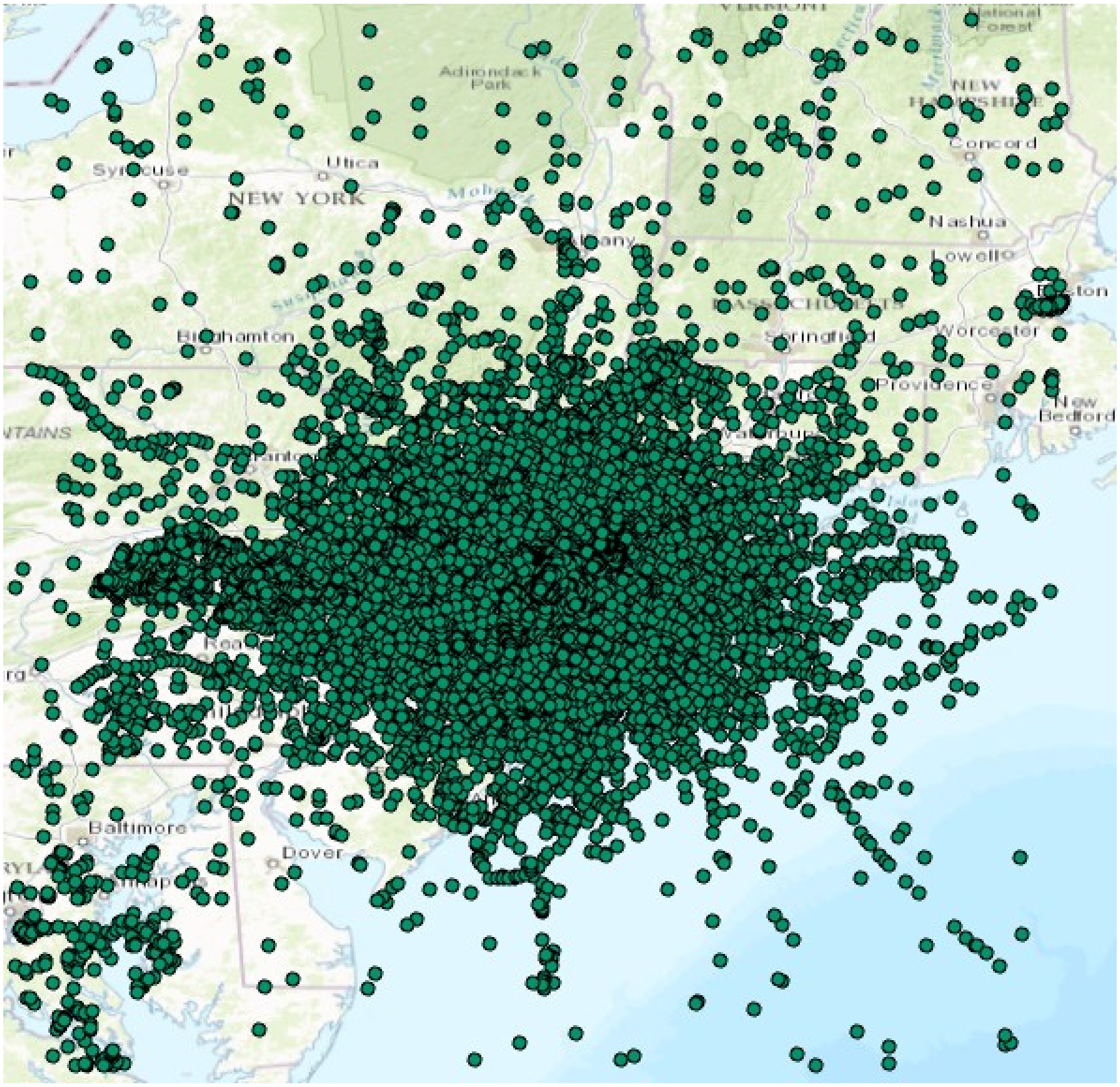
Variable	Obs	Mean	Std. Dev.	Min	Max
car_no	83,284,523	6697.592	3863.423	1	13403
driver_no	83,284,523	18035.37	10404.11	1	36057
car_driver	83,284,523	153783.8	89579.4	1	305831
shift_no	83,284,523	56.15056	49.12239	1	548
trip_no	83,284,523	13.64345	9.360817	1	82
passenger_count	83,284,523	1.693827	1.252426	0	7
trip_distance	83,284,523	2.764343	3.154383	0.1	50
start_lon	83,284,523	-73.97465	0.0480716	-77	-71.0026
start_lat	83,284,523	40.7522	0.0362879	38.00115	43.99102
end_lon	83,284,523	-73.97362	0.0481177	-76.99386	-71.00261
end_lat	83,284,523	40.75246	0.0391051	38.00034	43.99066
trip_pick_date	83,284,523	18171.91	52.10016	18079	18262
trip_pickup_date_and_time	83,284,523	1.57E+12	4.50E+09	1.56E+12	1.58E+12
trip_dropoff_date_and_time	83,284,523	1.57E+12	4.50E+09	1.56E+12	1.58E+12
trip_time	83,284,523	12.13382	8.733168	0.5	90
day_of_week	83,284,523	3.130139	1.952622	0	6
day_of_year	83,284,523	274.9132	52.10016	182	365
fare_amt	83,284,523	9.926922	7.464076	2.5	200
