Journal of Environmental Economics and Management 67 (2014) 71–88

Contents lists available at ScienceDirect

Journal of Environmental Economics and Management

journal homepage: www.elsevier.com/locate/jeem

Value of time: Speeding behavior and gasoline prices

Hendrik Wolff *

Department of Economics, University of Washington, 349 Savery Hall, 98195 Seattle, WA, USA

ARTICLE INFO

Article history:
Received 9 February 2013
Available online 26 November 2013

Keywords:
Value of Time
Speeding behavior
Gasoline prices
Accidents
Traffic tickets

ABSTRACT

'Value of Time' (VOT) is a key parameter in economics and policy. This paper presents an alternative method to estimate VOT by analyzing an hourly dataset on drivers speeding behavior as a function of the gasoline price. Our identification strategy is novel as it is based on the intensive margin. In comparison, previous studies reveal VOT on the extensive margin, but choice alternatives have multiple attributes thereby potentially confounding estimates. Consistent with the range of the prior literature, we find a VOT of about 50% of the wage rate and analyze sources of bias from accidents and traffic tickets. These bias functions suggest that previous stated preference VOT estimates are likely downward whereas previous revealed preference estimates are likely upward biased.

Hurry! "Time is Money!" [1]Peter Sellers in 'Caccia Alla Volpe', 1966

1. Introduction

One of the fundamental constraints in life is time. To manage this scarce resource, in everyday decisions, people tradeoff money for time by ordering food instead of cooking, employing a landscaper instead of gardening, or choosing a taxi over the bus. Quantifying the benefits of saved time has long been a central interest in economics (Becker, 1965; DeSerpa, 1971) and the 'Value of Time' (VOT) parameter is now a key ingredient to a wide literature in academia and in policy.[2] Ashenfelter and Greenstone (2004) use the VOT to calculate the Value of Statistical Life. VOT estimates have been applied repeatedly in the recreation demand literature (Train, 1998; Phaneuf et al., 2000), in studies of hedonic travel cost methods (Brown and Mendelsohn, 1984), optimal pricing in the airline industry (Gale and Holmes, 1993) intrahoushold bargaining models (Gronau, 1973), monetary economics (Karni, 1973; Mulligan, 1997) and numerous policy evaluations (Calfee and Winston, 1998; Bento et al., 2011). Importantly, in most countries today, transportation agencies actively work with VOT coefficients to evaluate public infrastructure projects such as to decide whether to build a subway or an additional highway lane.[3]

This paper presents an alternative method to reveal the VOT parameter by analyzing drivers speeding behavior as a function of gasoline prices. In comparison to previous methods in the literature, our approach is different, as we identify the VOT based on the *intensive margin*, relying on the continuous choice of how fast to drive on a highway. So far, VOT has been

* Fax: +1 206 685 7477.
E-mail address: hgwolff@uw.edu

[1] The term *Time is Money* has first been coined by Benjamin Franklin in his essay *Advice to a Young Tradesman* (1748). *Caccia Alla Volpe* is a classic British–Italian movie with Peter Sellers, known in the U.S. as *After the Fox*.

[2] The concept VOT is described by many different terms (i.e. value of saved time, shadow price of time, opportunity cost of travel time). *Web of Science* lists over 484 published articles which include the term "Value of Time" in either the title or the abstract of the paper. http://scholar.google.com/ provides over 44,400 links under same search term.

[3] See (DOT (1997), Table 3–11) for VOT estimates used by the U.S. Department of Transportation to evaluate public infrastructure projects and similarly see Mackie et al. (2003) for VOT coefficients used in Great Britain.

0095-0696/$ - see front matter
http://dx.doi.org/10.1016/j.jeem.2013.11.002

measured by the following three methods which are all based on agents choosing options along the *extensive margin*:

- The first method to estimate VOT compares different modes of travel—car, plane or train—relative to the travel cost and time requirements (Beesley, 1965; Shiaw, 2004; Barrett, 2010). These results are likely confounded due to heterogeneous attributes of the travel mode itself. For example, while it is convenient to read a book on a train, one cannot read while driving.
- Studies that use datasets on the same mode of travel aim to overcome this first problem often applying highly creative research designs: the two most prominent papers using revealed preference methods are Deacon and Sonstelie (1985) and Small et al. (2005). The first uses a dataset of 170 drivers at differentially priced neighboring gasoline stations and estimates their willingness to pay to avoid waiting at the higher priced gas station, resulting in a VOT estimate of approximately 78% of the gross wage rate. More recently, Small et al. (2005) develop a novel econometric random parameter approach to compare choices of motorists paying for toll lanes to circumvent congestion in Los Angeles, finding a VOT of 93% of the wage rate. This set of studies also faces the problem potential confounders. Agents could have a distaste of being trapped in traffic jam or waiting at a gasoline station due to psychological costs. Fuel consumption is higher in a stop and go setting as well as the risk of getting involved in an accident differs between lanes. Unpredictability at what time to arrive has its own disamenity value, a feature that generated the literature on the 'Value of Reliability' (i.e. Carrion-Madera and Levinson, 2011), which Small et al. (2005) estimate to represent one third of the willingness to pay for the toll. The most recent revealed preference study is Fezzi et al. (in press), collecting an unique dataset from long recreation trips on a network of toll and free access roads in Italy. Implementing a Monte Carlo simulation, their results suggest a VOT specific for recreation demand models of 75% of the wage rate.
- Third, stated preference studies use survey designs to orthoganalize the confounding variables. This method generally leads to VOT estimates of around 50% and lower. Calfee et al. (2001) estimate stated preference VOTs in the range of 14–27% of the wage rate, based on rank ordered dichotomous choice models estimating the willingness to pay for toll lanes to avoid congestion.

To better understand the diverging results of the previous literature, this paper presents an alternative method and derives VOT bias functions. First, in our research design, the gasoline price affects a motorist in the same vehicle freely making the choice of how fast to drive on an uncongested highway. In the data analysis, we select long unobstructed horizontal segments of highway only. None of our speed measuring stations is located at a hill, highway curve, on-ramp or off-ramp, where speeds could be influenced by peer drivers and where most accidents occur. Second, at horizontal rural sites, a driver typically has converged to her optimal constant speed, often set by cruise-control. Third, our driver is not required to make a discrete choice between a congested lane and a faster high occupancy vehicle (HOV) or toll lane (HOT),[4] that come with different bundled attributes that could interfere the estimation. Furthermore, while our estimate of the elasticity of speed with respect to the price of gasoline of -0.01 is low in magnitude, we actually see this as an advantage because this small change of speed (corresponding to -0.27 mph for a one dollar increase in the price per gallon of gasoline) is arguably much less confounded with other variables.

Our identification rests on the assumption that drivers know that speeding increases gas expenditures. First, repeatedly, news outlets cover 'tips' on how to save gas. For example the statement by the U.S. Department of Energy "*You can assume that each 5 m.p.h. you drive over 60 m.p.h. is like paying an additional $0.24 per gallon for gas*", is found a striking 2.2 million times on internet media, including major newspapers such as the *New York Times*.[5] Second, most vehicles have the option to display the gas mileage in real time at the "Instant Fuel Consumption Display" (IFCD). Having this reminder at the dashboard could impact price sensitive drivers' speeding behavior. Third, the most recent *Consumer Reports* survey of May of 2007 finds that 73% of all drivers claim to *drive more slowly and accelerate more smoothly* because of elevated gas prices.[6]

Clearly, our method has also important limitations and could suffer from bias even for small changes in speed. First, in order to investigate VOT bias functions, we evaluate (i) changes in traffic safety due to the 0.27 mph reduction in speed, as well as (ii) changes to the probability of obtaining a traffic ticket. We find that these two sources contribute to a striking bias of 27% of the VOT value. After correcting for these, we find that the average driver values time at roughly fifty percent (or 45% to 63%) of the gross wage rate. Given that the small *marginal* change of 0.27 mph produces this substantial bias of 27%, we ask how *non-marginal* changes in speed affect VOT estimates (as in previous dichotomous choice settings). We simulate various VOT bias functions (related to linear and nonlinear accident risk, psychological costs of driving and fuel efficiency) which help to understand some of the diverging prior VOT estimates.

Second, the small elasticity of 0.01 is unlikely the result of a conscious mathematical calculation by the motorist, optimizing speed as a function of the gas price and the wage rate. Only few drivers will have the math skills to do so in real time. We view our result rather as a response to the information effect (that speeding above 60 mph increases fuel

[4] Typically, single occupancy vehicles are banned to use High Occupancy Vehicle (HOV) highway lanes. An increasing number of highways allow however single passengers to use these lanes when a toll (T) is paid. These lanes are referred to as HOT lanes. Calfee et al. (2001) and Small et al. (2005) study toll lanes.

[5] Watkins and Wolff (2013) find—using the same dataset as in this article, augmented with information by *Seattle Times* and *New York Times*—that the change of speed is mainly explained by the price at the pump (rather than through media reports).

[6] Interestingly, the same survey question asked in May of 2006 resulted in 38%. The difference in these percentages might be either explained by the temporal increase in gas price or by the sampling technique: The 2006 sample of 2400 adults was drawn from the nationally representative U.S. population of drivers and adult non-drivers, whereas the 2007 survey of 1804 adults was drawn from the population of drivers only.

consumption), and that hence drivers pay more attention at times of elevated gas prices, either by dialing back the cruise-control (most Americans use cruise control at long horizontal uncongested highways) or easing off the gas pedal.

Third, heterogeneity is beyond the scope of the present paper. We intend to understand the behavior of the 'average' and do not observe socio-economic characteristics of individual drivers. For a first analysis of heterogeneous speeding behavior, see Watkins and Wolff (2013).

To put our VOT estimate into context, the magnitude is overall in accordance with the range of previous estimates in the literature. In fact 50% is often cited to be the preferred estimate used by the Department of Transportation in cost benefit analyses. More specifically, 50% is between *stated preference* derived estimates and *revealed preference* methods. 45–63% is lower than most of the revealed preference work, indicating that prior studies may have capitalized into the VOT the omitted disamenities of the outside option—i.e. being agitated when waiting in line or in traffic jam. On the other hand, at 45–63% our estimate is higher than what is estimated by most stated preference methods. We suggest new interview questions to reveal attitude and preference values which can potentially help to close the gap of the diverging VOT estimates in the literature. In fact, some of our simulated VOT bias functions are alarming and call for careful designs in future revealed and stated preference VOT studies.

