Flexible Ubers and Fixed Taxis

The Effect of Fuel Prices on Car Services

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Research Q&A

Questions

- How does fuel price impact the quantity of car service trips?
- Will taxi and Uber drivers react differently?

Answers

- When fuel prices rise by 1%, the number of Uber rides will *decrease* by 0.367% while the number of taxi rides will slightly *increase* by 0.088%.
- This difference comes from their distinct regulatory environments and technology.

Types of Car Services in New York City (NYC)

Taxis

Yellow Taxi

Green (Boro) Taxi

Transportation Network Companies (TNCs)

lyft

via

Uber

Gett

JUNO

Taxi Background

- Taxis are regulated by the New York City Taxi and Limousine Commission (TLC) that sets the price schedule and determines a fixed supply through medallions.
- The medallion system makes licensed taxis very expensive, so most cab drivers must lease a taxi for regularly scheduled 12-hour shifts (Bagchi 2018).
- Drivers decide when to end their shift and tend to work longer as expected income goes up (Farber 2015, Chen et al 2017).
- Taxi drivers keep all revenue but pay for their lease and their own gasoline.

TNC Background

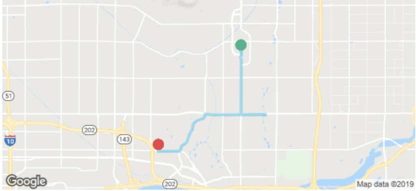
- TNCs are not subject to taxi regulation since they pick up customers through an app, not from a street hail.
- TNCs have a flexible supply, flexible price model that adjusts in real time according to relative supply and demand.
- 84% of surveyed Uber drivers chose the job "to have more flexibility in my schedule and balance my work with my life and family" (Hall & Krueger 2018, p713).
- TNC drivers pay about 25% of their revenue to the platform while also paying for all vehicle costs, including gasoline.

Dynamic Pricing Model of TNCs

8 October 2016, 1:36 am Request

Rate trip ★ ★ ★ ★ ★

Resend Receipt   Save Invoice



Car	Miles	Trip Time	Total Fare
uberX	6.22	00:19:07	$11.06

[redacted] Scottsdale, AZ 85251, USA
1:36 AM

[redacted] Phoenix, AZ 85008, US
1:59 AM

Fare Breakdown

Base Fare	0.40
Distance	5.60
Time	1.72
Normal Fare	**US$7.72**
Surge x1.2	1.54
Subtotal	**US$9.26**
Booking Fee	1.80
Total	**US$11.06**
VISA Personal •••• [redacted]	US$11.06

ADD A TIP

Figure 1: Sample Uber Receipt with Fare Breakdown

Taxi v TNC Literature

- Cramer & Krueger (2016) show Uber drivers have higher utilization rates and income than taxi drivers, attributing the difference to Uber's
  - Superior customer-driver matching technology
  - Larger scale
  - Lower regulatory burden
  - Ability to meet supply with demand through dynamic pricing

- Frechette et al (2018, p3) estimated for the average 12min ride, NYC taxis spend 5-15min driving in search of a customer.

- Berger et al (2018) used a triple difference-in-difference to find that after Uber enters a city, taxi driver wages decrease but not employment.

Gasoline Costs Matter

- Nam (2017, unpublished) used a fixed-effect probit model to find that fuel efficiency of NYC taxicabs does not predict the probability of working but does predict the distance a driver travels in search of customers.
- According to anecdotal interviews, gasoline costs consume about 16% of taxi and TNC driver income.[1 2]
- "I am still shocked by folks using new cars and cars with such poor fuel economy to drive Lyft and UberX. You're going to lose money doing this. The margins are way to narrow driving UberX - you need to do everything you can to trim expenses, minimize dead miles, etc. Sad as it may be, this is a world where pennies count." —*Andy, TNC Driver* [3]

