Analysis of Heterogeneous Speeding Behavior and Gasoline Prices with Hourly Washington State Data

Kari Edison Watkins and Hendrik Wolff

Previous research has produced mixed results for a hypothesis that drivers reduce speeds to conserve gasoline when gasoline prices are high. An analysis that builds on 2012 research by Hendrik Wolff is replicated with an hourly data set of highway speeds from Washington State. A decline in speeds due to increasing gasoline prices is modest but statistically significant. Specifically, a $1/gallon increase in gas prices reduces the average speed by 0.27 mph and changes the average highway speed from 70.82 to 70.55 mph. The change could translate to substantial gas expenditure savings—on the order of $1 billion annually—if similar reductions were seen on all U.S. highways. Study results indicate that in terms of heterogeneity, the fastest drivers do not reduce speeds proportionately; such behavior could undermine the safety objective of a gasoline tax. The speed changes are caused mainly by the gasoline price that drivers pay at the pump. The intense public media attention given to gas prices has relatively little effect on speeding behavior.

It has been repeatedly hypothesized in the literature that drivers reduce speeds to conserve gasoline when gasoline prices are high (*1–4*). Studies making this claim have used annual U.S. traffic speed data and generally find strong evidence in favor of this gasoline conservation hypothesis. However, annual data can be problematic because of changes in trends in vehicle composition, different types of measuring stations used, and fluctuating yearly weather patterns.

More recently, Burger and Kaffine evaluate the speed–price relationship with weekly speed data from Los Angeles, California, and find the opposite result: speeds increase with rising gasoline prices (*5*). This result appears to be counterintuitive but stems from the fact that high gas prices decrease congestion. Burger and Kaffine also investigate the speed–price relationship exclusively during uncongested nighttime periods and reject this gasoline conservation hypothesis.

In agreement with earlier work and in disagreement with Burger and Kaffine, Wolff takes a fresh look at the data and estimates a statistically significant and robust negative relationship between drivers' speeding behavior and gasoline prices (*6*). Instead of annual data (*1–3*) or weekly data (*5*), Wolff collected the most disaggregated available hourly data set of speeds for the Washington state highway system. Also, because gasoline prices are highly cyclical over the calendar year (higher in summer and lower during the dark winter months), Wolff shows that neglecting to cautiously control for external driving conditions leads to an erroneous rejection of the gasoline conservation hypothesis (*6*).

The same data set is used in the present study. It is constructed with the most homogenous exterior environment possible, controlling for effects of weather- and traffic-related congestion. These changes to the estimation method are essential to obtain a cleaner, more precise coefficient estimate of the causal effect of gasoline prices on drivers' speeding behavior.

The research presented here revisits the findings of the relationship between vehicle speed and gasoline price and investigates two more questions. First, is the incentive mechanism heterogeneous across different types of drivers? This data set contains the entire distribution of speeds in each hour so the relationship can be estimated at various percentiles. Second, are changes in speed due to price signals at the gas pump or public media attention? News outlets repeatedly offer tips on how to save gas, for example, "You can assume that each 5 mph you drive over 60 mph is like paying an additional $0.24 per gallon for gas" (*7*). The information mechanism by which drivers are affected is isolated in this study to allow this analysis. A weekly data set was constructed from the number of articles from the *New York Times* and the *Seattle Times* that refer to gasoline prices.

STUDY DATA

The ideal situation for observing the effect of gasoline price on vehicle speed would be a freeway with no speed limit in a location with no congestion under perfect weather conditions. In this situation, drivers would be constrained only by perceived gas use and perceived safety impacts related to their speed. Therefore, this study is limited to locations with a speed limit of 70 mph, the highest speed limit in Washington.

Data were merged from five data sets dated January 3, 2005, to December 31, 2008:

1. Hourly speed data collected by the Transportation Data Office of the Washington State Department of Transportation (DOT) at eight rural locations in Washington (Table 1) (*8, 9*);
2. Hourly temperature, precipitation, and visibility information from the weather stations closest to the speed measurement sites, downloaded from the Local Climatological Data database of the National Oceanic and Atmospheric Administration (NOAA) (*10*);

K. E. Watkins, School of Civil and Environmental Engineering, Georgia Institute of Technology, 790 Atlantic Drive, Atlanta, GA 30332. H. Wolff, Department of Economics, University of Washington, 349 Savery Hall, Box 353330, Seattle, WA 98195-3330. Corresponding author: K. E. Watkins, kari.watkins@ce.gatech.edu.