Moreover, our study contributes to the rapidly evolving transportation literature asking: Do motorists seek to conserve gasoline by reducing speeds in times of high gasoline prices? While this hypothesis has been repeatedly investigated (Peltzman, 1975; Dahl, 1979; Blomquist, 1984; Goodwin et al., 2004),[7] recently Burger and Kaffine (2009) find the opposite: with *rising* gas prices, speeds *increase*. Though at first counterintuitive, this result stems from the fact that higher gas prices decrease congestion. Burger and Kaffine (2009) then investigate the price-speed relationship exclusively during uncongested night time periods and they (contrary to the result of our study) reject the energy saving hypothesis that drivers reduce speeds when gas prices are high. A recent working paper by Erb (2010) uses hourly speed data in Oregon. His OLS estimate at rural sites is -0.32 mph for a one dollar increase in the price of gas, hence remarkably similar to the point estimate of $-.27$ in the present study.

In this paper, we take a fresh look at the data and estimate a statistically significant and robust negative relationship between speeding behavior and gasoline prices. We make a number of methodological contributions. First—instead of using annual (as in Peltzman, 1975; Dahl, 1979; Blomquist, 1984) or weekly data (Burger and Kaffine, 2009)—we collect the most disaggregated hourly dataset of speeds available for the State of Washington. Second, because gasoline prices are highly seasonal (with increasing prices during the summer and lower prices during darker winter months), we show that neglecting to control for external driving conditions produces an erroneous rejection of the gasoline conservation hypothesis. To this end, we construct a dataset with the most homogenous exterior environment possible, controlling for high frequency intraday weather and traffic related congestion effects. In sum, these changes are essential to obtain, what we believe to be a cleaner estimate of the causal effect of the gasoline price on speeding behavior.

This paper proceeds in two broad stages. In the first stage we estimate the impact of the price of gasoline on speed and in the second stage we introduce a model to derive the VOT parameter and discuss the derivation of bias functions. In the next section we describe the data of the first stage. Section 3 discusses the econometric framework and provides the estimation results. Section 4 develops our VOT approach, analyzes sources of bias and discusses the results in the context of previous studies. We conclude in Section 5. Finally, the appendix provides details on the data collection and data processing, describes some estimation and analytical methods and presents additional robustness checks.

2. Datasets

The ideal situation to observe the effect of gas price on vehicle speed would be a freeway with no speed limit in a location with no congestion under perfect weather conditions. Drivers would only be constrained by their value of time compared to gas prices and the perceived safety impacts of speed. We have therefore limited our study to locations with a speed limit of 70 mph, the highest speed limit in Washington State.

For this study, we merge hourly data from the following five datasets from January 3, 2005 to December 31, 2008. First, we use hourly speed data collected by the Transportation Data Office of the Washington State Department of Transportation (WSDOT) at eight rural locations in Washington. Because uphill or downhill locations can vastly increase the variance of speeds due to different types of drivers and vehicle attributes,[8] we choose those speed measuring sites that are located in long horizontal segments of the highway. Furthermore, all sites are located away from on-ramps and off-ramps where vehicles can be merging. We also ensure that none of the sites include horizontal curves. Finally we only pick sites with speed limits of 70 mph in *both* directions of the highway.[9] Our sites are entirely located in low traffic volume areas, with a per-lane average of one vehicle passing the loop detector every 29.5 s. This has the advantage that neighboring vehicles have relatively little influence on peer drivers. Each hour WSDOT records all vehicles passing over the loop detectors and

[7] Using aggregate annual speed data, this literature empirically is inconclusive. Burger and Kaffine (2009) are the first to use disaggregated weekly speed data while exploiting intra-year changes in gasoline prices.

[8] Hilly sites may also interfere peer drivers when lines of vehicles build behind slower moving trucks.

[9] A speed limit of 70 mph in one but not the other direction may indicate that the chosen segment of highway is not unobstructed, shortly after or before the loop detector, which could influence driving dynamics. We limited our selection to sites where we could verify that the speed limit is 70 mph in both directions.

Table 1
Site locations of speed, weather and socioeconomic data.

(1) Site	(2) WSDOT site	(3) WSDOT jurisdiction	(4) Freeway	(5) Direction	(6) NOAA weather site	(7) Closest MSA for income and unemployment	(8) County/Micropolitan statistical area*
1	R045	Woodland	I-5 MP 20.14	North	Kelso	Longview	Cowlitz
2	R045	Woodland	I-5 MP 20.14	South	Kelso	Longview	Cowlitz
3	R061	Eltopia	SR 395	North	Tri-cities	Kennewick-Pasco-Richland	Franklin
4	R061	Eltopia	SR 395	South	Tri-cities	Kennewick-Pasco-Richland	Franklin
5	R014	Tyler	I-90	West	Spokane	Spokane	Spokane
6	R014	Tyler	I-90	East	Spokane	Spokane	Spokane
7	R055	Moses Lake	I-90	West	Ephrata	Yakima	Moses Lake
8	R055	Moses Lake	I-90	East	Ephrata	Yakima	Moses Lake

Note: Description of the sites of the WSDOT speed data, NOAA Weather data, unemployment and income data. For details see the text and Appendix.
* Data for Moses Lake are taken from the Micropolitan Statistical Area definition of the Bureau of Economic Analysis. For all other sites of column (8), the data are taken from the indicated county.

quantifies speeds in five mile per hour (mph) increments from 35 mph to above 100 mph. Information on the site locations are provided in Table 1 and further details on the WSDOT data are discussed in the Appendix.

Because weather conditions can severely impact driving, we collect hourly temperature precipitation and visibility information from the weather stations closest to our speed measurement sites, as indicated in Table 1. Hourly weather data are downloadable from the NOAA Local Climatological Data database from January 2005 to December 2008. We collect gasoline prices from the Department of Energy's Energy Information Administration. Prices are given as an average of retail prices across the state of Washington using sales of all grades.

Finally, we collect site specific monthly local unemployment rate statistics and per capita personal income of the metropolitan statistical areas (MSA) nearest to the respective highway location.[10] Unemployment data are drawn from Local Area Unemployment Statistics of the Bureau of Labor Statistics (2005–2008) and income from the CA1-3 series of the Regional Economic Accounts at the Bureau of Economic Analysis (2008). Table 2 summarizes the descriptive statistics of our data collection.

The relationship between gasoline price and weekly average vehicle speed is displayed in Fig. 1 using the data of our eight speed measuring sites. Often observations are missing in large portions of the dataset, which is typical for speed measures. Rather than interpolating the missing hourly speed data, all observations are dropped from the dataset with missing speed information, which reduced the original dataset by 18.9%. Also Fig. 1 shows that gas prices are cyclical in nature with higher prices in the summer and lower prices in the winter months corresponding with the cyclicality in speeds.

3. Method and results

In order to test whether motorists seek to conserve energy by reducing speeds, our main task is to estimate the direct causal effect of the price of gasoline on speeding behavior. Burger and Kaffine (2009) show that this direct effect has to be estimated in the absence of congestion because otherwise observed speeds are merely a reaction of changes in travel demand affecting congestion.[11]

3.1. Weekly data and estimation method

As a reference, here we first start by estimating the relationship between speed and gasoline using the same method as in Burger and Kaffine (2009). Using the night hours of 2 am to 4 am as the time of the uncongested condition, the average speed in week t of year j and highway i is estimated by

$$\text{Speed}_{jit} = \alpha + \beta \times \text{price}_{jt} + \gamma X_{jit} + F_i + Y_j + \varepsilon_{jit} \tag{1}$$

[10] Our speed data do not contain information where drivers live. In robustness checks suggested by one referee (a) data are used of the specific county where the speed data measuring site is located, see column (8) of Table 1, and (b) the State of Washington average. These alternative specifications do not lead to qualitatively different results as compared to using the data of the closest MSA.

[11] Burger and Kaffine (2009) analyze vehicle speeds both on uncongested and congested freeways in Los Angeles. They find that in an uncongested condition there does not exist any statistically significant effect on gasoline prices. In contrast, in congested conditions (from 6 to 8 am and 4 to 6 pm), they find that for every $1 increase in gas prices, the average increase in freeway speeds is 3.4 mph. Based on the insignificant change in uncongested speeds, they conclude that perhaps the value of time is high enough that the difference in speed cannot be controlled by a change in gasoline prices. Instead of freeways in urban areas of California, we turn to speed data in less populated portions of Washington State. These areas have the advantage of having speed limits of 70 mph which is higher than the maximum speed limit of 65 mph in the more densely populated areas in L.A.

Table 2
Descriptive statistics.

Variable	Unit	Observations	Mean	Std. dev.	Min.	Max.
Speed data						
Average speed	mph	227158	69.19	2.70	32.5	76.88
Gas price	U.S. dollar	227158	2.91	0.59	1.831	4.412
Volume	vehicles per hour	227158	510.79	586.81	0.0	2852
Weather data						
Visibility	statute miles	219644	9.35	2.00	0.0	10.0
Precipitation	inches per hour	227158	.002	.023	0.0	6.60
Temperature	Fahrenheit	219546	51.42	17.45	– 14	111
Economic indicators						
Income	U.S. dollar	227158	29948.1	2239.6	25963.0	34011.0
Unemployment	%	227158	6.12	1.27	4.00	10.50

Note: Unit of observation is per site and hour.