1 `https://www.timeout.com/newyork/things-to-do/a-shift-in-the-life-of-a-cab-driver` (accessed 6/6/19)
2 `http://gothamist.com/2016/02/12/driver_fatigue_nyc.php` (accessed 6/6/19)
3 `https://uberpeople.net/threads/a-few-words-on-gas-and-operating-costs.255121/` (accessed 3/30/19)

Research Questions

1. How does fuel price impact the quantity of car service trips?
2. Will taxi and TNC drivers react differently?

Theoretical Model: Assumptions

I construct a theoretical model built on the following:

- Assumption 1: Taxi drivers must drive in search of customers and thus pay more in gas costs per hour of work.
- Assumption 2: TNC drivers have matching technology allowing them to drive less per hour and thus pay less in gas costs.
- Assumption 3: The number of taxi drivers is fixed and does not change with fuel prices.
- Assumption 4: The number of TNC drivers is flexible and changes with fuel prices.

Theoretical Model: Results

An *increase* in fuel price *decreases* the number of TNC drivers but not the number of taxi drivers.

Then, that decrease in TNC drivers will *increase* the utilization rate of taxis from lower competition.

Therefore, the number of taxi drivers will remain fixed, their gasoline costs will increase, but their revenue will increase from the higher utilization rate.

- Taxis receive a “rigidity dividend” from higher fuel prices.
- The impact on taxi driver profits is ambiguous.

Note: See Section 3 of paper for the full theoretical model.

Estimated Model

$$
\begin{aligned}
quantity\ of\ car\ service\ trips = f(&fuel\ price,\\
&previous\ supply\ \&\ demand,\ economic\ activity,\\
&weather, traffic\ flow, supply\ \&\ demand\ patterns)
\end{aligned}
$$

$$
\begin{aligned}
ln(trips_t) = \ & \beta_0 + \beta_1 ln(fuel\ price_t) + \beta_2 ln(trips_{t\text{-}1})\\
& + \beta_3 ln(stock\ activity_t) + \beta_4 temperature_t + \beta_5 rain_t\\
& + \beta_7 ln(collisions_t) + \beta_8 ln(collisions_t) * rain_t\\
& + \beta_9 ln(collisions_t) * snow_t + \beta_{10} holiday_t + \beta_{11} trend\\
& + \boldsymbol{\gamma}'\mathbf{day\text{-}of\text{-}week_t} + \boldsymbol{\phi}'\mathbf{week\text{-}of\text{-}year_t} + \epsilon_t
\end{aligned}
$$

Estimation Method

- Estimate separately for TNCs and taxis

- Include multiple specifications for robustness
  - With and without a lagged dependent variable
  - With and without a measure of economic activity

- Evaluate using OLS regression and SUR estimation
  - I do not include the competing car service in the model since that would introduce endogeneity.
  - Seemingly Unrelated Regression (SUR) estimation corrects for the contemporaneous correlation of residuals between the TNCs and taxis by estimating them together (Zellner 1962).

The Role of Economic Activity

- One possible concern with using daily fuel prices is if the variable also captures broad economic activity.
- Flores-Guri et al (2003) show that taxi services in NYC are very sensitive to changes in the level of economic activity.
- I consider two candidate variables:
  - Aruoba-Diebold-Scotti Business Conditions Index (ADS Index) (Arouba et al 2009)
  - Count of market transactions on the New York Stock Exchange (NYSE)

The Role of Economic Activity

I evaluate each measure of economic activity according to two criteria:

- Correlation coefficient with quarterly Gross City Product (GCP)
  - The ADS Index and GCP correlate at 0.221 while NYSE activity and GCP correlate at 0.409.
- Better predictive power in the estimated model
  - The ADS Index is only significant in a few specifications while NYSE activity is statistically significant at the 0.001 level in half the specifications.

NYSE activity is the preferred, though imperfect, measure of economic conditions for New York City at the daily level.

