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Gas Prices and Red light Violations in Chicago

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Abstract

Fuel efficient speeds in the US range between 40 and 50 mph. With increasing gas prices, to maintain fuel efficient speeds, drivers reduce speeds on highways. However, as most urban driving is below 50 mph, a reverse is possible – drivers could increase speeds to increase fuel efficiency. We use the context of running a red light as a decision to speed, a context not driven by lower congestion resulting from higher gas prices. For $1 increase in price of gas per gallon, number of red-light violations in Chicago increased by 5.95 percent. The findings are robust to controlling for daily congestion levels in Chicago.

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1. Introduction

Past studies have found that rising gas prices are positively (Wolff 2014) or negatively (Burger and Kaffine 2009) associated with speeding on highways and positively associated with accidents in Mississippi (Chi *et al.* 2011). While these studies have focused on highway speeding in response to higher gas prices, studies on gas prices and urban speeding remain unexplored. According to the US Department of Energy "gas mileage usually decreases rapidly at speeds above 50 mph [and for] each 5 mph [sic] over 50 mph is like paying an additional $0.19 per gallon for gas" (US Department of Energy 2015). To realize higher fuel efficiency, drivers on urban roads who generally drive at speeds below 50 mph could increase driving speed, possibly resulting in negative externalities.

To test the association between gas prices and speeding in urban environment, we ask whether higher gas prices are associated with red light violations? In face of increasing gas prices, stopping at a red light could decrease fuel efficiency. Based on distance from the intersection and expected duration of yellow light a driver may choose to speed, increasing chances of red light violations. Speeding is the primary reason for running a red light (NHTSA 1998). We match data on automatically issued red light violation tickets in Chicago with two-years of inflation-adjusted daily gas price data. The data helps overcome previous drawbacks in studies, by controlling for weather, seasonality (Watkins and Wolff 2013; Wolff 2014), and location-specific time-trend effects (by controlling for time-trend at fixed camera locations at red lights). We find that for $1 increase in price of gas per gallon, number of red-light violations in Chicago, increased by 5.95 percent.

The testing context allows for the following advantages. First, red light violations provide a unique test for speeding in urban environments and is less influenced by the level of congestion. If a light is yellow, the drivers have to make a decision to stop or to speed 'to make it through the yellow light'. The decision to speed is based on distance from the intersection, expected length of the yellow light, and is less influenced by congestion as a couple of cars at the most are generally ahead of the driver when deciding whether to speed at the yellow light. Other contexts such as speeding in safety zones (e.g. schools or parks) could be influenced by driver inattention to signs for slowing down. Traffic lights are clear signal for the driver to stop and the decision to speed allows for a less confounded testing of gas price and speeding behavior in urban environments.

Second, in the sample, the red lights tickets are issued automatically by traffic cameras. As the issuance of ticket is automatic through the traffic camera, it is not based on presence or ticketing efficacy of the traffic police personnel. As traffic patterns vary at different locations and as the driving behavior could also vary over time at the same location, we control for location specific fixed effects by using traffic camera identification number, time trend, and camera identification number specific time trend.

Third, recently, Watkins and Wolff (2013) called on controlling for weather related effects on driving behavior. To draw more reliable inferences, instead of analyzing available data at rural- (Erb 2010), state- (Chi *et al.* 2011) or week-level (Watkins and Wolff 2013), building on Watkins and Wolff (2013) we include day-of-the-week, month-, year-fixed effects and weather variables.

Fourth, specific to the empirical context, driving under influence or being distracted, or being male are related to running the red light (Hu, McCartt, and Teoh 2011). By aggregating daily red light violations at an intersection, such drivers are less likely to systematically bias red light violations, as repeating traffic violation penalties would lead to suspension of driving privileges. Consistently distracted or aggressive drivers would also be ticketed more frequently, leading to behavioral changes over time.

The findings are practically important. According to the Federal Highway Administration (2014) report, running a red light at an intersection is the most common cause of urban crashes (Federal Highway Administration 2014). Running through red light injures 165,000 individuals, including motorists, pedestrians, and cyclists each year, and 7 of the 1,000 *daily* crashes occur at signalized intersections. In urban driving conditions individuals "are more likely to be injured due to a red-light running related crash than any other type of crash" (Federal Highway Administration 2014). Policy makers could consider tradeoff between increasing revenues from higher gas tax (that add to gas prices) and increasing negative externalities from red light violations.