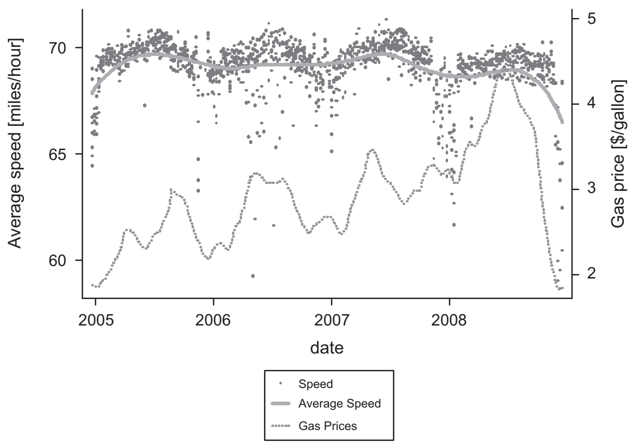

Fig. 1. Average Speed per Week and Gas Prices, 2005–2008. *Notes*: The bold gray line displays average speed estimated by the locally weighted scatterplot smoothing method with bandwidth of 0.3. Each dot represents the average weekly speed by highway location.

where $price_{jt}$ is the weekly average gas price, F_i are freeway site fixed effects, Y_j are year j fixed effects and X_{jit} are precipitation, holiday and summer dummies as well as income and unemployment. The results in Table 3 column (1) show that across all sites, speeds significantly *increase* by 0.46 mph for a one U.S. dollar *increase* in gasoline prices. Hence, similar to the results by Burger and Kaffine (2009), according to this methodology, our dataset would suggest that the energy conservation hypothesis should be rejected.

To explore the causes that drive this result, we analyze the potential effect of road conditions that could confound this estimate. Seasonality turns out to be important because of its correlation with the cyclicality of gas prices. In the summer, speeds may be higher because of better visibility—extended daylight and less rain—and no freezing temperatures. On the other hand, speeds may be lower as the proportion of vacation travelers increases in the Summer season. In column (2), we hence control for seasonality by introducing month dummies M_k. The estimates of column (2) confirm this hypothesis: speeds are 2.4 mph lower in December compared to the fastest month of the year, July, and the gas price coefficient renders insignificant. Because of this cyclicality, in this paper we will control for seasonality in all further regressions. Also, since the composition of the vehicle fleet changes both over seasons and years, in addition to the month fixed effects also year fixed effects will be always included. To investigate the robustness of these weekly results, in column (3) we add to Eq. (1) all the amenable regressors and interaction of fixed effects of our later preferred hourly specification model and find that the price effect is still insignificant using the weekly average speed method.

Finally, column (4) to (6) repeat the estimation for the workday hours from 4 pm to 6 pm, which we define as the PM time period.[12] Here, again, we find that the within year speed difference of 2.7 mph shows the importance of controlling for seasonality and we show that over the various specifications (analogous to the specifications in column (1) to (3)) the coefficient on price leads to non-robust results.

[12] The PM period refers to the set (4:00 pm, 6:00 pm) on weekdays, which is the peak traveling period under daylight conditions. Afternoon weekend and holiday hours are excluded from the PM period. Holidays are defined in the data Appendix.

Table 3
Regression results for freeway speeds in Washington state.

Variables	(1) 2 am to 4 am 'Basic'	(2) 2 am to 4 am 'Basic' with Month FE	(3) 2 am to 4 am Robustness Test	(4) PM 'Basic'	(5) PM 'Basic' with Month FE	(6) PM Robustness Test
Gas price	0.4592***	0.2088	0.022	0.4135***	0.1902	0.0843
	(0.131)	(0.155)	(0.130)	(0.149)	(0.168)	(0.136)
February		1.2715***	0.6754**		1.2930***	1.4482***
		(0.212)	(0.328)		(0.158)	(0.301)
March		1.3916***	0.6493*		1.4135***	1.1409***
		(0.225)	(0.331)		(0.180)	(0.348)
April		1.5354***	0.8372**		1.3319***	0.9221***
		(0.256)	(0.372)		(0.219)	(0.348)
May		1.3375***	0.2794		1.0108***	0.4422
		(0.305)	(0.404)		(0.282)	(0.397)
June		1.6728***	0.4315		1.1731***	−0.0598
		(0.302)	(0.376)		(0.267)	(0.382)
July		1.9494***	0.9531**		1.5063***	0.3642
		(0.313)	(0.372)		(0.276)	(0.310)
August		1.8543***	0.6352		1.6251***	0.7565**
		(0.293)	(0.425)		(0.255)	(0.317)
September		1.5828***	0.4722		1.3038***	0.5576*
		(0.308)	(0.374)		(0.272)	(0.338)
October		1.5432***	0.4647		1.2999***	0.4999
		(0.297)	(0.347)		(0.254)	(0.355)
November		1.3222***	0.7525**		0.4278**	−0.4768
		(0.252)	(0.347)		(0.210)	(0.350)
December		−0.4078	0.2725		−1.1169***	−1.0634*
		(0.402)	(0.420)		(0.356)	(0.592)
Hourlyrain	−1.5908***	−0.7376		−3.2813***	−2.1718***	
	(0.565)	(0.541)		(0.512)	(0.485)	
Summer	0.6467***	0.2746***		0.3939***	0.0425	
	(0.073)	(0.100)		(0.071)	(0.096)	
Christmas	−1.3189***	−0.1292		−1.1907***	0.39	
	(0.447)	(0.563)		(0.404)	(0.477)	
Unemployment	−0.3658***	−0.1474**	−0.2727**	−0.3206***	−0.1677***	−0.3120***
	(0.038)	(0.063)	(0.121)	(0.036)	(0.056)	(0.105)
Income	−0.0004***	−0.0002*	0.0006	−0.0001	0.0000	−0.0011
	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.001)
Constant	78.4473***	71.4716***	52.3471	74.7275***	69.9904***	102.3908***
	(2.9)	(2.988)	(43.663)	(3.262)	(3.179)	(35.761)
Observations	1429	1429	1429	1428	1428	1428
R-squared	0.351	0.422	0.566	0.317	0.434	0.564

Notes: All regression includes site and year fixed effects. Columns (3) and (6) include interacted fixed effects. Robust standard errors in parentheses clustered by site and week.

*** $p < 0.01$.

** $p < 0.05$.

* $p < 0.1$.

Overall, with *weekly* data, the energy saving hypothesis could not be confirmed in the above regressions. The weekly estimation results are also inconsistent with the finer conditioning method that we will apply in the following section using *hourly* data.

3.2. Hourly dataset refinement

In order to further eliminate factors that confound the relationship between speed and gas price, some data refinements are applicable. Compared to the above estimation method, in the following, we make two major changes. First, instead of using weekly averages, we will work with hourly speed data. Secondly, we rely on constructing a dataset with the most homogenous exterior conditions as possible. Our first step is the filtering (dropping) of data for any hour and site with the following conditions:

A. Precipitation can substantially alter traffic behavior. To account for this all hours with rain, including hours with trace, are dropped from the data set (see Appendix for our handling of trace in the dataset). We also delete all observations two hours after any rain occurred because the spray from wet roads may still alter visibility and traffic flow.
B. All hours are dropped with outside temperatures of 32 °F or less. In addition all hours are dropped if temperature is missing in a 'winter' month, whereby we define 'winter' site-specific as the set of months with historic (2005 to 2008) minimum temperatures below 32 °F.

Table 4
Data removed for regressions.

Panel a: percentage of data removed by each condition A to D separately

Condition	Data restriction	All day		PM period	
		(1) Observations	(2) (%)	(3) Observations	(4) (%)
A	Rain	30617	13.5	1754	13.7
B	Temperature ≤ 32	29967	13.2	892	6.9
C	Visibility < 10	28674	12.6	1117	8.7
D	Average speed < 67	33326	14.7	294	2.3
	Total observations removed	82,409	36.3	3003	23.4

Panel b: percentage of data removed, conditional on pre-conditions in the above rows

Condition	Data restriction	PM period	
		(3) Observations	(4) (%)
A	Rain	1754	13.7
B∣A	Temperature ≤ 32∣A	756	5.9
C∣(A & B)	Visibility < 10∣(A & B)	430	3.3
D∣(A & B & C)	Average Speed < 67∣(A & B & C)	63	0.49
	Total observations removed	3003	23.4

Notes:—Panel a: The sum over the observations removed by each variable do not add to the ‘total observations removed’.
In the ‘conditional’ Panel b: the sum over the observations removed by each ‘restriction’ add to the ‘total observations removed’. *M*∣*N* reads as ‘condition *M* is implemented conditional on condition *N*’.

C. We only like to work with traffic information at times of perfect sky conditions. The ‘visibility’ variable provided by NOAA measures visibility in one mile increments from below one mile to at least 10 miles of visibility. In our study we drop all observations with a visibility of less than ten miles.
D. Finally, all observations are dropped if the average speed is less than 67 mph. By filtering for time periods with unusually low speeds (due to accidents, temporal construction activities, congestion or other factors) any unusual hour is removed from these typically uncongested segments of roadway.

Note that none of the conditions A to D. should be correlated with the direct behavioral response of speeds due to a change in gas price.[13] To obtain this dataset, the total number of observations was reduced by 36%. The percentage reductions by each variable are displayed in Table 4 in columns (1) and (2) and specifically for the PM time period in columns (3) and (4). As will be explained below, for various reasons the PM period is our preferred time period in the analysis. Overall Table 4 shows that the weather variables have the largest influence on the reduction of the number of observations. Condition D—that the average speed is below 67 mph—reduces the dataset by 15% in the 24 h period. However, in the more important afternoon PM period, only 2.3% of the data are dropped because of this condition. Moreover, the vast majority of the 2.3% can be explained by observed external factors: Conditional on first dropping all hours with rain, freezing temperatures and visibility below 10 miles, the 67 mph data restriction drops only 63 additional observations, which represents 0.49% of all hourly observations.

3.3. Hourly estimation and results

By conditioning on the set A through D to obtain the dataset of speeds with the most homogenous exterior conditions as possible, we are now in the position to estimate the direct impact of the price of gasoline on drivers speeding behavior by

$$\text{Speed}_{jih} = S(P, \theta) = \alpha + \beta \times \text{price}_{jt} + M_k + Y_j + F_i + \gamma X_{jih} + \varepsilon_{jih} \tag{2}$$

where *Speed* is the average speed at hour *h* and site *i* and all the remaining variables are defined as under the specification in (1). The resulting estimates of coefficients together with their robust standard errors which are clustered by week are shown in Table 5, along with the adjusted R-squared statistic measuring the fit for each equation.