surcharge	83,284,523	0.2421798	0.3490033	0	7.5
hours_since_last_tripp	82,978,783	2.485308	46.98258	-1.25	4405.564
trip_id	83,284,523	4.18E+07	2.42E+07	1	8.37E+07
NFL_gameday	83,284,523	0.0956843	0.2941578	0	1
NFL_gameon	83,284,523	0.0267281	0.1612877	0	1
near_fid_end	83,284,523	2.921292	0.5835441	0	5
near_dist_end	83,284,523	9240.898	13031.94	2.425889	1365627
near_fid_start	83,284,523	2.929793	0.4776537	0	5
near_dist_start	83,284,523	9012.333	13152.89	0.2770139	1321240
holiday	83,284,523	0.0134928	0.1153721	0	1
precip	83,284,523	0.2615702	0.8579419	0	8
shift_start	83,284,523	1.57E+12	4.50E+09	1.56E+12	1.58E+12
shift_end	83,284,523	1.57E+12	4.50E+09	1.56E+12	1.58E+12
trip_speed	83,284,523	12.87961	6.420469	0.0668027	69.9784
quit	83,284,523	0.045964	0.209407	0	1
cum_shift	83,284,523	4.929648	3.432653	0.0083333	20
cum_fare	83,284,523	129.2751	86.67467	2.5	992.1
cum_dist	83,284,523	34.8802	24.60932	0.1	291.2
cum_time_w_fare	83,284,523	160.3212	110.1605	0.5	720
cum_surcharge	83,284,523	3.161444	5.302692	0	63