2. Data and Methods

2.1 Red light violations in Chicago

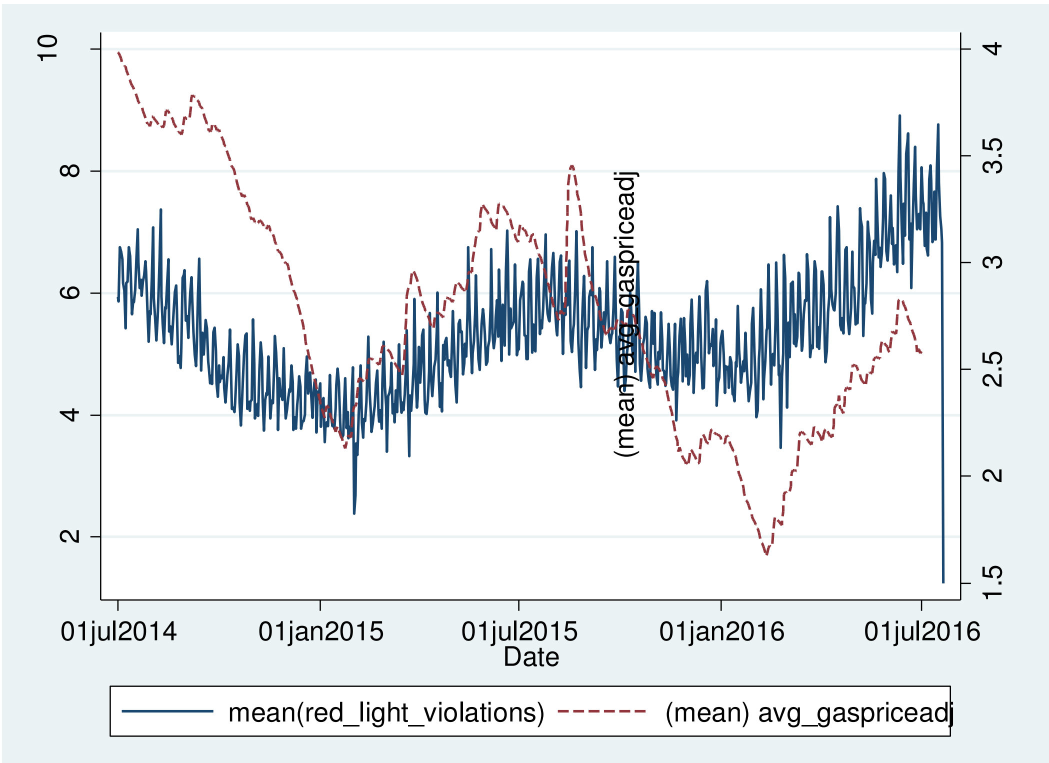
We matched count of daily red light violation tickets automatically issued by cameras located at intersections across the City of Chicago with inflation adjusted daily gas prices in the metropolitan Chicago area. Daily red light violations in Chicago are captured from 354 red light cameras, representing a total 196,923 location-days starting July 1, 2014 and ending July 1, 2016. Signs for red light violation enforcement are posted at all four sides of an intersection. Using traffic signal and radar, the camera takes a still picture and video of the rear of the vehicle(s) entering the intersection after the light has turned red. After a camera vendor reviews the image quality a citation is issued.

According to a meta-analysis by Zaidel (2002), most studies on red light violations fail to control for bias based on selection of sites for installing red light cameras or possible design and safety improvements over time at an intersection. Inclusion of camera-fixed effects based on unique camera identification number and linear time trend effects allow control for site-specific changes over time. Also, intersections are more resistant to regression-to-mean effect as higher accidents at the intersection may not be a part of statistically anomaly of regression to the mean but persistent traffic violations at an intersection is the very reason for installation of red light cameras.