Panel A of Table 5 shows that speeds significantly decrease by 0.16–0.19 mph. Column (1) confirms the significance of the month dummies. Note, however, that the inter-year speed range is equal to 0.6 mph from January to July and hence the cyclicality is much less pronounced compared to the cyclicality in the weekly regression of Table 3. Hence, as expected, the

[13] The robustness Section 4.5.3. shows that the gas price coefficient is estimated with more precision because of the data restrictions A to D.

Table 5
Hourly vehicle speed regressions.

Panel A: Basic models

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

Table 5 (*continued*)

Panel A: Basic models

Coefficient	(1) Basic model (month, site and year fixed effects)	(2) Basic model and hour fixed effects	(3) Basic model and hour and work and non-work time fixed effects
		(0.0225)	(0.0233)
Hour 22:00		−1.6253***	−1.4796***
		(0.0235)	(0.0239)
Hour 23:00		−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	0.06	0.36	0.54

Panel B: Interacted fixed effects models

Coefficient	(1) Interacted fixed effects model	(2) Interacted fixed effects model, gas price effect unpooled over timeblocks	(3) Interacted fixed effects model and unemployment, income	(4) Interacted fixed effects model, gas price effect unpooled over timeblocks and unemployment, income
Gas price	−0.1950***	−0.2724***	−0.2206***	−0.3009***
	(0.0329)	(0.0490)	(0.0318)	(0.0477)
Gas price × "AM"		0.1233***		0.1279***
		(0.0467)		(0.0465)
Gas price × "Midday"		0.0622		0.0572
		(0.0404)		(0.0401)
Gas price × "Evening"		0.0133		0.0195
		(0.0448)		(0.0449)
Gas price × "Night"		0.1435**		0.1582**
		(0.0623)		(0.0623)
Gas price × "Non-workday"		0.1059		0.1091
		(0.0689)		(0.0671)
Unemployment			−0.1986***	−0.1993***
			(0.0361)	(0.0362)
Income			0.0000	0.0000
			(0.0000)	(0.0000)
Constant	70.8179***	71.1027***	71.0899***	71.4287***
	(0.1370)	(0.1903)	(1.2549)	(1.2684)
Observations	138,162	138,162	138,162	138,162
Adjusted R^2	0.65	0.65	0.65	0.65

Notes—Panel A: Robust standard errors in parentheses clustered by week. All regressions include month, site and year fixed effects (Basic Model). Panel B: The interacted fixed effects model includes month, site, hour, year, timeblock fixed effects as well as the interacted fixed effects of month–timeblock, month–site, month–hour, hour–timeblock, hour–site, site–timeblock, year–site and year–timeblock. Timeblocks are defined in footnote 14. Robust standard errors in parenthesis clustered by week.

*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

within-a-year driving conditions are already much more homogenous. Column (2) in addition displays the hourly fixed effects and shows that speeds are generally highest in the afternoon/after-work time period of 4 pm to 6 pm. The final regression, column (3), additionally controls for timeblock dummies which account for non-workdays (Saturday, Sunday and Holidays), and weekday time periods whereby weekday time periods are further divided into AM, Midday, PM, Evening and Night fixed effects.[14]

Building upon this basic regression framework, in Panel B of Table 5 we interact all fixed effects with each other and we find that the magnitude of the gas price coefficient slightly increases from −.20 to −0.22 in column (1) and (3), the latter also controlling for income and unemployment. While both income (correlation of 0.41) and unemployment (correlation of 0.32) are highly correlated with gas price, we find that only unemployment has a modest but significant negative effect on

[14] The timeblocks are defined on weekdays as AM 6 am–10 am, Midday 10 am–4 pm, PM 4 pm–6 pm, evening until midnight and nighttime from 0 am to 6 am. Holidays and weekends comprise the non-workday timeblock whereby Holidays are defined as in Appendix.

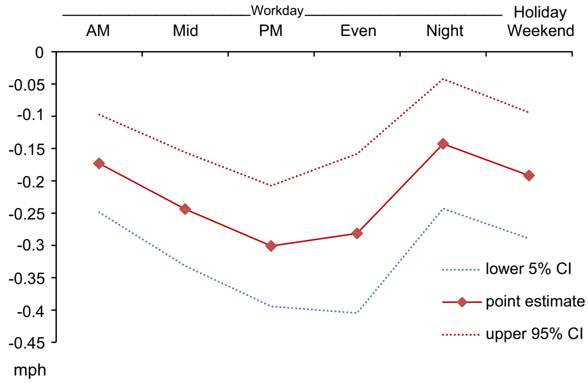

Fig. 2. Speed Reduction Effects due to a One Dollar Increase in Price per Gallon of Gas. *Notes*: The vertical axis displays speed reductions in mph due to a one dollar increase in the price per gallon of gas. The 95% confidence intervals are calculated using standard errors clustered by week from regression column (4) of Panel B of Table 5. Time periods as defined in footnote 14.

speed, while income instead is insignificant. Finally in column (2) and (4) we unpool the gas price coefficient over the timeblocks and find that generally speeds reduce most in the weekday PM period and reduce least in the AM period and at night time (statistical significant based on $p < 0.01$ level Wald-tests). The speed reduction effects due to a one dollar increase in the price per gallon of gas are displayed in Fig. 2 joint with their 95% confidence intervals.

Because speeds are generally highest in the PM timeblock (see the hourly fixed effects in Panel A of Table 5), with our objective to work with a sample of drivers as homogenous as possible, we will continue to analyze the PM time period in more detail. This PM vehicle fleet is likely more representative with respect to the behavior of private vehicle owners. Instead, in other time periods of the day, the share of private vehicles to trucks and commercial vehicles is lower. Speed reactions by trucks and commercial vehicles are arguably more heterogeneous because their speeds are constrained by vehicle type and weight.[15] Also, the incentive to conserve gasoline by commercial drivers is different if gasoline expenses get reimbursed. Table 6 displays the results of the PM models analogous to the previous specifications and shows that gas prices reduce speeds by 0.25 or 0.29 mph for a $1 increase in the price of gasoline per gallon. Also note that for the PM model now income renders significant with a positive sign, as expected. Our preferred estimate of the PM model is column (3) implying a significant reduction of speed by 0.27 mph or equivalent an elasticity of speed with respect to the price of gasoline of minus 0.01.[16] While the estimated speed reduction is low in magnitude, this has the advantage that the corresponding VOT may be less confounded by other attributes, an issue that we will discuss in Section 4.

4. Value of time (VOT)

The literature on estimating VOT started with the seminal work by Beesley (1965) and today can be categorized into the following three approaches. First, VOT estimates are derived by comparing different modes of travel with each other relative to the travel cost and time requirements (Beesley, 1965; Shiaw, 2004; Barrett, 2010). Second, pricing studies use datasets on the same mode of travel (e.g. Deacon and Sonstelie, 1985; Small et al., 2005) where motorists make discrete choices of either paying to avoid congestion or waiting in line, often for a prior unknown amount of time. Finally, stated preference methods (Calfee et al., 2001; Small et al., 2005) are estimated via discrete choice models.

This paper provides an alternative method which permits to address some of the conceptual problems. Our method does not depend on either different travel modes, or substantially different travel characteristics, such as choosing a HOT lane. As such, our empirical estimate promises to be less confounded. In our preferred specification, we find that speeds reduce by 0.27 mph per dollar increase per gallon of gasoline in column (3) of Table 6. At first, this relatively small change in speeds suggests that concerns of other confounding factors are likely smaller as well. We show in the next sections that biases can still be large, however, and discuss implications of such biases for this present VOT estimate as well as for better understanding non-marginal speed changes that were used in the prior VOT literature. More generally, the advantage of our study is that the VOT is derived by basing the estimate on the intensive margin and not (as in previous studies) on the extensive margin of making choices among different bundles of attributes. These attributes, we argue, have their own values and hence can interfere with the estimation of the VOT parameter if they are not carefully controlled for.

[15] While our data does not distinguish between type of vehicles (by counting the number of axles or weight), the variance of speeds within the PM period is 50% lower compared to other time periods (variance calculated based on conditions A to D). This indicates that the PM time period is more homogenous with respect to the composition of the type of vehicles, and more homogenous with respect to their speed preference.

[16] If taking literally (assuming external validity), this elasticity estimate would translate into 1.07 billion dollar of gas expenditure savings on all U.S. highways annually if all drivers reduce the speed by 0.27 mph.

Table 6
Hourly gas price speed relationship in the PM time period.

Coefficient	(1) Basic model	(2) Interacted fixed effects model	(3) Interacted fixed effects model with unemployment and income
Gas price	−0.2874***	−0.2491***	−0.2701***
	(0.0528)	(0.0488)	(0.0483)
Unemployment			−0.1514***
			(0.0547)
Income			0.0001***
			(0.0000)
Constant	71.2125***	71.0748***	68.3257***
	(0.2122)	(0.1908)	(1.5866)
Observations	9390	9390	9390
Adjusted R^2	0.27	0.37	0.38

Notes: All regressions include month, site and year fixed effects (Basic model). The interacted fixed effects include month, site, hour, 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 clustered by week.
$^{**}p<0.05$; $^{*}p<0.1$.
*** $p<0.01$.

4.1. Model

From the theory point of view, the approach is simple. Increasing the speed S above 60 mph increases gasoline consumption $g(S)$. Given the price of gasoline P, a driver minimizes total costs $C(S|P)=Pg(S|P)+\mathrm{VOT}t(S|P)+d(S|P)$. Hence drivers equalize the marginal cost of gasoline expenditures $P\delta g/\delta S$ with the marginal time saving with respect to speed, $\delta t/\delta S$, times the drivers subjectively perceived value of time (VOT), minus the marginal disamenity of driving at a higher speed $\delta d/\delta S$. Here, $d(S)$ can represent the dollar value of any disamenity of fast driving such as the cost of stress or the risk of getting involved in a traffic accident, with $d(S)$ monotonic increasing and convex in S over the range of values considered here. Totally differentiating

$$VOT = -[P\delta g/\delta S + \delta d/\delta S]/\delta t/\delta S \tag{3}$$

it is easy to show that $\mathrm{d}S/\mathrm{d}P<0$, hence a rational motorist will reduce speeds with higher gasoline prices.