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TABLE 1 Site Locations of Speed Data in Washington State

Site No.	Washington State DOT Site	Jurisdiction	Freeway	Direction	NOAA Weather Site
1	R045	Woodland	I-5; MP 20.14	Northbound	Kelso
2	R045	Woodland	I-5; MP 20.14	Southbound	Kelso
3	R061	Eltopia	SR-395	Northbound	Tri-Cities
4	R061	Eltopia	SR-395	Southbound	Tri-Cities
5	R014	Tyler	I-90	Westbound	Spokane
6	R014	Tyler	I-90	Eastbound	Spokane
7	R055	Moses Lake	I-90	Westbound	Ephrata
8	R055	Moses Lake	I-90	Eastbound	Ephrata

NOTE: No. = number; NOAA = National Oceanic and Atmospheric Administration; MP = milepost; SR = state road, I = Interstate.

3. Weekly average gasoline prices from the U.S. Energy Information Administration, averaged across Washington for sales of all grades (*11*);
4. Site-specific monthly local unemployment rate statistics from the Bureau of Labor Statistics (*12*); and
5. Site-specific personal income per capita in the metropolitan statistical areas nearest to the respective highway location, from the Bureau of Economic Analysis (*13*).

For speed data, sites free of horizontal curvature, with relatively level terrain, away from on- and off-ramps, and with speed limits of 70 mph in both directions of the highway were chosen to minimize the influence of outside factors. All sites are entirely located in areas of low traffic volume, with a per-lane average of one vehicle passing the loop detector every 29.5 s; neighboring vehicles have relatively little influence on peer drivers. Each hour, Washington State DOT records all vehicles passing over the loop detectors and quantifies speeds in 5 mph increments from 35 mph to more than 100 mph. The descriptive statistics of the data used in the analysis are summarized in Table 2.

The relationship between gasoline price and weekly average vehicle speed is illustrated in Figure 1 for data from the eight sites where speed was measured. Gasoline prices clearly have increased over time (with a peak spike in mid-2008) and are cyclical in nature (higher in summer, lower in winter). Speed measurements represent average weekly speed by highway location. Average speed is estimated by the locally weighted scatterplot smoothing method with a bandwidth of 0.3. Observations are missing in large portions of the data set, which is typical for this type of data. All observations with missing hourly speed data were dropped from the data set (rather than interpolated), reducing the size of the original data set by 18.9%.

REFINEMENT OF DATA SET

After studying uncongested and congested freeways in Los Angeles, Burger and Kaffine posit that the direct effect of gasoline price on speeding behavior must be estimated in the absence of congestion, because otherwise, observed speeds are merely reactions to changes in travel demand that affect congestion (*5*). They find that no statistically significant effect on gasoline prices under uncongested conditions. In contrast, under congested conditions (i.e., 6 to 8 a.m. and 4 to 6 p.m.), they find an average increase in freeway speeds of 3.4 mph for every \$1/gallon increase in gasoline price. Given the insignificant change in uncongested speeds, Burger and Kaffine conclude that the value of time may be high enough that the difference in speed cannot be controlled by a change in gasoline price.

As a point of reference, Wolff estimates the relationship between speed and gasoline with the same method used by Burger and Kaffine. Aggregated to weekly data, the Washington State DOT data set suggests that the energy conservation hypothesis should be rejected (*6*).

Therefore, to further eliminate the factors that confound the relationship between speed and gasoline price, some data refinements are applicable. Two major deviations from previous estimation methods are made: Hourly speed data are used instead of weekly

TABLE 2 Descriptive Statistics

Variable	Observations[a]	Mean	SD	Min.	Max.
Average speed (mph)	227,158	69.189	2.70	32.5	76.88
Gasoline price (US\$)	227,158	2.91	0.59	1.831	4.412
Volume (vehicles/h)	227,158	510.79	586.81	0.0	2,852
Visibility (statute miles)	219,644	9.35	2.00	0.0	10.0
Precipitation (in./h)	227,158	0.002	0.023	0.0	6.60
Temperature (°F)	219,546	51.42	17.45	−14	111
Income (US\$)	227,158	29,948.1	2,239.6	25,963.0	34,011.0
Unemployment (%)	227,158	6.12	1.27	4.00	10.50

NOTE: SD = standard deviation; min. = minimum; max. = maximum.
[a]Per site and hour.