Explanation of Variables

Table 1: Explanation of Variables

Name	Definition	Type	Data Source
taxi trips	Number of taxi trips (includes yellow and green boro taxis)	Count	New York City Taxi and Limousine Commission
TNC trips	Number of TNC trips (includes Uber, Lyft, Via, Juno and Gett)	Count	New York City Taxi and Limousine Commission
fuel price	Price of regular gasoline sold on New York Harbor (USD/gallon)	Continuous	U.S. Energy Information Administration
stock activity	New York Stock Exchange trading count	Count	Cboe Global Markets, Inc.
rain	Rain, as measured in Central Park (inches)	Continuous	U.S. National Centers for Environmental Information
snow	Snow, as measured in Central Park (inches)	Continuous	U.S. National Centers for Environmental Information
temperature	Relative temperature, as measured in Central Park, calculated as the difference from previous week's average temperature (degrees Fahrenheit)	Continuous	U.S. National Centers for Environmental Information
collisions	Motor vehicle collisions within New York City	Count	New York Police Department
holiday	Holidays, including the business day before and after (full list of days in footnote 22)	Binary	--
day-of-week	A dummy variable for each day of the week with Monday as the reference group	Binary	--
week-of-year	A dummy variable for each week of the year with the first full week as the reference group	Binary	--

Descriptive Statistics

Table 2: Descriptive Statistics

	Min.	Median	Max.	Mean	St. Dev.	Obvs.
Taxi trips	107,913	394,962	563,678	379,522	66,391	1002
TNC trips	24,855	325,255	826,044	345,082	195,729	1002
Fuel price ($/gal)	0.95	1.61	2.22	1.64	0.28	1002
Stock activity	1,091,918	2,682,274	6,391,235	2,801,180	620,730	1002
Rain (in)	0	0	3.02	0.13	0.34	1002
Snow (in)	0	0	9.8	0.10	0.75	1002
Vehicle collisions	188	663	1064	663.2	83.30	1002
Holidays (binary)	0	0	1	0.06	--	1002
Relative temp. (°F)	-27.71	0.29	31.86	0.30	8.48	1002

Descriptive Statistics

Table 3: Descriptive Statistics by Car Service Type

	Min.	Median	Max.	Mean	St. Dev.	Mean Group Percent
Yellow taxis	100,323	340,178	498,957	342,831	55,983	90.3%
Green taxis	6,519	35,307	70,191	36,691	11,267	9.7%
Total taxi trips	**107,913**	**374,962**	**563,678**	**379,522**	**66,391**	**100%**
Uber	24,855	232,256	572,736	248,013	129,622	71.9%
Lyft	0	42,474	175,765	53,347	41,684	15.5%
Via	0	24,314	44,183	22,882	12,468	6.6%
Juno	0	20,258	61,728	18,649	16,247	5.4%
Gett	0	0	18,872	2,190	3,711	0.6%
Total TNC trips	**24,855**	**325,255**	**826,044**	**345,082**	**195,729**	**100%**

Big Data

- Collected over 726 million ride-level observations from NYC.
- Aggregated to 1002 day-level observations from 2015 through 2018.

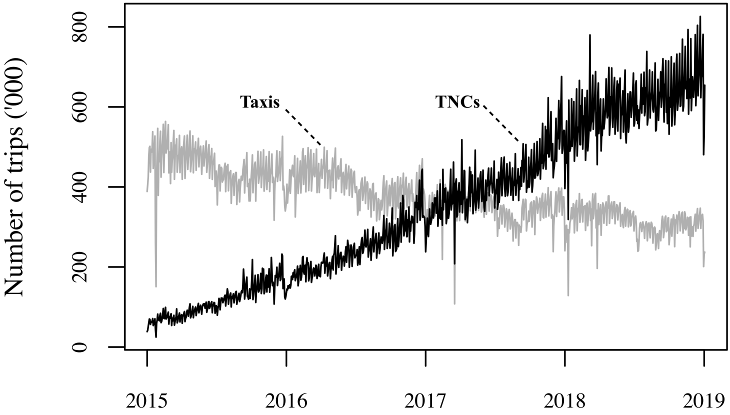


Figure 3: Daily Taxi and TNC Trips

Fuel Price by Product

- I use New York Harbor Regular Gasoline since it is a more fundamental price.
- Correlates 93% with NYC Retail Regular Gasoline.