In order to calculate VOT, we need to derive a number of additional parameters that we re-estimate from prior results in the engineering literature. First, $t(S)=n/S$ is simply a physical relationship assuming a vehicle occupancy rate $n=1.2$ during the workday period from 4:00 pm to 6:00 pm (see data Appendix). Second, for now, for simplicity, we assume that $\delta d/\delta S=0$ (an assumption that we will carefully examine in the discussion section below to derive the bias functions). Finally, we derive $g(S)$ by using the data of West et al. (1999). Based on nine vehicles sampled from a mix of automobiles and light trucks of model years 1988–1997, we piece-wise linearly estimate that the derivative $\delta g/\delta S=0.06018$ in the relevant interval of $S\in[70,75]$ (see details on the function g in Appendix).

To exemplify, consider a driver traveling exactly the distance of 70.82 miles. For a price increase from three to four dollar per gallon, we estimate that speeds reduce by 0.27 from 70.82 mph to 70.55 mph. Hence her travel time increases from one hour to one hour and 14 s. This increase in travel time comes at the benefit of savings of 43.56 cm^3 in gasoline consumption equivalent to expenditure savings of 4.6 cents over the distance of 70.82 miles. These saved 4.6 cents over the additional 14 s per passenger (equal to a total of nx14=17 saved seconds per vehicle) results in a

$$\mathrm{VOT}_{lower\ bound}=\$10.02$$

per hour with a standard error of 0.20. The standard error of VOT is derived via the delta method (see Appendix). This VOT estimate is however a lower bound as we omitted the benefits of reducing speeds in terms of the probability of obtaining a traffic ticket and the probability of getting involved in an accident. The impact of these disameninities will be discussed next.

4.2. The disamentity function

4.2.1. The impact of speed on accident rates and speeding tickets

To derive the lower bound of VOT, we so far assumed that $d/\delta S=0$. This has been also the standard assumption in previous work which identifies VOT via non-marginal changes in travel or waiting time. In this subsection, we assess the resulting bias from this assumption for small changes in speed (and address implications for non-marginal changes below). Reducing speeds may in fact have three benefits, first by increasing fuel efficiency, secondly by decreasing the probability of getting involved into an accident, and lastly by decreasing the costs from speeding tickets. So far, in our calculation of VOT we considered the first benefit, but not the second or third.[17] We quantify these benefits of reducing speed by 0.27 mph as

$$\Delta d(S) = \Delta d^{A,\mathrm{PD}} + n(\Delta d^{A,H} + \Delta d^{A,F}) + \Delta d^{\mathrm{T}},$$

with d^{A} being the monetary cost of accidents (A), separated in property damages (PD), hospitalization (H), and fatality costs (F) as well as d^{T} representing the costs due to the probability of obtaining a speeding ticket (T).

4.2.2. *Traffic safety*

In order to evaluate the safety benefits Δd^{A} we draw parameters from various sources. First, the accident literature generally finds that faster driving increases accident rates. The most comprehensive recent estimates of the relationship between speeds and accidents are derived from Cameron and Elvik (2010). In order to transfer these accident rates into monetary values, we use estimates of costs for property damage, hospitalization and fatality—the latter expressed as the Value of Statistical Life (VSL)—from AASHTO (2010).[18] Furthermore, we in detail analyze the U.S. Fatality Analysis Reporting System (FARS) dataset using the universe of all crashes from 2005 to 2008. Controlling for fourteen distinct weather and highway characteristics (see footnote 19 for the details of the FARS conditioning variables), we estimate accident rates for our workday PM time period that would occur under near-perfect weather and driving conditions.[19] With this, we estimate that $\Delta d^{\mathrm{A}} = 0.6$ cents per hour of driving. This implies a VOT of $[P^2 \Delta g + \Delta d^{\mathrm{A}}]/[t(S|P^2) - t(S|P^1)] = \$11.52$ when we take into account the additional benefits of slower driving due to the reduction in the probability of getting involved in an accident.

Since fatal accidents constitute the majority of the disamenities from speeding, as an additional robustness check we investigate the literature that particularly relates speeding to fatalities. Ashenfelter and Greenstone (2004).[20] find that U.S. states increasing the speed limit from 55 mph to 65 mph experienced an average speed increase of 2.5 mph, and the fatality rate in these states increased by 35%. Extrapolating this Ashenfelter and Greenstone accident-speed parameter and applying further alternative measures of the VSL suggested in the literature, we find the safety benefits associated of Δd^{A} equal to 0.4 to 1.3 cents per hour of driving. See Appendix for the details on the data sources and calculations of the various scenarios.

Overall, we anticipate that our calculation of Δd^{A} represents an upper bound measure of the true cost of accidents for several reasons. First, due to several missing variable problems in the FARS dataset (see Appendix for details), we overestimate the accident rates under ideal driving conditions by conservatively always including all crashes when any of the FARS conditioning variables were not recorded in the police reports.[21] Second, in our calculations we assumed that an *individual* motorist reduces the *average* highway speed $\overline{S}$ by 0.27 mph. An individual driver can however only moderately influence $\overline{S}$ by her contribution of reducing her individual speed S_i. Her safety benefit Δd^{A} would then be a function of $\Delta S_i/v$, with v the number of vehicles on the road surrounding her which produces a much lower safety benefit.[22] Finally, we somewhat conservatively assumed that the injury and fatality costs are multiplied to equally affect all n vehicle occupants, while in fact not all passengers may be harmed in a crash.

4.2.3. *Speeding tickets*

To estimate Δd^{T}, the benefit of reducing speed with respect to the probability of obtaining a speeding ticket, we submitted a public disclosure request to the Washington State Patrol to obtain the total number of speeding tickets issued on Washington rural highways from 2005–2008. Secondly, we collected the schedule of fines from the Washington Court which expresses the fines to be paid in 5 mph bins above the speed limit of 70 mph. For example driving 1–5 mph over the limit warrants a \$93 ticket, while speeding by 6–10 mph earns a \$113 ticket. To be conservative (essentially calculating an upper bound for Δd^{T}), we make the assumptions that (a) no vehicle traveling up to 75 mph obtains a speeding ticket and (b) that the observed speeds in our speed measurement dataset are equivalent with the speed recorded on the ticket, whereas in reality police officers often reduce the recorded speed on the ticket[23]. By matching our distribution of vehicle speeds to

---

[17] Conceptually, any other confounder (such as the stress of speeding or the joy of speeding) can be incorporated in bias function $d(S|P)$. These confounders are assumed to have zero affect here and their magnitude is to be evaluated in future research.

[18] The periodic publication by the American Association of State Highway and Transportation Officials, AASHTO (2010) also known as the 'Redbook', is the leading document and tool in public transportation providing the key estimates needed for cost-benefit analysis for any larger public transportation infrastructure project.

[19] Research has repeatedly shown that most highway crashes occur on off and on-ramps (McCartt et al., 2004), mountainous areas (Ahmed et al., 2011) and under rainfall (Eisenberg, 2004) and icy conditions (Eisenberg and Warner, 2005). To control for this, we use the FARS data and estimate condition specific accident rates based on weather, road condition and other temporal restrictions (see Appendix for details).

[20] Ashenfelter and Greenstone (2004) model the tradeoff between increased risk and time-savings to estimate the VSL. The study provides fatality estimates for the increase in speeds observed in those states adopting the 65 mph speed limit.

[21] For example, in the year 2005 6.5% of the crashes (conditional on the conditions specified in footnote 34) occurred at an 'unknown' hour. To be conservative, we still added these crashes at an 'unknown' hour to our sum of the PM time period crashes.

[22] Hence, instead of cost minimizing $d^{\mathrm{A}}(\overline{S})$ an individual can only influence the risk of getting involved into an accident $r(S_i|f(S))$ by changing her individual speed S_i conditional on the other drivers distribution of speeds $f(S)$. At any point in time, the speeds of the other drivers are draws from a random distribution f. For example, if three motorists are surrounding her and she slows down by 27 mph, she actively reduces the average speed by 0.0675 mph only and induces herself safety benefits of 22% of our presented Δd^{A} estimate.

[23] While we are unaware of any official statistic, anecdotal evidence from Washington suggests that speeding tickets are written for less than the actual recorded speed on the measuring device, sometimes providing substantial speed breaks. According to the law enforcement forum *Real Police*, the two most common arguments for officers providing speeding breaks are (i) be lenient to drivers with clean records and (ii) to lower the probability that the motorist argues the ticket in court, thus reducing officers court commitments. One police officer stated: "*I can't remember the last time I wrote a speeding ticket and*

the schedule of fines, we find that the speeding ticket cost of the average driver equals to $d^{T}(S|P^{1}) = 11.5$ cents per hour of driving. Next, we recalculate the distribution of the ticket costs conditional on $S|P^{2}$. The difference between the new and old distribution produces the estimate of $\Delta d^{T} = 0.5$ cents per hour of driving.[24] Hence, correcting for the potential bias from the probability of obtaining a speeding ticket contributes to an increase in the hourly VOT by $\Delta d^{T}/[t(S|P^{2}) - t(S|P^{1})] = \$1.17$. Appendix describes the data sources and details of our methodology.

To summarize, the lower and upper bounds of our VOT estimates produce the range \$10.02 to

$$\mathrm{VOT}_{\text{upper bound}} = [P^{2}\Delta g + \Delta d^{A} + \Delta d^{T}]/[t(S|P^{2}) - t(S|P^{1})] = \$10.02 + \$1.50 + \$1.17 = \$12.70$$

if the assumption of a constant $d(S)$ function within the small interval $S \in [70.55, 70.82]$ is relaxed. Again, we consider \$10.02 as a lower bound and \$12.70 as an upper bound because in calculating $\Delta d^{A} + \Delta d^{T}$ we made assumptions which likely lead to an overestimate of the benefits of reducing speeds.

