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ABSTRACT

Value of Time: Speeding Behavior and Gasoline Prices*

Do drivers reduce speeds when gasoline prices are high? Previous research investigating this energy conservation hypothesis produced mixed results. We take a fresh look at the data and estimate a significant negative relationship between speeding and gasoline prices. This presents a new methodology of deriving the 'Value of Time' (VOT) based on the intensive margin (previous VOT studies compare across the extensive margin) which has important advantages to circumvent potential omitted variable problems. While our VOT is 50% of the gross wage rate, we show that previous stated preference estimates are likely downward, whereas previous revealed preference estimates are systematically upward biased. We discuss implications, as VOT today is a key parameter in economics and policy.

JEL Classification: D70, J17, K32, Q26, R41

Keywords: value of time, speeding, gasoline price

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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 Value of Time (VOT) parameter by analyzing drivers speeding behavior as a function of gasoline prices. In comparison to previous methods in the literature, our approach is fundamentally 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 measured by

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[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 III-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.

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 that the VOT estimate could potentially be confounded. Agents can 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.
- Third, stated preference studies use survey designs to orthoganalize the confounding variables. This method generally leads to lower estimates. Calfee *et al*. (2001) estimate stated preference VOTs in the range of 14% to 27% of the wage rate, based on rank ordered dichotomous choice models estimating the willingness to pay for toll lanes to avoid congestion.

Given this divergence in VOT estimates, in this paper we aim to overcome some of the previous methodological problems. 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, 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 minus 0.01 is low in magnitude, we actually see this as an advantage because this small change of speed (corresponding to minus 0.27 mph for a one dollar increase in the price per gallon of gasoline) is arguably much less confounded with other variables.

In order to investigate such VOT bias functions, we evaluate changes in traffic safety due to the change of 0.27 mph, as well as changes to the probability of obtaining a traffic ticket. We find that these 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 57%) 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). Our simulations of various bias functions show distressing results and call for careful experimental designs in future VOT studies.

To put our VOT estimate into context, the magnitude is between *stated preference* derived estimates and *revealed preference* methods. 45%-57% 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%-57% our estimate is higher than what is estimated by most stated preference methods. We suggest new interview

[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.

questions to reveal attitude and preference values which can potentially help to close the gap of the diverging VOT estimates in the literature.

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)[5], 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.

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 cautiously 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 much 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 simple model to derive the corresponding VOT parameter. In the next section we describe the data of the first stage. Section 3 discusses the econometric framework and provides the estimation

[5] 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.

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. Data

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[6], 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.[7] 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 seconds. 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 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.

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

[7] 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.

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 nearest to the respective highway location. 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 (2005-2008). Table 2 summarizes the descriptive statistics of our data collection.

The relationship between gasoline price and weekly average vehicle speed is displayed in Figure 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 Figure 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.[8]

[8] 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 8am and 4 to 6pm), they find that for every $1

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 2am to 4am as the time of the uncongested condition, the average speed in week *t* and highway *i* is estimated by

$$Speed_{it} = \alpha + \beta * price_t + \gamma X_{it} + F_i + Y_t + \varepsilon_{it} \qquad (1)$$

where $price_t$ is the weekly average gas price, F_i are freeway site fixed effects, Y_t are year fixed effects and X_{it} 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 miles per hour 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. In column (2), we control for seasonality by introducing month dummies M_t. 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 gas prices exhibit 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 equation (1) all the amenable regressors and interaction

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increase in gas prices, the average increase in freeway speeds is 3.4 miles per hour (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 miles per hour which is higher than the maximum speed limit of 65 mph in the more densely populated areas in L.A.

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 4pm to 6pm, which we define as the PM time period.[9] Here, again, we find that the within year speed difference of 2.7 miles per hour 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.

Overall, with weekly data, these first estimation results of the effect of gasoline price on speed are inconsistent with the energy saving hypothesis. The estimation results are also inconsistent with the finer conditioning method that we will apply in the following section.

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. 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.
B. 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 ten miles of visibility. In our study we drop all observations with a visibility of less than ten miles.

[9] The PM period refers to the set [4:00pm, 6:00pm) 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.

C. 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 the 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.

D. Finally, all hours are dropped with outside temperatures of 32 degrees Fahrenheit 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 Fahrenheit.

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. 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 A—that the average speed is below 67 mph—reduces the dataset by 15% in the 24 hour period. However, in the more important afternoon PM period, only 2% of the data are dropped because of this condition.