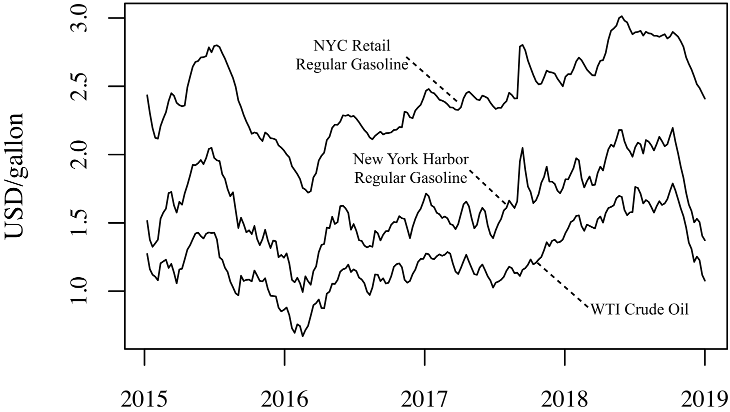


Figure 5: Prices of Oil Products

Geographic Distribution of Gasoline in NYC

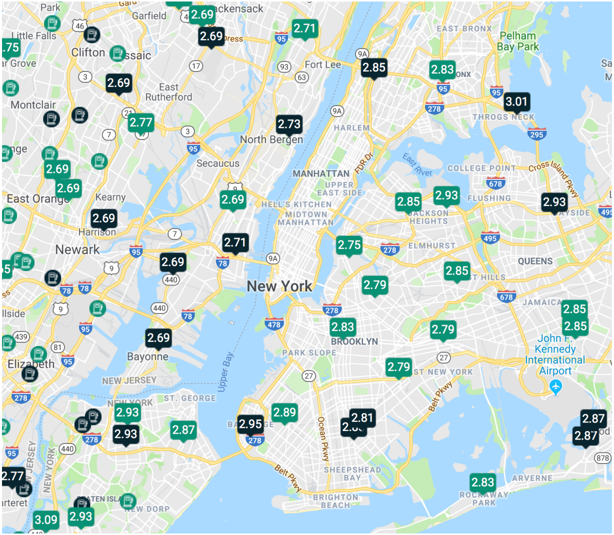


Figure 2: Map of Regular Gasoline Prices from GasBuddy.com on May 30, 2019

OLS Results

Table 4: Model Output with OLS

	(1)	(2)	(3)	(4)
Method	OLS	OLS	OLS	OLS
Dependent Variable (DV)	Taxis	TNCs	Taxis	TNCs
intercept	11.863***	8.361***	11.863***	8.831***
	(0.112)	(0.308)	(0.112)	(0.512)
ln(fuel price)	0.033**	-0.465***	0.072***	-0.486***
	(0.012)	(0.033)	(0.013)	(0.037)
lagged DV				
ln(stock activity)			0.062***	-0.003
			(0.010)	(0.029)
relative temperature	-0.002***	-0.003***	-0.002***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
ln(collisions)	0.166***	0.462**	0.157***	0.467***
	(0.017)	(0.048)	(0.017)	(0.048)
rain	-0.435†	2.226**	-0.425	2.220**
	(0.263)	(0.721)	(0.258)	(0.721)
*ln(collisions)*rain*	0.063	-0.331**	0.062	-0.331**
	(0.040)	(0.110)	(0.039)	(0.110)
snow	-0.661***	-0.333*	-0.666***	-0.330*
	(0.056)	(0.154)	(0.055)	(0.154)
*ln(collisions)*snow*	0.095***	0.045†	0.096***	0.045†
	(0.008)	(0.024)	(0.009)	(0.024)
holiday	-0.068***	-0.072***	-0.064***	-0.074***
	(0.008)	(0.021)	(0.007)	(0.021)
trend	-0.0005***	0.0024***	-0.0005***	0.0024***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Day-of-week controls	True	True	True	True
Week-of-year controls	True	True	True	True
Observations	1002	1002	1002	1002
Adjusted R-squared	0.921	0.959	0.924	0.959