4.3. Context of previous stated and revealed preference studies

According to the Bureau of Labor Statistics (2008), the average hourly wage in 2008 in the State of Washington was \$22.32 before taxes, or \$20.07 when considering the rural MSAs only of Table 1.[25] Hence, our VOT estimate of \$10.02 to \$12.70 per hour accounts for 45–63% of the average gross wage rate. This is in the range of previous VOT estimates. In fact, some of the studies have their preferred VOT estimate at exactly 50% (Shaikh and Larson, 2003) and Small and Verhoef (2007), summarizing the VOT literature, conclude that the VOT parameter *varies widely by circumstance*, *usually between 20% to 90% of the gross wage and averaging around 50%*. Our estimate is between most *stated preference* derived estimates and *revealed preference* methods. 63% is considerably lower than the 93% estimate by Small et al. (2005) and also lower than the earlier estimate by Deacon and Sonstelie (1985) referring to VOT as approximately being the after tax wage rate (hence approximately 78% of the gross wage rate). We interpret our lower VOT estimate as evidence that these prior studies may be confounded by other psychological costs of waiting in a queue at a gasoline station, as in the study by Deacon and Sonstelie (1985) or, as in the case of the study by Small et al. (2005), by further emotional frustration costs of stop and go driving and other variables. In the next subsection we provide some approximate ideas on the direction of bias and potential magnitude of such unobserved driving costs.

At the same time our VOT is larger than in most prior stated preference studies. The investigation of the divergence between revealed and stated preference studies continues to be an active research area by John List et al. and is beyond the scope of this paper. We may add here however, that in survey situations respondents can be inexperienced as well as inaccurate to express preferences over travel time for at least two reasons. First, the economic paradigm that ‘time is money’ can make respondents feel uncomfortable in truly answering hypothetical questions on the benefits of time savings. Secondly, the disamenity of being frustrated in traffic jams might not be adequately recalled by the respondent during the interview. In fact, to our knowledge previous questionnaires (see Calfee et al., 2001 or Small et al., 2005) do not include any questions related to stress costs in traffic jams compared to the potential ‘stress release’ (some may even feel malicious joy) when traveling freely on the toll lane next to a congested non-toll lane. Note that the omission of both these factors downward bias stated preference willingness to pay estimates.[26] We therefore suggest that future stated preferences questionnaire designs should include such questions and it is hoped that the answers may help to close the gap between stated preference and revealed preference VOT estimates.

4.4. VOT bias functions: disamenities of driving simulated at non-marginal speed changes

While in our context we assumed the function $d(S)$ to be convex and monotonic increasing within the domain above 70 mph, in general the derivatives of other subcomponents of $d(S)$ can have any signs. To give an idea how various disamenity functions (potential VOT bias functions) are signed, we set up a simple dichotomous traffic choice model where drivers can circumvent a typically congested main lane by paying a toll on the HOT lane. To fill our example with data, we use the setting of Small et al. (2005), where for a 44.8 mile long highway commute on a toll lane in Los Angeles the traffic fee amounts to \$3.85.[27] We further assume that the hourly VOT of Los Angeles is 50% of the Los Angeles Metropolitan county wage rate of \$22.88.

(*footnote continued*)
DIDN'T lower the speed". http://www.realpolice.net/forums/ask-cop-112/98412-lowering-speed-citation.html. For further details see www.realpolice.net/forums/traffic-school-accident-investigation-80/16553-writing-speeding-tickets-lower-speed.html (both sites accessed August 18, 2011).

[24] We assume that police officers do not stop any vehicle traveling below 75 mph. As a robustness check, we vary this assumption that (i) no ticket is issued below 80 mph and (ii) below 70 mph. This yields Δd^{S} estimates of 1.0 cent and 0.3 cent per hour of driving respectively. See Appendix for details.

[25] The estimate of \$20.07 is derived by weighting the BLS hourly wage data of the MSAs of Table 1 by the number of drivers passing over the various loop detectors.

[26] The relationship between traffic congestion, aggression, health and well being is explored in i.e. Hennessy et al. (2000), Wickens and Weisenthal (2005) and Gottholmseder et al. (2008).

[27] We refer to the ‘Brooking revealed preference’ setup in Small et al. (2005). Our calculation of time saving assumes that the speed difference between the HOT lane and the main lane is 9.57 mph, increasing speeds from 36.54 mph to 46.11 mph by paying the toll. This estimate is derived from the rush hour setting in Bento et al. (2011). All further details on our data collection in this subsection and our calculations are detailed in Appendix.

First, to give an idea how the disamenity function from accidents $\Delta d^A = d^A(S|\text{toll-lane}) - d^A(S|\text{main-lane})$ can impact a VOT estimate in this setting, we analyze the FARS crash database of California and collect vehicle miles traveled statistics from California State Department of Transportation. Using the same method to derive Δd^A as in the previous subsection (for details see Appendix), we find $\Delta d^A/[t(S|\text{toll-lane}) - t(S|\text{main-lane})] = \$10.75$. In other words, the omission of Δd^A alone produces a bias of striking 94% of the VOT.[28]

Secondly, at the typical low speeds of Los Angeles highways, fuel efficiency *increases* with speed, which causes additional benefits from switching to a HOT lane. The omission of the change in gas expenditure $P\Delta g$ produces a bias of an additional 4% of the VOT. Note that 4% is probably a severe underestimate of the true bias because we do not account for the extra gas consumed with the typical frequent accelerations in stop and go traffic.

Third, the probability of getting involved into a traffic accident is also a function of the speed variance (Lave, 1985). That accident cost substantially increase with congestion has long been hypothesized in economics (Vickrey, 1969) and recent empirical research in the transportation literature (Golob and Recker, 2003) finds that slower moving but congested traffic conditions has a *larger impact* on the severities of accidents compared to the impact of speed itself. Hence, going from a stop-and-go main lane to an uncongested toll lane, we expect the bias function $\Delta d^{Acc}(\text{var}(S))$ to be negatively signed and potentially of substantial magnitude.

Fourth, the traffic literature suggests that psychological benefits of circumventing frustration of a potential traffic jam are likely significant (i.e. Johnson and McKnight, 2009). Starkly simplifying our model and assuming that $\Delta d^A = -\Delta d^{Acc}(\text{var}(S))$, the potential psychological costs of being in a traffic jam would amount to 29% of the VOT. While it is beyond the scope of this paper to estimate all disamenity effects in this L.A. setting—and the above calculation are clearly very approximate in nature—this subsection suggests that a VOT research design based on this extensive margin can be very challenging.[29]

4.5. Robustness

4.5.1. An alternative gasoline consumption function g(S)

In order to calculate the VOT, one of the crucial parameters is the relationship between gasoline consumption and speeds, $g(S)$. Today, the most widely used estimates are from West et al. (1999), applied equally in academics (Burger and Kaffine, 2009) as well as in policy evaluations by government agencies (Gaffigan and Fleming, 2008; DOT, 2011). Given the age of the study by West et al. (1999), we aim to contrast the results with a newer estimate of $g(S)$ as the function may have shifted. While, unfortunately, we could not find any other study which could be considered representative for the U.S. vehicle fleet, the recent work by Davis et al. (2010) provides measures of $g(S)$ for large, medium and small SUVs separately. We average these estimates to form an alternative approximation for $g(S)$, see the output of column (2) of Table A1 summarized in Appendix. Again piecewise interpolating between the provided 5 mph speed intervals, we find that $\delta g^{Davis10}/\delta S = 0.0610093$ in the relevant interval of $S \in [70,75]$. Using these data, the corresponding lower bound $\text{VOT} = [P^2\{g^{\text{Davis10}}(S|P^1) - g^{\text{Davis10}}(S|P^2)\}]/[t(S|P^2) - t(S|P^1)] = \$10.16/\text{h}$ (or 46% of the wage rate) with a standard error of 0.21.

4.5.2. Traffic density and highway speeds

The workday PM time period is our preferred time of the day to estimate the VOT parameter because we consider these drivers to be most representative. By using the rush hour PM data however, one concern is that higher traffic volumes may impact the speed gasoline mechanism in the same spirit as Burger and Kaffine (2009) have shown this in the case of the Los Angeles setting. To investigate the impact of traffic volume, we re-estimate our preferred specification of column (3) in Table 6 by conditioning on the number of vehicles per hour as an additional regressor variable. Contrary to expectations, the point estimate of the total number of vehicles traveled per hour shows that adding 100 vehicles on the road modestly *increases* speeds by 0.05 mph. In terms of robustness, the gas price coefficient estimate changes slightly from −0.27 (0.05) in Table 6 column (3) to −0.28 (0.05).[30] Similarly, adding the number of total vehicles traveled per hour as an additional regressor to the ‘all data’ specification of column (3) in Panel B of Table 5 does change the point estimate of gas price slightly at the third digit from −0.221 (0.032) to −0.223 (0.031). As further evidence that congestion is likely not a confounder at our rural sites, Fig. 3 displays speeds on the right side vertical axis as scatter dots over the 24 h of the day and graphs the average number of vehicles per hour on the left vertical axis. Fig. 3 shows that drivers speed most around the PM period although this is the time when these highways are most frequently used. In summary, we interpret this positive relationship as a composition effect that faster types of vehicles travel during the day and evening compared to at night times when relatively more trucks are on the road.

[28] We expect this bias to be a lower bound because we conservatively assume that the speed difference between a HOT lane compared to the main lane is the same as the speed difference between a HOV lane and the main lane from Bento et al. (2011). We were unable to find precise data on the typical speed difference in Los Angeles between a HOT lane and the corresponding main lane, but we expect that the HOT to main lane difference is larger at those times when the average driver has the incentive to pay the toll.

[29] Small et al. (2005) develop a random parameter logit model to account for unobserved heterogeneity in preferences across agents. Our approach differs in that we aim to reduce the omitted variable bias directly by estimating the VOT based on the intensive margin.

[30] Robust standard errors in parenthesis clustered by week.