Changes in gas prices, based on geographic location of a city and driven by a complex confluence of macroeconomic and geopolitical forces, is a 'treatment' towards sensitivity for fuel efficiency. As daily gas price data is used in the current analysis, it may be argued that drivers fill their tank on a weekly basis and may not be affected by gas prices on a daily basis. While drivers may fill the gas tank on a weekly basis, prominently displayed signs of gas prices around the city influence sensitivity to fuel prices. Studies in consumer psychology have showed that knowledge of product prices influence current consumption levels (Haucap and Müller 2013; Ma, Ailawadi, Gauri, and Grewal 2011). Studies have shown that expectation of paying more at the gas pump, proactively changes behaviors ranging from grocery shopping to leisure travel (Haucap and Müller 2013; Ma *et al.* 2011).

In Figure 1 we plot the relationship between gas prices and red light violations. Red light violations declined with declining gas prices between July 2014 and July 2016, however, with increasing gas prices after January 2015 red light violations also increased.

Figure 1: Daily Red light violations vs. gas prices



Next, the analyses for data are presented.

2.2 Empirical Model

To estimate the association between gas prices and red light violations, panel fixed effects model is specified. The dependent variable, $ln\_red\_violations_{it}$, is the log of number of daily red light violations at a camera location. The model specification is as follows:

$$ln\_red\_violations_{it} = \pi_{it} + \theta\ gasprice_t + \rho\ W_t + \chi\ T_t + Dow_t + Month_t + Year_t \qquad (2)$$

Where subscript i is the camera location id and t is the reference day gas price per gallon in metropolitan Chicago adjusted for inflation.

W is the vector of day-specific weather variables -- rain, snow, and fog
T is the linear time-trend control
Dow is the Day of the week fixed-effects,

month is the month fixed-effects,
year is the year fixed-effects,
π is the individual camera specific fixed effects.

The average daily gas price for the Chicago area was obtained from gasbuddy.com. The nominal gas prices were adjusted for inflation using 2016 dollars. We include camera id fixed effects to take into account the unobserved confounders in the camera location that may be correlated with violations. To control for seasonality, month fixed effects are included in the model.

As the violations may be changing over a period of time at a camera location (such as traffic violation fines changing driver behavior over time), linear time trend is included to capture time-varying behavior. Controls for rain, snow and fog days were obtained from wunderground.com. We also include day-of-the-week fixed effects to account for unobserved heterogeneity during individual day of the week that are correlated with violations (such as heavy congestion in Chicago on Fridays). Year fixed effects are included in the analysis.

To account for serial correlation of idiosyncratic errors across time period in the model, the standard errors were clustered by camera id to take into account the time invariant unobservables (e.g. traffic density, congestion) at a location.

The summary statistics of variables are presented in Table 1.

Table 1. – Summary Statistics (N=196,923 total days from 354 cameras)

Variables	**Description**	**mean**	**sd**	**min**	**max**
redviolations	Number of red light violations per day	5.287	6.314	1	108
ln_red_violations	Log of red light violations	1.251	0.877	0	4.682
gasprice	Average daily gas prices in Chicago	2.777	0.555	1.626	3.986
rain	Dummy variable =1 , if it rained on that day, and 0 otherwise	0.334	0.472	0	1
snow	Dummy variable =1 , if it snowed on that day, and 0 otherwise	0.156	0.363	0	1

fog	Dummy variable =1 , if there was fog on that day, and 0 otherwise	0.044	0.204	0	1
time trend	Linear time trend	361.162	213.812	1	732

3. Results

Table 2 shows the effects of gas prices on red light violations. Specification (1) is the baseline model with month and year. Specification (2) shows baseline model with day of the week fixed effects. Specification (3) additionally controls for linear time trends. Finally, specification (4), our preferred model, includes all controls including camera id × time trends, allowing control for changes in traffic patterns at a camera location over time. A $1 increase in gas prices increases the speeding violations in red light violations by 5.95%.