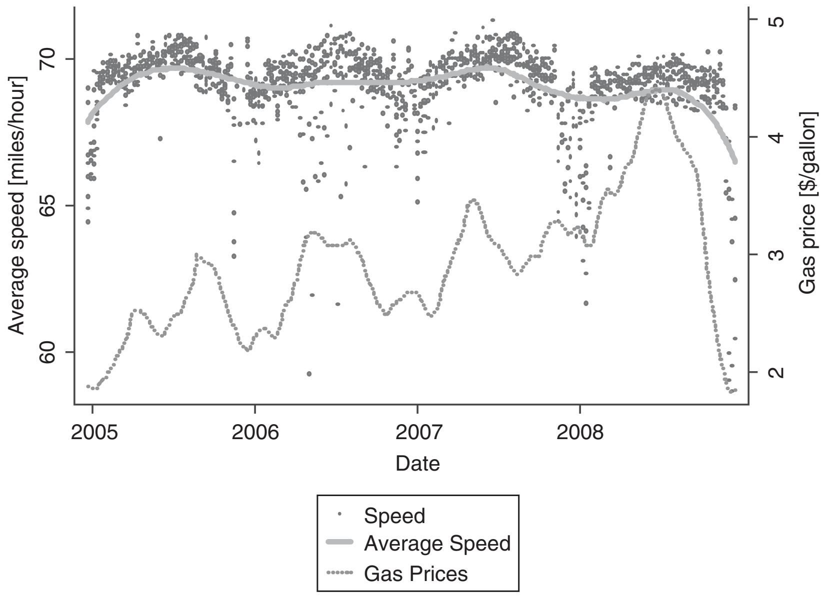

FIGURE 1 Average speed per week and gasoline price, 2005 to 2008.

averages, and a data set is constructed with the most homogenous exterior conditions possible. Also, data are dropped for any hour or site that meets any of the following four conditions:

1. When the average speed is less than 67 mph, to remove periods with unusually low speeds (caused by accidents, temporary construction activities, congestion, or other factors) along these typically uncongested roadway segments;
2. When NOAA variable visibility is less than 10 mi, because traffic information is desired only when sky conditions are perfect;
3. Within 2 h of rain, including hours with trace amounts of rain, to account for the effect of precipitation on traffic behavior; and
4. When the outside temperature is ≤32°F and when the temperature data are missing during a winter month [with winter defined site specifically as the months during which minimum temperatures historically (2005 to 2008) are below 32°F].

None of these four conditions should be correlated with the direct behavioral response of driver speed due to a change in gasoline price. Filtering reduced the total number of observations in the data set by 36%. The percentage reductions are listed in Table 3 by variable, and as explained later, the afternoon period is the focus in this analysis. Table 3 shows that overall, the weather variables have the greatest influence on the reduction of the number of observations.

The data set was filtered with the four conditions to obtain a sample of speeds with the most homogenous exterior conditions possible. The direct impact of gasoline price on drivers' speeding behavior is estimated by

$$\text{speed}_{ih} = S(P, \theta) = \alpha + \beta * \text{price}_t + M_t + Y_t + F_i + \gamma X_{it} + \varepsilon_t$$

where

speed_{ih} = average speed at hour h and site i;
$S(P, \theta)$ = mathematical notation to represent the parameters;
α, β, and γ = regression coefficients to be estimated;
price_t = weekly average gasoline price;
M_t = monthly fixed effects;
Y_t = year fixed effects;
F_i = freeway site fixed effects;
X_{it} = precipitation, holiday, and summer dummies as well as income and unemployment; and
ε_t = error term.

TABLE 3 Data Removed for Regressions

	All Day		Afternoon Period	
Factor	Observations	Percentage	Observations	Percentage
Rain	30,617	13.5	1,754	13.7
Temperature ≤ 32°F	29,967	13.2	892	6.9
Visibility < 10 mi	28,674	12.6	1,117	8.7
Average speed < 67 mph	33,326	14.7	294	2.3
Total observations removed	82,409	36.3	3,003	23.4
Total observations remaining	144,749	63.7	9,850	76.6

NOTE: The sum of observations removed by each variable does not equal the total observations remaining.