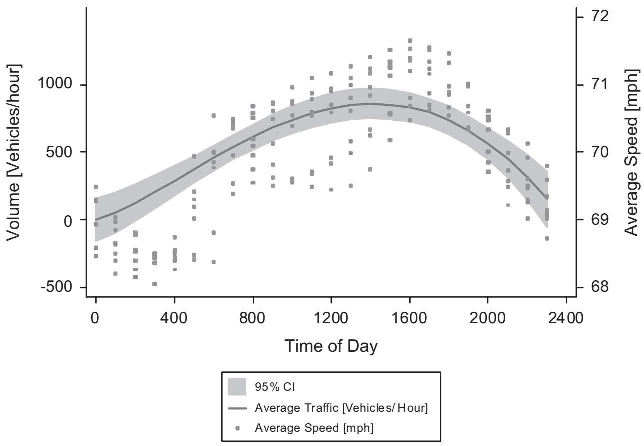

Fig. 3. Vehicles per Hour and Average Speeds. *Notes*: Unit of observation is hour by site. Predicted traffic volume and 95% confidence interval based on standard fractional polynomial regression minimizing the deviance (Royston and Altman, 1994) using the STATA fpfit command.

4.5.3. Sensitivity of the results with respect to the data refinement procedure

One major goal of our estimation strategy was to create external driving conditions that are as homogenous as possible, except for the influence of the price of gas. This was achieved through filtering our data by conditions A to D in Section 3.2. How sensitive is our coefficient of interest with respect to these data refinements?[31] Table 7 displays the results. Overall, going from right to left, Table 7 shows that the data restrictions A to D lead to more homogenous driving conditions as measured by the increase in the goodness of fit of the regressions and increasing the precision of the estimated gas price coefficients (increasing the R^2 from 28 to 38 while reducing the standard error from 0.25 to 0.048). Note that this increase in model fit and precision is achieved although the number of observations decreases with conditioning on A to D For example, does dropping the 0.49% of the data (see Table 4) make a difference because of Condition A? It turns out that the preferred gas price coefficient of -0.27 (0.05) changes to $-.33$ (0.06). The latter estimate, however shows a slightly increased standard error of 0.06 and the estimation overall produces a reduced R^2. This suggests, that -0.27, ultimately, is the preferred method: by filtering for time periods with unusually low speeds (due to potential accidents, temporal construction activities, congestion or other factors) any unusual hour is removed from these typically uncongested segments of roadway.

4.5.4. Conditional average speed analysis dropping individual outlier vehicles

The endogenous variable in our main regressions of Table 6 is measured as the average hourly speed. Theoretically, changes in this speed measure could occur because of a change in the tail of the speed distribution for drivers that have very different fuel economy benefits, invalidating our approach to calculate the VOT. In order to check this, robustness tests are run, sequentially dropping speed bins in the tail(s) of the speed distribution. Our estimates of interest are numerically very robust to these changes. See Appendix Table A0 for further explanations and details.

4.5.5. Matching of differentially frequently timed datasets

Due to the matching of the NOAA with the WSDOT we cannot guarantee that the time periods always overlap (see Appendix for details on the matching of the time stamps). For this reason we run robustness tests which are more conservative in that we delete all hours with 1 h precipitation leads and two hour precipitation lags. Similarly we proceeded for visibility and temperature. The results remain very similar to those reported in this paper.

5. Conclusion

This paper presents an alternative methodology of deriving the VOT parameter and provides an opportunity to cross check empirical results from previous discrete choice settings. Our research design exploits the variation in gasoline prices and relies on the re-optimization of a motorist cost function varying her continuous choice of how fast to drive on an uncongested highway. We find that speeds modestly reduce by 0.27 mph for a one dollar increase of the price of gas per gallon. In calculating the corresponding VOT from the first order condition, we show that second order effects regarding traffic safety and the probability of obtaining a traffic ticket are important to obtain an unbiased estimate. Summarizing, we find a VOT around fifty percent of the gross wage rate. To put this into context, all prior studies on revealing the VOT parameter are based on discrete choice models of traffic behavior or mode alternatives. We show that in such studies the bias of the VOT can potentially be large because choice alternatives are bundled with attributes which have their own values.

[31] I owe this suggestion to one of the anonymous referees.

Table 7
Sensitivity of the hourly gas price speed relationship with respect to the data refinement conditions A to D.

	(1) **Reference Model** as in Table 6 column (3) (all observations with rain, temperature < 32, visibility < 10 and speed < 67 are **dropped**)	(2) As in (1), except that all observations with speeds < 67 are **included**	(3) As in (2), but all observations with visibility < 10 are **included**	(4) As in (3) but all observations with temperature < 32 are **included**	(5) As in (4), but all observations with rain are **included**
Gas price	-0.2701^{***}	-0.3338^{***}	-0.3339^{***}	-0.1764	-0.1258
	(0.048)	(0.060)	(0.054)	(0.11)	(0.25)
Observations	9390	9453	9883	10,639	12,393
Adjusted R^2	0.38	0.37	0.27	0.30	0.28

Notes: All regressions include month, site and year fixed effects (Basic model). The interacted fixed effects include month, site, hour, 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 clustered by week.
$^{**}p < 0.05$; $^{*}p < 0.1$.
*** $p < 0.01$.

For example, we simulate that the linear accident risk of speed can contribute to a striking 94% of the VOT bias when comparing a toll lane to the main highway lane. Our findings particularly suggest that congestion disamenities of the outside option may be capitalized in prior revealed preference studies, hence obtaining relatively higher VOTs of 78% to 93% (Deacon and Sonstelie, 1985; Small et al., 2005). At the same time, our VOT estimate is larger than in most prior stated preference studies and we argue that several factors of the survey design likely downward bias their willingness to pay estimate. We suggest new interview questions to reveal attitude and preference values by agents, which can potentially help to close the gap of the diverging VOT estimates in the literature. More generally, our methodology is based on the intensive margin of behavioral adjustments and with around fifty percent we find a VOT estimate which confirms the range of the previous literature.

Moreover, our study has policy implication. The U.S. Department of Transportation currently uses a VOT baseline of 50% of the gross wage rate (DOT, 2010) and must conduct cost benefit analysis for any large public infrastructure project. DOT projects demonstrate that this VOT assumption is often the key parameter whether a project passes a cost benefit test. For example, for the U.S. federal highway maintenance alone, DOT (2010) recently estimates that a baseline VOT value of 75% (instead of the current baseline of 50%) would lead annually to an additional 8.6 billion U.S. dollar in expenditures (an increase of 8.2%). More precisely, in DOT's scenario this would dramatically shift public expenditures towards highway lane ‘widening’ and system expansion projects, while strictly reducing the spending on road maintenance and surface smoothing projects, currently the largest share of DOT's highway expenditures.[32]

Finally, our study contributes to the rapidly evolving transportation literature asking: Do drivers seek to conserve gasoline by reducing speeds in times of high gasoline prices? The time period from 2005 to 2008 saw an unprecedented increase in retail gas prices from below $2.00 to over $4.40 per gallon of gasoline. The headlines from the summer 2008 tell the story best: “Outraged consumers look to sustainable fuel solutions for gas price pain relief” (FOX Business, 6/16/08). As the debate on gasoline taxes continues to unfold (Parry and Small, 2005; Bento et al., 2009), economists are increasingly interested in the mechanisms by which prices affect gasoline demand. Vehicle miles traveled, as well as scrappage and adoption rates of vehicles are important determinants of the elasticity of demand (Austin and Dinan, 2005, Hughes et al. 2013; Klier and Linn, 2010). Here, we add to this literature by providing the first empirical study using disaggregated hourly speed data and estimate an elasticity of speed with respect to the price of gasoline of -0.01. While this change is small, it enables us to calculate the VOT. In fact, for any much larger change of speeds, instead, the method of estimating VOT would be increasingly challenging due to simultaneously changing attributes. As this study uses a particularly rural set of observations in the State of Washington only, future research should evaluate the external validity of the estimated VOT coefficient in other contexts.

Acknowledgment

I would like to thank two anonymous referees and the editor Dan Phaneuf for very valuable suggestions which improved the manuscript. Further I would like to thank Maximilian Auffhammer, Yoram Barzel, Glenn Blomquist, Daniel Brent, Robert Deacon, Mark Jacobsen, David Layton, Daniel Kaffine, Fahad Khalil, Kenneth Small and Kari Watkins as well as seminar participants at Arizona State University, Cornell, Resources for the Future, University of Washington, University of Wisconsin, the 32nd Annual NBER 2011 Summer Institute, the 2011 Inaugural AERE Summer Conference and the TREE seminar for many helpful comments and suggestions. Thanks are also due to Jim Hawkins of the Washington Department of

[32] Of the total $82.7 billion of federal highway spending in 2008, 51.1% was used for system rehabilitation (resurfacing existing pavements and bridges). 36.8% was used for system expansion (constructing new roads and bridges or adding lanes to existing roads); and 9% went for ‘system enhancements’ (such as safety or environmental improvements).

Transportation for providing the speed data. Jim was himself quite speedy with providing the data and answers to numerous questions. All remaining errors are mine.

Appendix A. Supplementary information

Supplementary data associated with this article can be found in the online version at http://dx.doi.org/10.1016/j.jeem.2013.11.002.

References

Ahmed, Mohamed, Huang, Helai, Mohamed, Abdel-Aty, Bernardo, Guevara, 2011. Exploring a Bayesian hierarchical approach for developing safety performance functions for a mountainous freeway. Accid. Anal. Prev. 43 (4), 1581–1589.

AASHTO, American Association of State Highway and Transportation Officials, 2010. User and Non-User Benefit Analysis for Highways. ISBN:978-1-56051-467-1.

Ashenfelter, Orley, Greenstone, Michael, 2004. Using mandated speed limits to measure the value of a statistical life. J. Polit. Econ. 112 (S1), 226–267.

Austin, David, Dinan, Terry, 2005. Clearing the air: the costs and consequences of higher CAFE standards and increased gasoline taxes. J. Environ. Econ. Manag. 50, 562–582.

Barrett, James, 2010. The Impact of Transportation Infrastructure on the Value of Time. Dissertation at University of California. Davis. UCTC-DISS-2010-03.

Becker, Gary S., 1965. A theory of the allocation of time. Econ. J. 75 (299), 493–517.

Beesley, Michael E., 1965. The value of time spent in travelling: some new evidence. Economica 32 (126), 174–185.