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

$$Speed_{ih} = S(P,\theta) = \alpha + \beta * price_t + M_t + Y_t + F_i + \gamma X_{it} + \varepsilon_{it} \tag{2}$$

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 to 0.19 miles per hour (mph). Column (1) confirms the significance of the month dummies. Note, however, that the inter-year speed range is equal to 0.6 miles per hour from January to July and hence the cyclicality is much less pronounced compared to the cyclicality in the weekly regression of Table 3. Column (2) in addition displays the hourly fixed effects and shows that speeds are generally highest in the afternoon/after-work time period of 4pm to 6pm. 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.[10]

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 to -.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 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 Figure 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

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

type and weight.[11] 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. This translates 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 at a current gas price of four dollar per gallon. 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 that have plagued the VOT literature. 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

[11] 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.

per gallon of gasoline in column (3) of Table 6. The relatively small change in speeds suggests that concerns of other confounding factors can likely be omitted in the interpretation of our resulting VOT estimate. 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.

From the theory point of view, the approach is simple. Increasing the speed S above 60 miles per hour increases gasoline consumption $g(S)$. Given the price of gasoline P, a driver minimizes total costs $C(S|P) = Pg(S|P) + \text{VOT}t(S|P) + d(S|P)$. 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

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

it is easy to show that $dS/dP < 0$, 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 4:00pm to 6:00pm (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 the 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 seconds. This increase in travel time comes at the benefit of savings of 43.56 cubic centimeter 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 seconds per passenger (equal to a total of $n \cdot 14=17$ saved seconds per vehicle) results in a

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

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.

Discussion and Robustness

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. We quantify these benefits of reducing speed by 0.27 mph as

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

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).

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).[12] 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 26 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.[13] With this, we estimate that Δd^{A} = 0.6 cents per hour of driving. This implies a VOT of $[P^{2}\Delta g+\Delta d^{A}]/[t(S|P^{2})-t(S|P^{1})]$ = \$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

[12]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.

[13] 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).

speeding to fatalities. Ashenfelter and Greenstone (2004)[14] 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 the 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.[15] Second, in our calculations we assumed that an *individual* motorist reduces the *average* highway speed $\bar{S}$ by 0.27 mph. An individual driver can however only moderately influence $\bar{S}$ 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.[16] 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.

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

[14] 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.

[15] For example, in the year 2005 6.5% of the crashes (conditional on the conditions specified in footnote 26) 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.

[16] Hence, instead of cost minimizing $d^A(\bar{S})$ 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.

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[17]. By matching our distribution of vehicle speeds to 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 Δd^T = 0.5 cents per hour of driving[18]. 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. The 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

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

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

[17] 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 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).

[18] 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 80mph and (ii) below 70 mph. This yields Δd^S estimates of 1.0 cent and 0.3 cent per hour of driving respectively. See the Appendix for details.

because in calculating $\Delta d^A + \Delta d^T$ we made assumptions which likely lead to an overestimate of the benefits of reducing speeds.

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. Hence, our VOT estimate of $10.02 to $12.70 per hour accounts for 45%-57% 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. 57% 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.[19] 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.

<u>*Disamenities of Driving at non-marginal Speed Changes*</u>

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 a general idea how various disamenity 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.[20] We further assume that the hourly VOT of Los Angeles is 50% of the Los Angeles Metropolitan county wage rate of \$22.88.

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 travelled statistics from California State Department of Transportation. Using the same method to derive Δd^A as in the previous subsection (for details see the Appendix), we find $\Delta d^A/[t(S|\text{toll-lane})-t(S|\text{main-}$

[19] 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.

[20] 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 the Appendix.

lane)] = \$10.75. In other words, the omission of Δd^{A} alone produces a bias of striking 94% of the VOT.[21]

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.[22]

[21] 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.

[22] 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.

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 the Appendix. Again piecewise interpolating between the provided 5mph 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 VOT = $[P^2\{g^{Davis10}(S|P^1)\text{-}g^{Davis10}(S|P^2)\}] / [t(S|P^2)\text{-}\ t(S|P^1)]$ = \$10.16/hour (or 46% of the wage rate) with a standard error of 0.21.

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 miles per hour. 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).[23] 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

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

Table 5 does change the point estimate of gas price slightly at the third digit from -0.221 (0.032) to -0.223 (.031). As further evidence that congestion is likely not a confounder at our rural sites, Figure 3 displays speeds on the right side vertical axis as scatter dots over the 24hour of the day and graphs the average number of vehicles per hour on the left vertical axis. Figure 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.

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 one hour 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 a new 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. 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 important 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 smoothening projects (which currently represents the largest share of DOT's expenditures).[24]

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

[24] 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).