Within Table 4 are presented day-of-week and hour-of-day tabulations of trips taken, with hour-of-day based on the time a trip originates.

Table 4 - Trips by Day of Week and Hour of Day

Hour	Sunday	Monday	Tuesday	Wednesday	Thurs	Friday	Saturday	Total
0	699,810	260,233	278,658	368,501	436,810	546,039	698,321	3,288,172
1	629,393	158,221	166,583	224,733	274,198	371,572	599,129	2,423,829
2	534,856	103,743	106,914	144,971	177,627	251,598	497,067	1,816,776
3	401,001	71,920	71,186	96,248	117,633	165,303	370,909	1,294,200
4	267,307	72,381	64,361	79,906	96,035	124,803	243,870	948,663
5	123,540	100,211	94,395	99,978	106,200	112,647	114,704	751,675
6	105,434	258,974	275,745	284,706	283,373	263,938	119,870	1,592,040
7	128,874	471,604	534,469	552,469	547,404	494,436	173,708	2,902,964
8	192,323	601,898	681,383	709,381	697,447	636,155	263,483	3,782,070
9	289,514	581,687	658,720	685,069	680,904	622,829	382,029	3,900,752
10	406,421	505,824	573,189	603,538	612,988	563,746	466,558	3,732,264
11	483,379	497,420	555,953	607,105	605,320	569,593	528,151	3,846,921
12	538,356	531,809	590,530	640,869	638,368	599,303	579,602	4,118,837
13	544,679	532,019	582,179	633,207	633,880	595,722	598,057	4,119,743
14	540,903	559,497	617,447	658,283	664,839	624,795	582,150	4,247,914
15	518,190	564,820	602,850	626,427	626,217	587,868	589,274	4,115,646
16	484,547	505,170	516,501	529,027	525,662	507,115	517,694	3,585,716
17	523,853	617,573	637,611	654,582	645,686	618,161	586,964	4,284,430
18	567,203	724,715	780,536	805,015	785,912	741,135	668,237	5,072,753
19	538,145	723,704	792,222	848,264	840,797	793,801	717,127	5,254,060
20	487,519	645,243	735,187	790,133	811,873	735,540	663,648	4,869,143
21	467,994	593,260	711,652	757,442	800,283	716,895	642,255	4,689,781
22	427,441	526,704	653,413	722,095	782,933	744,876	691,636	4,549,098
23	362,593	408,989	521,434	604,696	717,114	748,373	733,877	4,097,076
Total	10,263,275	10,617,619	11,803,118	12,726,645	13,109,303	12,736,243	12,028,320	83,284,523

Figure 2 - Trip Pickups - December, 2009



The New York Jets and New York Giants both hosted home games at Giants Stadium during 2009, both later moving to nearby Met Life Stadium. During the 2009/2010 season the New York Jets hosted a total of ten regular and pre-season games, nine of which were played in 2009. The New York Giants hosted a total of ten games in 2009. Homes games and scheduled kickoff times are outlined in the Appendix. By exporting unique trip identification numbers and trip start and end coordinates to ArcGIS I could map trip start and end locations, and then calculate the distance from both the start and end locations to the nearest venue having a seating capacity greater than 18,000. For purposes of this paper, trips starting and ending near Giants Stadium on game days (*NFL_gameday*), and during a window of time starting one hour before scheduled kickoff time and running to one hour after estimated game end time are of interest (*NFL_gameon*). There were a total of 8,036,569 trips on game days during 2009, and 2,241,855 of those originated within one hour before and one hour after scheduled kickoff time, but relatively few trips originated or ended in close proximity to Giants Stadium.

In Farber's 2005, 2008, and 2015 works Farber discusses incorporating driver fixed effects into the model, and how doing so eliminated observed earnings reference dependence. Close review of the TLC data suggests that it may be impossible to accurately incorporate driver fixed effects,as many drivers fail to clock out of the TPEP system in one car before starting a shift in another car, resulting in drivers appearing to be driving in two or more different cars at the same time, and, in some cases, the same driver appears to drive shifts lasting more than two weeks. Only be combining car and driver was I able to uniquely identify each shift, but as many drivers rent the car they drive daily, the car used changes from day-to-day, and since I am not exactly sure which of the multiple driver observations represents which driver, driver fixed effects seem impossible to eliminate.