Bento, Antonio M., Daniel, Kaffine, Kevin, Roth, Matthew, Zaragoza, 2011. Clearing the Air by Promoting Hybrids? The Unintended Consequences of Allowing Solo-Hybrid Drivers in High Occupancy Lanes. Mimeo.

Bento, Antonio M., Goulder, Lawrence H., Jacobsen, Mark R., von Haefen, Roger H., 2009. Distributional and Efficiency Impacts of Increased US Gasoline Taxes. Am. Econ. Rev. 99 (3), 667–699.

Blomquist, Glenn, 1984. The 55 m.p.h. speed limit and gasoline consumption. Resour. Energy 6 (1), 21–39.

Bureau of Economic Analysis, 2008. Regional Economic Accounts – Series CA1-3. United States Department of Commerce. Washington, D.C. ⟨http://www.bea.gov/regional/reis/drill.cfm⟩ (accessed 02.06.11).

Bureau of Labor Statistics, 2008. Occupational Employment Statistics of May 2008 Washington State Occupational Employment and Wage Estimates – OESS530000000000000000003. United States Department of Labor, Washington D.C. ⟨http://www.bls.gov/oes/2008/may/oes_wa.htm⟩ (accessed 12.09.13).

Bureau of Labor Statistics, 2005–2008. Local Area Unemployment Statistics. United States Department of Labor. Washington, D.C. http://data.bls.gov/cgi-bin/surveymost?la+53 (accessed 02.06.11).

Brown, Gardner, Mendelsohn, Robert, 1984. The hedonic travel cost method. Rev. Econ. Stat. 66 (3), 427–433.

Burger, Nicholas E., Kaffine, Daniel T., 2009. Gas prices, traffic and freeway speeds in Los Angeles. Rev. Econ. Stat. 91 (3), 652–657.

Calfee, John, Winston, Clifford, 1998. The value of automobile travel time: implications for congestion policy. J. Public Econ. 69 (1), 83–102.

Calfee, John, Winston, Clifford, Stempski, Randolph, 2001. Econometric issues in estimating consumer preferences from stated preference data: a case study of the value of automobile travel time. Rev. Econ. Stat. 83 (4), 699–707.

Cameron, Max H., Elvik, Rune, 2010. Nilsson's Power Model connecting speed and road trauma: applicability by road type and alternative models for urban roads. Accid. Anal. Prev. 42 (6), 1908–1915.

Carrion-Madera, Carlos, Levinson, David, 2011. Value of reliability: high-occupancy-toll lanes, general-purpose lanes, and arterials. In: Presented at 90th Transportation Research Board Conference. Washington, DC.

Dahl, Carol A., 1979. Consumer adjustment to gasoline tax. Rev. Econ. Stat. 61 (3), 427–432.

Davis, Stacy C., Diegel, Susan W., Boundy, Robert G., 2010. Transportation Energy Data Book. Oak Ridge National Laboratory. ORNL-6985 (Edition 29 of ORNL-5198). Center for Transportation Analysis. Energy and Transportation Science Division.

Deacon, Robert T., Sonstelie, Jon, 1985. Rationing by waiting and the value of time: results from a natural experiment. J. Polit. Econ. 93 (4), 627–647.

DeSerpa, Allan.C., 1971. A theory of the economics of time. Econ J. 81 (324), 828–846.

DOT, 1997. Federal Highway Cost Allocation Study. US Federal Highway Administration. Department of Transportation. Washington, D.C; DOT, 2000. Addendum to the 1997 Federal Highway Cost Allocation Study Final Report.

DOT, 2010. Status of the Nation's Highways, Bridges, and Transit: Conditions & Performance. US Federal Highway Administration, Department of Transportation, Washington, D.C..

DOT, 2011. Effect of Operating Speed on Fuel Consumption: Wisconsin Transportation Economic Analysis Guidelines, Financial Assumptions and Parameters. Department of Transportation, Washington D.C. ⟨http://www.wisdot.info/economics/index.php?title=Financial_Assumptions_and_Parameters⟩ (accessed 15.06.11).

Eisenberg, Daniel, 2004. The mixed effects of precipitation on traffic crashes. Accid. Anal. Prev. 36 (4), 637–647.

Eisenberg, Daniel, Warner, Kenneth H., 2005. Effects of snowfalls on motor vehicle collisions, injuries, and fatalities. Am. J. Public Health 95 (1), 120–124.

Erb, Jack, April 2010. Gasoline prices, driving efficiency and implications for gasoline tax policy. In: Paper presented at the Southern California Applied Microeconomics Conference at Claremont McKenna College.

Fezzi, Carlo, Bateman, Ian J., Ferrini, Silvia, 2013. Using revealed preferences to estimate the value of travel time to recreation sites. J. Environ. Econ. Manag. 10.1016/j.jeem.2013.10.003, in press.

Gaffigan, Mark E., Fleming, Susan A., 2008. Energy Efficiency: Potential Fuel Savings Generated by a National Speed Limit Would Be Influenced by Many Other Factors. United States Government Accountability Office, Washington, DC ⟨http://www.gao.gov/products/GAO-09-153R⟩ (accessed 15.06.11).

Gale, Ian L, Holmes, Thomas J., 1993. Advance-purchase discounts and monopoly allocation of capacity. Am. Econ. Rev. 83 (1), 135–146.

Golob, Thomas F., Recker, Wilfred W., 2003. Relationships among urban freeway accidents, traffic flow, weather, and lighting conditions. J. Transp. Eng. 129 (4), 342–353.

Goodwin, Phil, Dargay, Joyce, Hanly, Mark, 2004. Elasticities of road traffic and fuel consumption with respect to price and income: a review. Transp. Rev. 24 (3), 275–292.

Gottholmseder, Georg, Nowtony, Klaus, Pruckner, Gerald J., Theurl, Englerbert, 2008. Stress perception and commuting. Health Econ. 18 (5), 559–576.

Gronau, Reuben, 1973. The intrafamily allocation of time: the value of the housewives' time. Am. Econ. Rev. 63 (4), 634–651.

Hennessy, Dwight A., Wiesenthal, David L., Kohn, Paul M., 2000. The influence of traffic congestion, daily hassles, and trait stress susceptibility on state driver stress: an interactive perspective. J. Appl. Biobehav. Res. 5 (2), 162–179.

Hughes, Jonathan, Antonio, Bento, Daniel, Kaffine, 2013. Carpooling and Driver Responses to Fuel Price Changes: Evidence from Traffic Flows in Los Angeles. Journal of Urban Economics 77 (September), 41–56.

Johnson, Mark, McKnight, Scott, 2009. Warning drivers about potential congestion as a means to reduce frustration-driven aggressive driving. Traffic Injury Prev. 10 (4), 354–360.

Karni, Edi, 1973. The transactions demand for cash: incorporation of the value of time into the inventory approach. J. Polit. Econ. 81, 1216–1225.

Klier, Thomas H., Linn, Joshua, 2010. The price of gasoline and new vehicle fuel economy: evidence from monthly sales data. Am. Econ. J.: Econ. Policy 2 (3), 134–153.
Lave, Charles A., 1985. Speeding, coordination, and the 55 mph limit. Am. Econ. Rev. 75 (5), 1159–1164.
Mackie, Peter. J., Wardman, Mark, Fowkes, Anthony S., Whelan, Gene, Nellthorp, John, 2003. Values of Travel Savings in the UK. University of Leeds Working Paper 567. Institute of Transport Studies.
McCartt, Anne T., Northrup, Veronika S., Richard, A.Retting, 2004. Types and characteristics of ramp-related motor vehicle crashes on urban interstate roadways in Northern Virginia. J. Saf. Res. 35 (1), 107–114.
Mulligan, Casey B., 1997. Scale economies, the value of time, and the demand for money: longitudinal evidence from firms. J. Polit. Econ., 105; 1061–1079.
Parry Ian, W.H., Kenneth, A. Small, 2005. Does Britain or the United States have the right gasoline tax? The American Economic Review 95 (4), 1276–1289.
Peltzman, Sam, 1975. The effects of automobile safety regulations. J. Polit. Econ. 83 (4), 677–725.
Phaneuf, Daniel J., Kling, Catherine L., Herriges, Joseph A., 2000. Estimation and welfare calculations in a generalized corner solution model with an application to recreation demand. Rev. Econ. Stat. 82 (1), 83–92.
Royston, Patrick, Altman, Douglas G., 1994. Regression using fractional polynomials of continuous covariates: parsimonious parametric modelling. Appl. Stat. 43 (3), 429–467.
Shaikh, Sabina L., Larson, Douglas M., 2003. A two-constraint almost ideal demand model of recreation and donations. Rev. Econ. Stat. 85 (4), 953–961.
Shiaw, Ming-Shong, 2004. Value of leisure time based on individuals' mode choice behavior. J. Adv. Transp. 38 (2), 147–162.
Small, Kenneth A., Winston, Clifford, Yan, Jia, 2005. Uncovering the distribution of motorists' preferences for travel time and reliability. Econometrica 73 (4), 1367–1382.
Small, Kenneth A., Verhoef, Erik T., 2007. The Economics of Urban Transportation. Routledge, New York.
Train, Kenneth E., 1998. Recreation demand models with taste differences over people. Land Econ. 74 (2), 230–239.
Vickrey, William S., 1969. Congestion theory and transport investment. Am. Econ. Rev. 59 (2), 251–260.
Watkins, Kari and Hendrik Wolff, 2013. Analysis of Heterogeneous Speeding Behavior. In Transportation Research Record: Journal of the Transportation Research Board, No. 2375, Transportation Research Board of the National Academies, Washington, D.C., 2013, pp. 29–36. http://dx.doi.org/10.3141/2375-04.
West, Brian H., McGill, Ralph N., Hodgson, Jeffrey W., Sluder, Scott S., Smith, David.E., 1999. Development and Validation of Light-Duty Modal Emissions and Fuel Consumption Values for Traffic Models. Federal Highway Administration RD-99-068.
Wickens, Christine M., Weisenthal, David L., 2005. State Driver Stress as a Function of Occupational Stress, Traffic Congestion, and Trait Stress Susceptibility. J. Appl. Biobehav. Res. 10 (2), 83–97.