Table 2: Fixed Effects estimates of gas prices on red light violations

	(1)	(2)	(3)	(4)
	lnviolations	lnviolations	lnviolations	lnviolations
gasprice	0.0742***	0.0588***	0.0590***	0.0595***
	(0.0130)	(0.0130)	(0.0132)	(0.0133)
Rain	-0.0445***	-0.0386***	-0.0386***	-0.0390***
	(0.00362)	(0.00364)	(0.00363)	(0.00362)
Snow	-0.0544***	-0.0517***	-0.0517***	-0.0513***
	(0.00473)	(0.00463)	(0.00462)	(0.00455)
Fog	-0.0954***	-0.0718***	-0.0717***	-0.0722***
	(0.00733)	(0.00718)	(0.00716)	(0.00712)
timetrend			0.0000305	-0.000776***
			(0.000153)	(0.000150)
_cons	0.726***	0.782***	0.786***	0.781***
	(0.0486)	(0.0495)	(0.0492)	(0.0472)
N	196923	196923	196923	196923
Camera id fixed effects	Yes	Yes	Yes	Yes
Month dummy	Yes	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes
Day of the week	No	Yes	Yes	Yes

Camera-specific time trend	No	No	No	Yes

Standard errors clustered by camera id in parentheses
* p<0.10, ** p<0.05, *** p<0.01

4. Robustness Tests

4.1 Random walk test

Using augmented Dickey-Fuller test with three lags, a constant, and a time trend for average daily violations, we reject the null hypothesis for augmented Dickey-Fuller test (H_0: the time series needs to be differenced to make it stationary) for average daily red light violations (test statistic = -5.769; $p < 0.001$)], leading to inference that time series is trend stationary and must be analyzed using time trend in the regression model.

4.2 Alternate specification

As the data on violations in camera location is expressed as a count variable, we specify fixed-effects negative binomial regression with the raw count of daily red light violations as the dependent variable in the model. Tables 3 shows the effects of gas prices on red light violations are consistent with the main results.

Table 3: Fixed-effects Negative Binomial estimates on number of red light violations

	(1) violations	(2) violations
gasprice	0.0544***	0.0571***
	(0.00951)	(0.00918)
Rain	-0.0393***	-0.0389***
	(0.00284)	(0.00274)
Snow	-0.0529***	-0.0530***
	(0.00449)	(0.00433)
Fog	-0.0660***	-0.0689***
	(0.00700)	(0.00676)
timetrend	0.000137	-0.000770***
	(0.000147)	(0.000172)
_cons	1.807***	1.999***
	(0.0379)	(0.0371)
N	196923	196923
Camera id fixed effects	Yes	Yes
Day of the week fixed effects	Yes	Yes
Month fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Camera-specific time trends	No	Yes

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

4.4 Granger Causality test

As an alternate evidence of daily gas price changes are exogenous to red light violations we conduct a Granger causality test. Using three-lags, a pair-wise Granger Causality test of null hypothesis that log of total violation does not Granger cause daily gas prices could not be rejected. Conversely, the null hypothesis that the daily gas prices does not Granger cause log of total red light violations was rejected with Wald-statistics of 13.32 (p value = 0.004). Therefore, it appears that Granger causality runs from daily gas prices to log of total red light violations.

4.5 Gas prices and congestion

Higher gas prices are associated with lower congestion as commuters may seek alternate modes of transportation. With lower congestion, drivers closer to intersection on a yellow light may perceive a greater likelihood of making it through the light. Therefore, lower congestion associated with higher gas prices may confound the findings. We therefore control for congestion based on available data from the City of Chicago.

As a proxy for congestion during the day, we take the median speed during the day between January 1st 2015 and January 31st 2015 from Chicago Open Data portal. This is the only period for which the data is released by the city, therefore, the analysis is based on the subsample overlapping with this period.

We first find the association between average daily gas price and median speed conditional on other covariates in our original model. Table 4 Model 1 presents the results. An increase in gas price by $1 increases median speed (reduces congestion) by 6.6 miles per hour.

We then create an average day of the week congestion index for United States between June 2013 and July 2014 derived from INRIX index (INRIX 2014). We add this variable to the count data negative binomial specification as a control for congestion levels that vary over the day of the week. Table 4 shows the robust results of gas prices on red-light violations after controlling for congestion levels.

Further, the interaction of average gas prices and congestion index is not statistically significant implying that higher gas prices during increasing congestion has no effect on red-light violations.