RESULTS

The resulting estimates of coefficients with robust standard errors (clustered by week) are listed in Tables 4 and 5, along with the adjusted R^2 statistic to measure the fit for each equation. Speeds significantly decrease by 0.16 to 0.19 mph; the significance of the month dummies is confirmed for the basic model (Table 4, Column 1). However, the interyear speed range is equal to 0.6 mph from January to July; therefore, the cyclicality is much less pronounced than in the weekly regression of Table 3. With hourly fixed effects, speeds are generally highest in the afternoon (after work) period of 4 to 6 p.m. (Table 4, Column 2). The final regression adds controls for time block dummies that account for nonworkdays (weekends and holidays) and weekday periods (Table 4, Column 3). Weekday times are further divided into morning (6 to 10 a.m.), midday (10 a.m. to 4 p.m.), afternoon (4 to 6 p.m.), evening (6 p.m. to 12 midnight), and night (12 midnight to 6 a.m.) fixed effects.

Building on this basic regression framework, all fixed effects interact so the magnitude of the gasoline price coefficient increases slightly to –0.20 and –0.22 (Table 5, Columns 1 and 3, where the latter also controls for income and unemployment). Even though income and unemployment are highly correlated with gasoline price (0.41 and 0.32, respectively), only unemployment has a modest, but significant, negative effect on speed, whereas income is insignificant. Finally, with the gasoline price coefficient unpooled over the time blocks (Table 5, Columns 2 and 4), speeds are reduced most during weekday afternoon periods and reduced least during morning periods and at night (statistically significant at the $p < .01$ level according to Wald tests). The speed reduction effects due to a

TABLE 4 Hourly Vehicle Speed Regressions: Basic Models

Coefficient	Basic Model (month, site, and year fixed effects) (1)	Basic Model and Hour Fixed Effects (2)	Basic Model and Hour and Work and Nonwork Time Fixed Effects (3)
Gas price	–0.1587***	–0.1688***	–0.1856***
	(0.0478)	(0.0483)	(0.0359)
January	–0.2574***	–0.4730***	–0.5151***
	(0.0849)	(0.0911)	(0.0531)
February	–0.0203	–0.2795***	–0.3182***
	(0.0979)	(0.0900)	(0.0682)
March	–0.0347	–0.1152	–0.0864*
	(0.0787)	(0.0833)	(0.0490)
May	0.0869	0.1031	0.0937*
	(0.0660)	(0.0734)	(0.0529)
June	0.1076*	0.1730**	0.1861***
	(0.0642)	(0.0695)	(0.0546)
July	0.3806***	0.4794***	0.4253***
	(0.0654)	(0.0718)	(0.0482)
August	0.3317***	0.4273***	0.4648***
	(0.0613)	(0.0672)	(0.0439)
September	0.1036	0.1609*	0.1053**
	(0.0770)	(0.0854)	(0.0526)
October	0.0138	–0.0063	–0.0206
	(0.0612)	(0.0671)	(0.0479)
November	0.0216	–0.0956	–0.2369***
	(0.0975)	(0.1012)	(0.0650)
December	–0.0886	–0.2989*	–0.2897**
	(0.1513)	(0.1653)	(0.1338)
Hour 0:00	na	–2.2348***	–2.4409***
		(0.0278)	(0.0354)
Hour 1:00	na	–2.5490***	–2.8573***
		(0.0307)	(0.0346)
Hour 2:00	na	–2.7420***	–3.1392***
		(0.0354)	(0.0340)
Hour 3:00	na	–2.8335***	–3.2199***
		(0.0365)	(0.0370)
Hour 4:00	na	–2.7067***	–2.9306***
		(0.0318)	(0.0354)
Hour 5:00	na	–1.9833***	–2.1432***
		(0.0323)	(0.0405)
Hour 6:00	na	–1.4900***	–1.5932***
		(0.0294)	(0.0389)
Hour 7:00	na	–1.0669***	–1.1636***
		(0.0222)	(0.0324)
Hour 8:00	na	–1.0112***	–1.1080***
		(0.0201)	(0.0318)
Hour 9:00	na	–0.9508***	–1.0449***
		(0.0209)	(0.0322)
Hour 10:00	na	–0.8824***	–0.6043***
		(0.0187)	(0.0243)
Hour 11:00	na	–0.7951***	–0.5160***
		(0.0183)	(0.0246)
Hour 12:00	na	–0.6975***	–0.4193***
		(0.0170)	(0.0231)
Hour 13:00	na	–0.5820***	–0.2956***
		(0.0158)	(0.0235)
Hour 14:00	na	–0.4040***	–0.1194***
		(0.0155)	(0.0239)
Hour 15:00	na	–0.1628***	0.1205***
		(0.0133)	(0.0232)
Hour 17:00	na	–0.0153	–0.0171
		(0.0190)	(0.0186)
Hour 18:00	na	–0.1767***	–0.0162
		(0.0348)	(0.0375)
Hour 19:00	na	–0.5164***	–0.3513***
		(0.0412)	(0.0424)
Hour 20:00	na	–0.9375***	–0.7764***
		(0.0347)	(0.0361)
Hour 21:00	na	–1.3618***	–1.2065***
		(0.0225)	(0.0233)
Hour 22:00	na	–1.6253***	–1.4796***
		(0.0235)	(0.0239)
Hour 23:00	na	–1.9395***	–1.8118***
		(0.0252)	(0.0265)
Constant	69.9580***	71.0453***	70.7466***
	(0.1896)	(0.1963)	(0.1439)
Observations	138,162	138,162	138,162
Adjusted R^2	.06	.36	.54