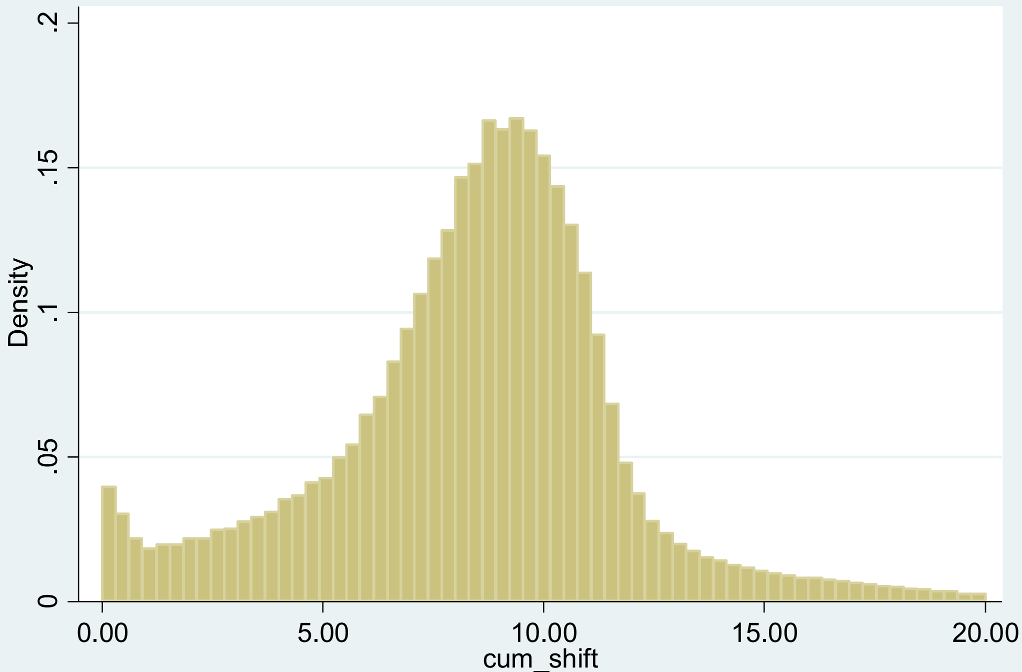


Figure 4 - Cum_Shift Histogram, Cum_Shift <= 20 Hours

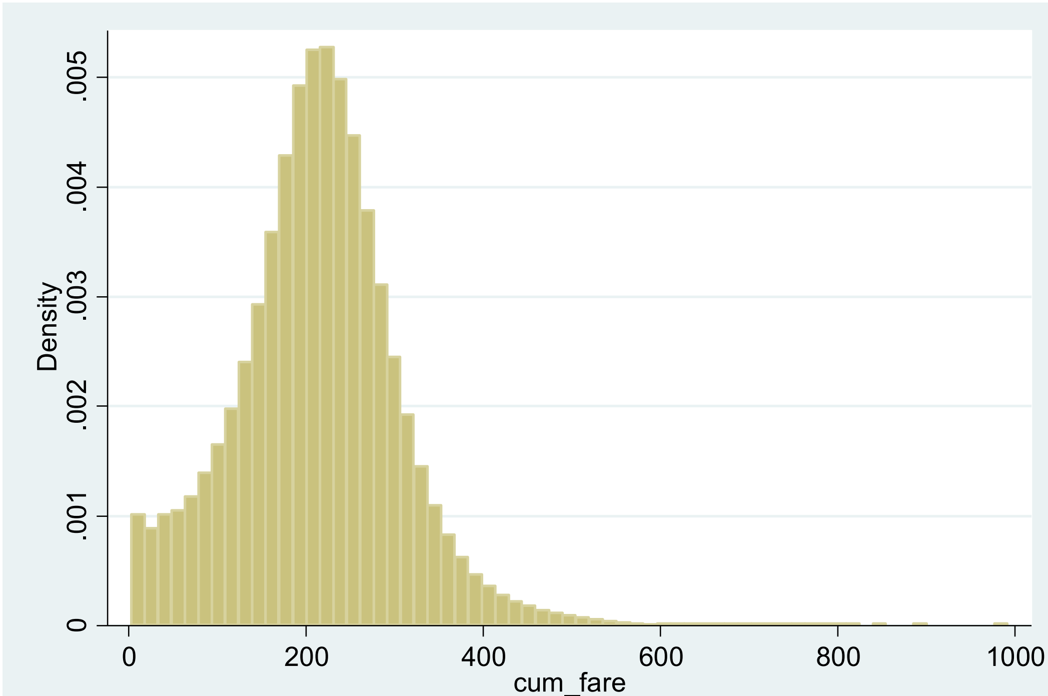


Figure 5 - Histogram of Cum_Fare, Cum_Shift <= 20

Empirical Results

Table 5 - Quit Regression Results

Regression Type	**REG**	**AREG**	**XTREG, FE**
Variables			
cum_fare	0.0000196***	-0.0000185***	-0.00000223
	(-4.62)	(-5.67)	(-0.69)
cum_surcharge	0.000932***	0.000615***	0.000785***
	(-145.1)	(-102.68)	(-133.22)
cum_shift	0.0163***	0.0165***	0.0165***
	(592.07)	(784.49)	(-787.98)
trip_no	-0.00132***	-0.0000325**	-0.000226***
	(-102.75)	(-3.13)	(-22.00)
cum_time_w_fare	-0.000207***	-0.000281***	-0.000264***
	(-134.11)	(-227.95)	(-216.18)
cum_dist	0.000950***	0.00124***	0.00114***
	(-123.38)	(207.95)	(-191.63)
precip	0.000170***	0.000142***	-0.000473***
	(6.51)	(5.42)	(-18.28)
holiday	0.0131***	0.0132***	0.0124***
	(56.36)	(-67.58)	(-63.84)
NFL_gameday	0.00140***	0.00124***	-0.00627***
	(11.73)	(11.33)	(-70.42)
NFL_gameon	-0.00460***	-0.00410***	-0.00370***
	(-28.77)	(-25.72)	(-23.24)
Sunday	0	0	
	(.)	(.)	
Monday	0.00896***	0.0109***	
	(78.83)	(100.17)	
Tuesday	0.0123***	0.0148***	
	(-108.35)	(-135.47)	
Wednesday	0.0131***	0.0157***	
	(116.03)	(144.44)	
Thursday	0.0103***	0.0124***	
	(92.66)	(116.91)	
Friday	0.00621***	0.00815***	
	(56.39)	(76.83)	
Saturday	0.00186***	'0.00303***	
	(16.89)	(28.87)	
Constant	-0.0295***	-0.0424***	-0.0313***
	(-285.80)	(-426.19)	(-742.62)
N	83284523	83284523	83284523

t statistics in parentheses
* p<0.05, **p<0.01, *** p<0.001

Regressing models similar in specification to Camerer (Camerer, Babcock, Lowenstein, & Thaler), and equation 1 from Chen & Sheldon (Chen & Sheldon), yields strongly negative wage elasticities, both without and with fixed effects, a finding counter to Farber (Farber H. S., 2008). To evaluate consistency, I ran a linear regression (REG), a linear regression absorbing driver fixed effects (AREG), and a panel linear regression with fixed effects (XTREG, FE). Errors are relatively consistent across the three regressions, with the greatest volitility seen in *precip* and *trip_no*. The large number of car-driver combinations prevented me from running XTLOGIT and XTPROBIT regressions.