*Robust standard errors are in parentheses. The associated significance is given as follows: '***' 0.001, '**' 0.01, '*' 0.05, '†' 0.1*

OLS Results

Table 4: Model Output with OLS				
	(1)	(2)	(3)	(4)
Method	OLS	OLS	OLS	OLS
Dependent Variable (DV)	Taxis	TNCs	Taxis	TNCs
intercept	11.863***	8.361***	11.863***	8.831***
	(0.112)	(0.308)	(0.112)	(0.512)
ln(fuel price)	0.033**	-0.465***	0.072***	-0.486***
	(0.012)	(0.033)	(0.013)	(0.037)
lagged DV				
ln(stock activity)			0.062***	-0.003
			(0.010)	(0.029)
relative temperature	-0.002***	-0.003***	-0.002***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
ln(collisions)	0.166***	0.462**	0.157***	0.467***
	(0.017)	(0.048)	(0.017)	(0.048)
rain	-0.435†	2.226**	-0.425	2.220**
	(0.263)	(0.721)	(0.258)	(0.721)
*ln(collisions)*rain*	0.063	-0.331**	0.062	-0.331**
	(0.040)	(0.110)	(0.039)	(0.110)
snow	-0.661***	-0.333*	-0.666***	-0.330*
	(0.056)	(0.154)	(0.055)	(0.154)
*ln(collisions)*snow*	0.095***	0.045†	0.096***	0.045†
	(0.008)	(0.024)	(0.009)	(0.024)

OLS Results with Lagged DV

Table 5: Model Output with OLS Estimation and Lagged Dependent Variable

	(5)	(6)	(7)	(8)
Method	OLS	OLS	OLS	OLS
Dependent Variable (DV)	Taxis	TNCs	Taxis	TNCs
intercept	9.919***	1.779***	8.764***	1.783***
	(0.267)	(0.233)	(0.275)	(0.333)
ln(fuel price)	0.033**	-0.104***	0.065***	-0.104***
	(0.011)	(0.020)	(0.013)	(0.023)
lagged DV	0.202***	0.738***	0.193***	0.738***
	(0.019)	(0.017)	(0.018)	(0.017)
ln(stock activity)			0.052***	-0.003
			(0.010)	(0.164)
relative temperature	-0.001***	-0.002***	-0.001***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
ln(collisions)	0.141***	0.162***	0.135***	0.162***
	(0.017)	(0.028)	(0.017)	(0.028)
rain	-0.590*	0.486	-0.574*	0.486
	(0.248)	(0.410)	(0.245)	(0.410)
*ln(collisions)*rain*	0.087*	-0.064	0.085*	-0.064
	(0.038)	(0.062)	(0.037)	(0.062)
snow	-0.636***	-0.464***	-0.641***	-0.464***
	(0.053)	(0.087)	(0.052)	(0.087)
*ln(collisions)*snow*	0.091***	0.067***	0.092***	0.067***
	(0.008)	(0.014)	(0.008)	(0.014)

SUR Results

Table 6: Model Output with SUR Estimation and Lagged Dependent Variable

	(9)	(10)	(11)	(12)
Method	SUR		SUR	
Dependent Variable (DV)	Taxis	TNCs	Taxis	TNCs
Intercept	7.850***	1.363***	7.335***	1.371***
	(0.232)	(0.225)	(0.259)	(0.328)
ln(fuel price)	0.032**	-0.080***	0.060***	-0.080***
	(0.011)	(0.020)	(0.013)	(0.023)
lagged DV	0.327***	0.785***	0.316***	0.782***
	(0.017)	(0.015)	(0.017)	(0.015)
ln(stock activity)			0.046***	0.001
			(0.010)	(0.016)
relative temperature	-0.001***	-0.002***	-0.001***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
ln(collisions)	0.125***	0.146***	0.120***	0.147***
	(0.017)	(0.028)	(0.017)	(0.028)
rain	-0.666**	0.299	-0.650**	0.302
	(0.248)	(0.409)	(0.245)	(0.409)
*ln(collisions)*rain*	0.099**	-0.035	0.096**	-0.036
	(0.038)	(0.062)	(0.037)	(0.062)
snow	-0.628***	-0.440***	-0.633***	-0.440***
	(0.053)	(0.087)	(0.052)	(0.086)
*ln(collisions)*snow*	0.089***	0.063***	0.090***	0.063***
	(0.008)	(0.014)	(0.008)	(0.014)