NOTE: Robust standard errors in parentheses are clustered by week. All regressions include month, site, and year fixed effects (basic model). na = not applicable.
$*p < .1$, $**p < .05$, $***p < .01$.

TABLE 5 Hourly Vehicle Speed Regressions: Interacted Fixed-Effects Models

Coefficient	Interacted Fixed-Effects Model (1)	Interacted Fixed-Effects Model, Gasoline Price Effect Unpooled Over Time Blocks (2)	Interacted Fixed-Effects Model and Unemployment Income (3)	Interacted Fixed-Effects Model, Gasoline Price Effect Unpooled Over Time Blocks and Unemployment, Income (4)
Gasoline price	–0.1950*** (0.0329)	–0.2724*** (0.0490)	–0.2206*** (0.0318)	–0.3009*** (0.0477)
Gas price × Morning	na	0.1233*** (0.0467)	na	0.1279*** (0.0465)
Midday	na	0.0622 (0.0404)	na	0.0572 (0.0401)
Evening	na	0.0133 (0.0448)	na	0.0195 (0.0449)
Night	na	0.1435** (0.0623)	na	0.1582** (0.0623)
Nonworkday	na	0.1059 (0.0689)	na	0.1091 (0.0671)
Unemployment	na	na	–0.1986*** (0.0361)	–0.1993*** (0.0362)
Income	na	na	0.0000 (0.0000)	0.0000 (0.0000)
Constant	70.8179*** (0.1370)	71.1027*** (0.1903)	71.0899*** (1.2549)	71.4287*** (1.2684)
Observations	138,162	138,162	138,162	138,162
Adjusted R^2	.65	.65	.65	.65

NOTE: Interacted fixed-effects model includes month, site, hour, year, and time block fixed effects as well as interacted fixed effects of month–time block, month–site, month–hour, hour–time block, hour–site, site–time block, year–site, and year–time block. Robust standard errors in parentheses are clustered by week.
$*p < .1$, $**p < .05$, $***p < .01$.

$1/gallon increase in gasoline price are shown in Figure 2, with 95% confidence intervals (CIs).

Because speeds usually are highest in the afternoon time block (Table 4, Column 2), this period is analyzed in more detail. The behavior of the afternoon vehicle fleet probably is most representative of private vehicle owners. During other periods, a larger percentage of the fleet consists of trucks and commercial vehicles, which can have more heterogeneous speeds because of vehicle type and weight. Even though these data do not include vehicle classification, the speed variance in the afternoon period is 50% lower than in other periods, indicating that the vehicle type composition is more homogenous in the afternoon period. Also, the incentive to conserve gasoline is different for commercial drivers, whose fuel expenses are reimbursed.