Evaluating shocks to supply and demand, as expected, in all regressions the coefficient on *NFL_gameon* is negative and statistically significant at all conventional levels (P = 0.000). Contrary to expectations, the coefficient on *NFL_gameday* is always positive and statistically significant at all conventional levels (P = 0.000). The coefficient on precip is positive in all regressions, implying that drivers are more likely, on average and under ceteris paribus conditions, to end their shift earlier if it is raining; this finding supports findings by Farber (Farber H. S., 2015).

The coefficient on *cum_fare* is positive in all regressions, except when absorbing driver fixed effects, and is statistically significant in all regressions (P = 0.00), but the coefficient is economically small. This finding may provide support for Farber's 2005 and 2008 finding that driver fare reference dependence disappears when fixed effects are incorporated into the model, but as discussed above, the ability to effectively isolate driver fixed effects seems challenging due to confounds within the data.

Contrary to expectations, the coefficient on *cum_shift* is positive and both economically and statistically significant in all regressions (P = 0.000), with t-values exceeding 800 in some regressions. This finding lends support to Farber's 2005 and 2008 findings. The likelihood that a driver ends a shift after any given trip is highly correlated with the number of hours that the shift has continued.

Coefficients on *cum_time_w_fare* and *trip_no* are negative in all regressions, and statistically significant (P = 0.000). Time with a fare in the taxi and the number of trips during a shift are perhaps perceived by drivers as a proxy for how successful a shift will be. Using a model like Sheldon & Chen's probability formula, with my own model first described above used to determine z_{it} , I calculate the probability of ending a session at after completion of any trip. Within Table 6 are presented comparisons of actual and predicted quits based on Stata AREG results. Predicted quits in the upper portion of Table 6 are based on setting quits equal to one if the result of $\frac{\exp(z_{it})}{1+\exp(z_{it})}$ is greater than 0.5, following common protocol; using 0.5 as the threshold for quits results in only 29% of quits being predicted correctly. If, however, the threshold for quits is raised to 0.525, a 5% increase in the threshold, quits correctly predicted increases to greater than 84%.