Table 4: Robustness tests of impact of gas price on congestion and violations controlling for congestion

	(1)	(2)
	Median Speed	Violations
gasprice	6.573***	0.0455***
	(0.0873)	(0.0123)
Rain	-0.0200***	-0.0394***
	(0.00511)	(0.00284)
Snow	-0.997***	-0.0525***
	(0.00905)	(0.00450)

Fog		-0.0656***
		(0.00701)
timetrend	0.0419***	0.000140
	(0.000237)	(0.000147)
Congestion index		0.130***
		(0.00832)
Congestionindex × gasprice		0.00191
		(0.00167)
_cons	1.613***	1.523***
	(0.227)	(0.0474)
N	8646	196923
Year fixed effects	No	Yes
Month fixed effects	No	Yes
Camera id fixed effects	Yes	Yes
Day-of-week fixed effects	Yes	Yes
Sample	January 2015	Full Sample
Method	Panel-OLS	Panel- negative binomial
Standard errors clustered by camera id	Yes	No

* p<0.10, ** p<0.05, *** p<0.01

5. Discussion

Prior research has found a negative relationship between gas prices and highway (Watkins and Wolff 2013; Wolff 2014) or rural (Erb 2010) speeding. Burger and Kaffine (2009), using weekly highway speed-gas price relationship, find that higher gas prices increase highway speeds. Controlling for location fixed effects (camera location at red light), linear time trend and joint effects of camera location and linear time trend, increasing gas prices are positively associated with red light violations. It is plausible that with increasing gas prices, both sensitivity of urban drivers towards fuel efficiency and value of time lost in traffic increase. Results in Table 4 (specification (2)) show that lower congestion and higher gas prices are not associated with red light violations, reducing concern for confounding effect of congestion.

With higher gas prices the ‘need for speed’ could be particularly greater in urban driving conditions as ideal driving speed of 50 mph is not feasible on urban roads and fuel efficiency also declines below 35 mph (US Department of Energy 2015). Higher transmission losses in urban driving and time lost in traffic congestion may further impel drivers to speed on urban roads. In urban (vs. highway) driving 17% (4%) of the fuel is lost in stand-by, 62% (69%) in engine losses, and 6% (2%) in friction losses to braking; of the 100% of the fuel, 19% (25%) energy goes to the drivetrain of which 13% (20%) goes to the wheels (US Department of Energy 2006). US commuters lose 38 hours each year in traffic, costing $818 per commuter (Schrank, Eisele, and Lomax 2012).

The effect sizes of red light violations in the current study are particularly alarming as a significant number of 90 degree crashes occur at intersections. Based on 2008 Federal Highway Administration 165,000 individuals were hurt by red light runners. Seven crashes of 1,000 injury crashes every day occur at signalized intersections and the cost of all the crashes in the US is about $230 billion, translating to cost of $1.61 billion from injuries at signalized intersections in the US per year. The 5.95 percent increase in red light violations for $1 increase in price of gas per gallon calls for a closer scrutiny of the impact of gas prices on driver behavior.

Chi *et al.* (2011) find that higher gas prices lower fatalities from drunk driving, however, Nishitateno and Burke (2014) find that 10% increase in gas prices increased road fatalities by 3 to 6%. As speeding increases the chances of accidents, managing red light violation behavior could also reduce traffic fatalities. According to one estimate total cost of road accidents in the US is 4.3% of the GDP (Parry, Walls, and Harrington 2007). Medical costs, decline in productivity, transaction costs among medical intermediaries are some of the significant costs that could potentially be mitigated by lower gas prices. The Department of Energy (DOE) may also consider education programs for urban driving for red light violations associated with higher gas prices.

The findings have implications for public policy decisions in weighing revenue gains from higher gas taxes and from paid tickets from red light violations against negative externalities of speeding. Increasing gas prices may reduce traffic safety and result in negative externalities. As gas taxes contribute to gas prices, the social and economic costs from traffic violations must be balanced against revenue gains from higher gas prices. While the data is available from the City of Chicago for a limited period of time we are unable to assess effects of very high gas prices (e.g. $4). Carpooling, use of fuel efficient cars, or use of public transportation could increase in response to higher gas prices, however, including red light camera location and time-trend effects to capture traffic conditions at a red light allows control for changing behaviors at camera locations and over time.

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