Results of the afternoon models, analogous to the previous specifications, indicate that gasoline prices reduce speeds by 0.25 or 0.29 mph for a $1/gallon increase in gasoline price (Table 6). Also, income becomes significant for the afternoon model, with the expected positive sign. The preferred estimate of the afternoon model implies a significant speed reduction of 0.27 mph or an equivalent elasticity of speed with respect to the price of gasoline of minus 0.01 (Table 6, Column 3).

EFFECT OF GASOLINE PRICE ON SPEED DISTRIBUTION

Results of the analysis indicate that gasoline prices do affect the drivers' speed. In addition, the fastest drivers are the least efficient from a consumption perspective. According to Davis et al., vehicles traveling 75 mpg consume, on average, 24% (midsize

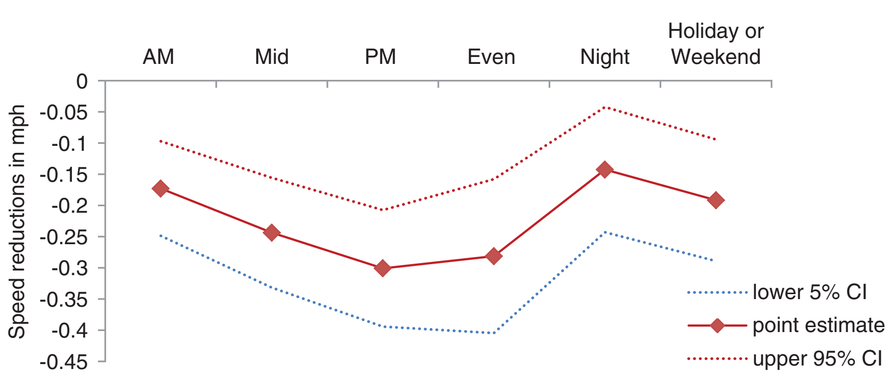

FIGURE 2 Speed reduction effects due to a $1/gallon increase in gasoline price (mid = midday; even = evening; CI = confidence interval).

TABLE 6 Hourly Gasoline Price–Speed Relationship, Afternoon Period

Coefficient	Basic Model (1)	Interacted Fixed-Effects Model (2)	Interacted Fixed-Effects Model With Unemployment and Income (3)
Gas price	−0.2874*** (0.0528)	−0.2491*** (0.0488)	−0.2701*** (0.0483)
Unemployment	na	na	−0.1514*** (0.0547)
Income	na	na	0.0001*** (0.0000)
Constant	71.2125*** (0.2122)	71.0748*** (0.1908)	68.3257*** (1.5866)
Observations	9,390	9,390	9,390
Adjusted R^2	.27	.37	.38

NOTE: All regressions include month, site, and year fixed effects (basic model). The interacted fixed effects include month, site, hour, and year fixed effects, as well as the interacted fixed effects of month–site, month–hour, hour–site, and year–site. Robust standard errors in parentheses are clustered by week.
$*p < .1$, $**p < .05$, $***p < .01$.

car) to 34% (large SUV) more gasoline than at 55 mph (*14*). Do high gasoline prices affect these fast drivers to a greater degree, or do these fast drivers enjoy speeding, irrespective of gasoline prices?

Hourly speed distributions were used to answer this question by running bin percentile regressions of the proportion of vehicles in each hour in the 10 speed bins from 55 mph to the fastest bin of drivers exceeding 100 mph, in 5 mph increments. The resulting estimated elasticity coefficients for the afternoon period are given in Figure 3*a.* The 10 displayed elasticity values are derived in 10 separate regressions in which the dependent variable is the natural logarithm of the proportion of vehicles driving in the indicated speed bin and the independent variable is defined as the logarithm of gasoline price. All regressions include year, month, and site fixed effects. The 95% CIs are computed via robust standard errors, clustered by week. For most drivers, this sequence of estimated elasticity values is approximately U-shaped, with a minimum at the 70 to 80 mph bin regressions. At the left tail, all estimated elasticity values are negative except for the two slowest bins. This finding is consistent with the story that some of the previously faster drivers accumulate in these bins. Elasticity is positive for the fastest drivers