Table 6 - Actual Quit v. Predicted Quits

	quits		
quit	**0**	**1**	**Total**
0	20,438,082	59,018,352	79,456,434
1	177,222	3,650,867	3,828,089
Total	20,615,304	62,669,219	83,284,523

Note - quits = 1 if prob > 0.50

	quits		
quit	**0**	**1**	**Total**
0	67,807,164	11,649,270	79,456,434
1	1,630,649	2,197,440	3,828,089
Total	69,437,813	13,846,710	83,284,523

Note - quits = 1 if prob > 0.525

Overall Findings

Within this paper I have analyzed the effect of exogenous shocks to supply and demand on taxicabs and taxi drivers licensed by the New York Taxi & Limousine Commission, finding that drivers react to some anticipated positive shocks (NFL games) and negatively to others (precipitation). I also confirm earlier findings by Camerer, et al, that drivers exhibit negative wage elasticities with respect to shift duration, and by Farber that negative wage elasticities become very small economically, or positive, when fixed effects are incorporated into the model. The probability that a driver quits after any given shift is correctly predicted only 29% of the time, where the threshold probability for setting the calculated quit equal to one is 0.50; when the threshold is set to .525 percent correctly predicted increases to 84%.

Conclusion

The purpose of this study was to evaluate the effect of supply and demand shocks on level of effort, using NFL games and rain as proxies. In addition, through this paper I hoped to resolve the opposing findings of Camerer, et al, and Farber, and findings by subsequent authors supporting both.

The Taxi & Limousine Commission provided by Farber includes a number of confounds which require special attention to resolve, including drivers operating more than one car at a time. Elimination of driver fixed effects from the coefficient estimates is impossible without being able to identify which driver is which.

In closing, I acknowledge the assistance of Shawn McCoy, Ph.D. and Ian McDonough, Ph.D. whose guidance was invaluable.

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	New York Jets	New York Giants
8/14/09 Preseason	St. Louis Rams, 7:00 PM	
8/17/09		Carolina Panthers, 8:15 PM
8/24/09		
8/29/09		New York Jets, 8:00 PM
9/3/09	Philadelphia Eagles, 7:00 PM	
9/13/09 Regular Season		Washington Redskins, 4:15 PM
9/20/09	New England Patriots, 1:00 PM	
9/27/09	Tenessee Titans, 1:00 PM	
10/4/09		
10/11/09		Oakland Raiders, 1:00 PM
10/12/09		
10/18/09	Buffalo Bills, 4:15 PM	
10/25/09		Arizona Cardinals, 8:20 PM
11/1/09	Miami Dolphins, 1:00 PM	
11/8/09		San Diego Charges, 4:15 PM
11/15/09	Jacksonville Jaguars, 1:00 PM	
11/22/09		Atlanta Falcons, 1:00 PM
11/29/09	Carolina Panthers, 1:00 PM	
12/3/09		
12/6/09		Dallas Cowboys, 4:15 PM
12/13/09		Philadelphia Eagles, 8:20 PM
12/20/09	Atlanta Falcons, 1:00 PM	
12/27/09		Carolina Panthers, 1:00 PM

New York Rangers (Madison Square Garden)

January 5	Pittsburgh Penguins
January 7	Montreal Canadians
January 20	Anaheim Ducks
January 27	Carolina Hurricanes
February 3	Atlanta Thrashers
February 11	Washington Capitals
February 15	Philadelphia Flyers
February 18	New York Islanders
February 22	Toronto Maple Leafs
February 26	Florida Panthers
March 8	Boston Bruins
March 15	Philadelphia Flyers

March 21	Buffalo Sabres
March 22	Ottawa Senators
March 24	Minnesota Wild
March 30	New Jersey Devils
April 7	Montreal Canadiens
April 9	Philadelphia Flyers
April 20	Washington Capitals
April 22	Washington Capitals
April 26	Washington Capitals