Marginal Effects: Methodology

Consider the following parsimonious equation

$$y_t = \alpha x_t + \beta y_{t\text{-}1} + \boldsymbol{\gamma}'\boldsymbol{\Gamma_t}$$

where y_t is the number of car service trips, x_t is fuel price, and $\boldsymbol{\Gamma_t}$ is a vector of all other variables.

Due to the lagged dependent variable $y_{t\text{-}1}$, the impact of fuel prices on the number of trips will persist for all future periods.

Thus, the cumulative marginal effect of a one-day change in gas prices is

$$\sum_{i=0}^{\infty} \frac{\partial y_{t+i}}{\partial x_t} = \frac{\alpha}{1-\beta}$$

Marginal Effects: Methodology

$$\sum_{i=0}^{\infty} \frac{\partial y_{t+i}}{\partial x_t} = \frac{\alpha}{1-\beta}$$

To calculate the standard error around the above marginal effect, I follow De Boef & Keele (2008) to estimate the variance using

$$Var\left(\frac{a}{b}\right) = \frac{a^2}{b^2}\left(\frac{Var\left(a\right)}{a^2} + \frac{Var\left(b\right)}{b^2} - \frac{2Cov\left(a,b\right)}{ab}\right)$$

where $a = \alpha$ and $b = 1 - \beta$. This gives me the estimator and its statistical significance.

Marginal Effects: Results

Table 7: Summary of Partial Effects

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Estimation Method	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	—— SUR ——		—— SUR ——	
Dependent Variable (DV)	Taxis	TNCs	Taxis	TNCs	Taxis	TNCs	Taxis	TNCs	Taxis	TNCs	Taxis	TNCs
Marginal effect of 1% Δ in fuel price on %Δ in car service trips	0.033** (0.012)	-0.465*** (0.033)	0.072*** (0.013)	-0.486*** (0.037)	0.041** (0.014)	-0.397*** (0.070)	0.081*** (0.016)	-0.397*** (0.082)	0.048** (0.016)	-0.372*** (0.086)	0.088*** (0.019)	-0.367*** (0.099)
Marginal effect of 1% Δ in fuel price on Δ in car service trips	125	-1,605	273	-1,677	157	-1,370	306	-1,370	180	-1,284	333	-1,266
Marginal effect of 1.729% Δ in fuel price on Δ in car service trips	217	-2,774	472	-2,900	271	-2,368	529	-2,368	312	-2,220	576	-2,190
Includes NYSE transactions	FALSE	FALSE	TRUE	TRUE	FALSE	FALSE	TRUE	TRUE	FALSE	FALSE	TRUE	TRUE
Includes lagged DV	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
Includes all other controls	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE

*The estimated impact on the number of car service trips is calculated at the 2015-2018 means of 379,522 taxi trips and 345,082 TNC trips. 1.729% represents the average absolute %Δ in daily gas prices. Marginal effects are calculated using the elasticity and, if present, the multiplier associated with persistent effects from the lagged dependent variable. Standard errors are in parentheses. The associated significance is given as follows: '***' 0.001, '**' 0.01, '*' 0.05, '†' 0.1. See Appendix I for details.*