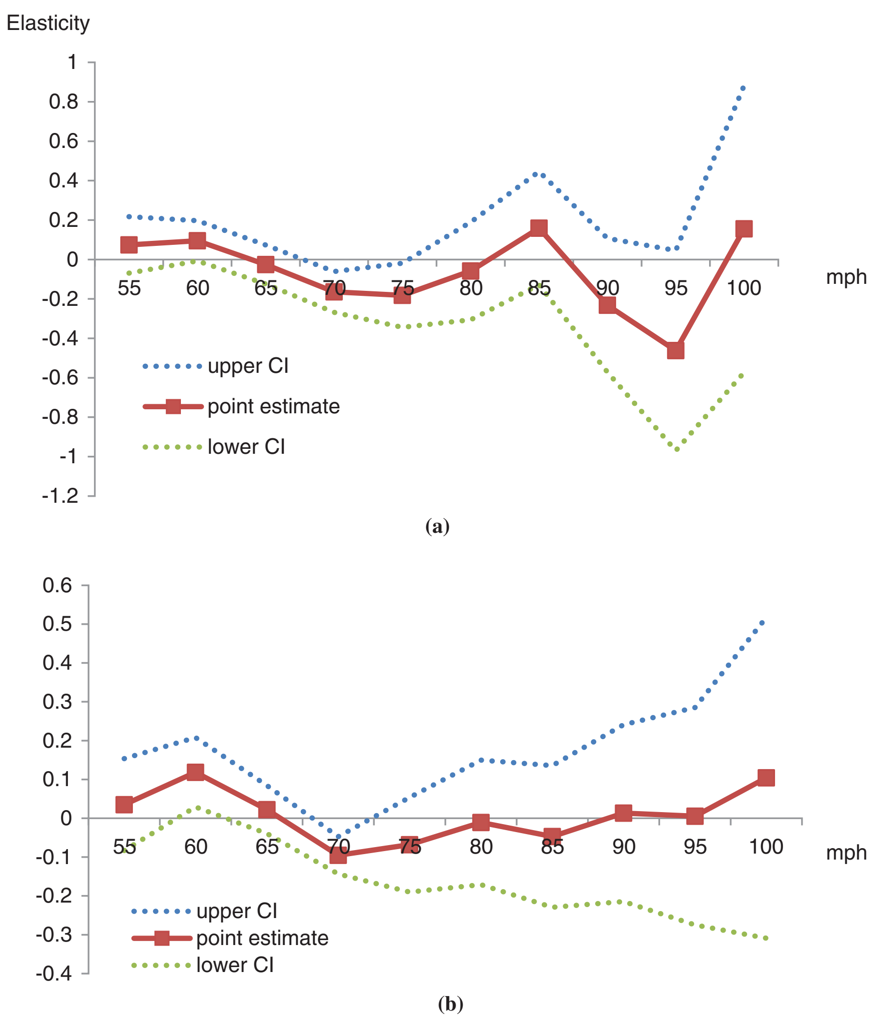

FIGURE 3 Percentage of speed elasticities with respect to gasoline price for (*a*) afternoon period only and (*b*) all 24 h in a workday.

with speeds exceeding 100 mph; however, the CIs in the tails become large.

To obtain a better picture, the relationship is estimated again with a larger data set including all observations from any workday (Figure 3*b*). Even though the CIs are still large, the U-shaped nature with negative elasticity values in the 70 to 85 mph range and a positive point elasticity for the fastest speed bracket are more clearly apparent. This positive elasticity for vehicles exceeding 100 mph can be interpreted as evidence that these drivers enjoy speeding, irrespective of the gasoline price. Furthermore, because traffic volumes decrease with higher gasoline prices, more space between vehicles on the highway may provide incentive to test a vehicle's ability to speed.

INFORMATION EFFECTS

It is useful to determine the cause of the information mechanism by which drivers are affected. Are changes in speed influenced by the price signal paid at the gas pump, or is public media attention affecting driving behavior? Using all articles from the *Seattle Times* from 2005 to 2008, the number of times the term "gas price" occurred was counted, by week (*15*).