Marginal Effects: Results

Table 7: Summary of Partial Effects *(truncated)*

Model	(3)	(4)	(7)	(8)	(11)	(12)
Estimation Method	OLS	OLS	OLS	OLS	—— SUR ——	
Dependent Variable (DV)	Taxis	TNCs	Taxis	TNCs	Taxis	TNCs
Marginal effect of 1% Δ in fuel price on %Δ in car service trips	0.072*** (0.013)	-0.486*** (0.037)	0.081*** (0.016)	-0.397*** (0.082)	0.088*** (0.019)	-0.367*** (0.099)
Marginal effect of 1% Δ in fuel price on Δ in car service trips	273	-1,677	306	-1,370	333	-1,266
Marginal effect of 1.729% Δ in fuel price on Δ in car service trips	472	-2,900	529	-2,368	576	-2,190
Includes NYSE transactions	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
Includes lagged DV	FALSE	FALSE	TRUE	TRUE	TRUE	TRUE
Includes all other controls	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE

*The estimated impact on the number of car service trips is calculated at the 2015-2018 means of 379,522 taxi trips and 345,082 TNC trips. 1.729% represents the average absolute %Δ in daily gas prices. Marginal effects are calculated using the elasticity and, if present, the multiplier associated with persistent effects from the lagged dependent variable. Standard errors are in parentheses. The associated significance is given as follows: '***' 0.001, '**' 0.01, '*' 0.05, '†' 0.1. See Appendix I for details.*

Nonlinear Estimation

I consider the nonlinear impact of fuel prices by adding a dummy variable for days of above-average changes in fuel prices ($0.022) and also interacting that dummy with fuel price.

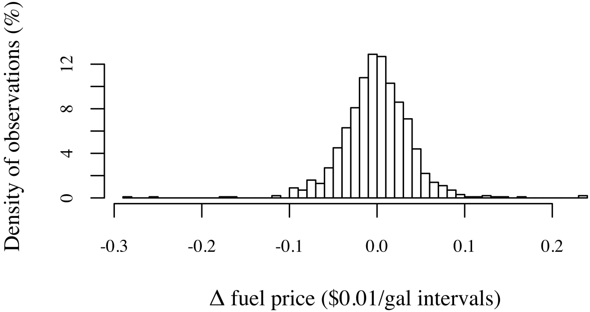


Figure 6: Distribution of Daily Price Changes for New York Harbor Gasoline

Nonlinear Results

Table 8: Nonlinear Results *(truncated)*

Model	(15)	(16)	(19)	(20)	(23)	(24)
Estimation Method	OLS	OLS	OLS	OLS	—— SUR	——
Dependent Variable	Taxis	TNCs	Taxis	TNCs	Taxis	TNCs
ln(fuel price)	0.077***	-0.546***	0.067***	-0.139***	0.060***	-0.114***
	(0.017)	(0.047)	(0.015)	(0.028)	(0.016)	(0.028)
lagged DV			0.191***	0.736***	0.316***	0.780***
			(0.185)	(0.017)	(0.017)	(0.015)
large Δ	0.010	-0.076**	0.003	-0.046**	-0.001	-0.044**
	(0.010)	(0.027)	(0.009)	(0.015)	(0.009)	(0.015)
*large Δ*ln(fuel price)*	-0.012	0.122*	-0.004	0.070*	0.001	0.067*
	(0.019)	(0.053)	(0.018)	(0.030)	(0.018)	(0.030)
Includes NYSE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
Includes other controls	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE

*Only select variables shown for simplicty, with robust standard errors in parentheses. The associated significance is given as follows: '***' 0.001, '**' 0.01, '*' 0.05, '†' 0.1.*

On days of large fuel price changes, TNCs (only) have a diminishing marginal elasticity of trips with respect to fuel prices.

Summary of Results

1. A one-day 1% increase in fuel prices is associated with a 0.367% *decrease* in TNC trips and a 0.088% *increase* in taxi trips.
2. On a typical day when fuel prices change 1.729%, there will be an average change of 2,190 TNC trips and 576 taxi trips in New York City alone.
3. TNC drivers are very flexible and can reduce their supply when an input cost like gasoline increases.
4. Due to heavy taxi regulation, cab drivers are stuck paying the higher fuel price but receive a “rigidity dividend” as the competing TNC drivers exit the market.

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thank you

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