As shown in Table 7, the gasoline price and the magnitude of news reporting reduce traffic speeds significantly (Columns 1 and 3). When both variables are included simultaneously in the regression (Column 2), the news variable becomes insignificant, even though the price coefficient is qualitatively the same as in the basic model (yet reduced 15% in magnitude from –0.27 to –0.23). Drivers react primarily to the price signal, and the news reports correlate with gasoline prices but do not seem to substantially affect driving behavior. Regressions for the *New York Times* articles are repeated (Columns 4 and 5), leading to similar implications that drivers in Washington state react mostly to the pain at the pump. The gasoline price coefficient in the joint estimation (–0.18; Column 4) is 33% less than in the basic model without news (–0.27; Column 1). In summary, these regressions indicate that media impact explains about 15% (the *Seattle Times*) to 33% (the *New York Times*) of the speed reduction behavior and that most of the effect is caused by the price signal at the pump.

CONCLUSIONS

This paper contributes to the rapidly evolving transportation literature that asks whether drivers reduce speed to conserve gasoline when gasoline prices are high. The increase in retail gasoline prices from 2005 to 2008 was unprecedented, from less than \$2.00/gallon to more than \$4.40/gallon. Two headlines from summer 2008 tell the story best: Record Gas Prices May Curb Summer Demand (*16*) and Outraged Consumers Look to Sustainable Fuel Solutions for Gas Price Pain Relief (*17*). As the debate on gasoline taxes continues, economists are increasingly interested in the mechanisms by which gasoline prices affect gasoline demand (*18*).

The present research adds to this literature by providing the first empirical estimate of habit formation effects from disaggregated hourly speeding data. Study results indicate that a \$1/gallon increase in gasoline price reduces the average speed by 0.27 mph, reducing the average highway speed from 70.82 to 70.55 mph. This speed reduction could translate to gasoline consumption savings on the order of \$1 billion annually if similar reductions were seen on all U.S. highways. However, these results may not be generalizable to other areas of the country because of different psychologies of driving patterns and usage habits. This study should be replicated in other locations where similar hourly speed data are available.

Furthermore, this research sought to determine whether the incentive mechanism is heterogeneous across driver types. The relationship was estimated at various percentiles from a data set containing the entire distribution of speeds in each hour. Speeds are reduced most in the range of 70 to 80 mph. Fast drivers (more than 85 mph) reduce speeds to a lesser degree. In the extreme tail of the distribution, the number of drivers exceeding 100 mph even increases with gasoline prices. High prices reduce traffic volumes, and the additional space between motorists may provide incentives to test the speeding ability of a vehicle. Therefore, because gasoline prices influence the fastest drivers the least, a gasoline tax targeting safety has limited effects.

Finally, this research isolates the information mechanism by which drivers are affected to investigate whether speed changes are due to the price signal at the gasoline station or public media attention. Repeatedly, news outlets have offered tips on how to save gas, for example, "You can assume that each 5 mph you drive over 60 mph is like paying an additional \$0.24 per gallon for gas" (*6*). Constructed

TABLE 7 Prices Versus Information Effects, Afternoon Period

Variable	Basic Model (1)	Basic Model and *Seattle Times* News (2)	As Column 2 Without Gasoline Price Regressor (3)	Basic Model and *New York Times* News (4)	As Column 4 Without Gasoline Price Regressor (5)
Gas price	–0.2701*** (0.048)	–0.2308*** (0.053)	na	–0.1780*** (0.052)	na
New York Times	na	na	na	–0.0097*** (0.002)	–0.0128*** (0.002)
Seattle Times	na	–0.0024 (0.002)	–0.0046*** (0.002)	na	na
Constant	68.3257*** (1.587)	68.3841*** (1.556)	84.3958*** (0.793)	67.5751*** (1.507)	83.8480*** (0.775)
Observations	9,390	9,390	9,390	9,390	9,390
Adjusted R^2	.375	.375	.372	.377	.376

NOTE: Here, basic model refers to the interacted fixed-effects model, with unemployment and income as additional regressors as in Table 5, Column 3, and includes month, site, hour, year, and time block fixed effects as well as the interaction of fixed effects of month–time block, month–site, month–hour, hour–time block, hour–site, site–time block, year–site, and year–time block. Robust standard errors (in parentheses) are clustered by week.
$*p < .1$, $**p < .05$, $***p < .01$.

from the *New York Times* and the *Seattle Times,* a weekly data set on the number of articles that refer to gasoline prices shows that the time series of gasoline prices and media coverage are highly correlated. Statistically, the price at the pump dominates the observed changes in speeding behavior.

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