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*. 2010, 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 minus 0.01 translating into over one billion dollar gas expenditure savings on all U.S. highways annually for a one dollar increase in the price of gas per gallon. 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.

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[PARTS OR ALL OF THIS APPENDIX COULD BE FOR ONLINE PUBLICATION]

Appendix:

Speed data: WSDOT records the total number of vehicles passing over the loop detectors per highway direction and quantifies speeds in j = {0,2,...14} bins per hour h, the first bin b_0 representing the total number of vehicles traveling below 35 mph and then in five mile per hour (mph) increments from 35 to 100 mph. The final bin b_{14} quantifies the number of vehicles with any speed above 100 mph. In order to calculate the average speed per hour, we assume that the speed per bin is the average within-bin speed and we set $S(b_0)$ and $S(b_{14})$ as 32.5 and 102.5 mph respectively, such that

$$speed_h = \Sigma_j\{(S(b_0) + 5j)\, b_{jh}\} / \Sigma_j b_{jh}.$$

Precipitation: In the NOAA dataset precipitation is provided by hour in inches of rain. In 42% of all hours with rain, however, precipitation is defined nonnumerically as "Trace" which is precipitation of an unknown quantity below 0.01 inches per hour. In our weekly regressions, the sum over the hours with trace do not contribute to the overall weekly total precipitation measured in inches.

Data frequency and timing: The WSDOT speed dataset is provided by hour h and site s in clock time. Each year one hour is missing in the dataset, which is the clock time when Daylight Saving Time transfers to Standard Time (where in fact this clock hour should appear twice). In contrast the weather NOAA files have their own time variable which represents the exact time in minutes the weather reading was taken (which varies over time and locations). We changed the weather time to round to the closest clock hour time.

Holidays: We define a day as a holiday by following the typical state employee holiday calendar. Holidays are Martin Luther King, Presidents Day, Memorial Day, 4th of July, Labor Day, Veterans Day, Thanksgiving, the day after Thanksgiving, Christmas Eve, Christmas and New Years. If a holiday falls on a Saturday, we use the Friday before as the holiday. If the holiday falls on a Sunday, we use the Monday after. If Christmas Eve and New Years Eve fall on midweek, these days are not coded as Holidays. The exact list of Holidays is: 17 jan 2005, 21 feb 2005, 30 may 2005, 04 jul 2005, 05 sep 2005, 11 nov 2005, 24 nov 2005, 25nov 2005, 26 dec 2005, 02 jan 2006, 16 jan 2006, 20 feb 2006, 29 may 2006, 03 jul 2006, 04 jul 2006, 04 sep 2006, 10 nov 2006, 23 nov 2006, 24 nov 2006, 25 dec 2006, 01 jan 2007, 15 jan 2007, 19 feb 2007, 28 may 2007, 04 jul 2007, 03 sep 2007, 12 nov 2007, 22 nov 2007, 23 nov 2007, 24 dec 2007, 25 dec 2007, 31dec 2007, 01 jan 2008, 21 jan 2008, 18 feb 2008, 26 may 2008, 04 jul 2008, 01 sep 2008, 10 nov 2008, 11 nov 2008, 27 nov 2008, 28 nov 2008, 25 dec 2008, 26 dec 2008.

Vehicle Occupancy Rate:

While we were unable to find specific estimates of the vehicle occupancy rate for speed measuring sites in our dataset, by reviewing the literature we find that at highways with similar characteristics on workdays at the PM period the vehicle occupancy rate is ranging from 1.1 to 1.3 persons per vehicle. We draw these estimates from Heidtman *et al*. (1997) and Area Plan Commission (2003, 2010). For this study we assume a vehicle occupancy rate of 1.2.

Gasoline Consumption as a Function of Traveling Speeds:

A crucial input for the calculation of the VOT parameter is the construction of the gasoline consumption function $g(S)$. To investigate the robustness on our $g(S)$ assumption, in this paper we

(a) use the commonly utilized West *et al*. (1999) data and

(b) as a robustness we contrast our results with a more recent study by Davis *et al*. (2010) that uses newer data on $g(S)$.

Ad (a): For cost benefit analysis, U.S. governmental agencies rely on the West *et al*. (1999) data, as summarized by Davis (2001) which is based on nine vehicles sampled from a mix of automobiles and light trucks of model years 1988–1997. The average of the vehicle gas consumption data are displayed in Table A1, column (2). By piece-wise linearly interpolating between the data points we estimate that the derivative $\delta g^{West99}/\delta S$ = 0.06018 in the relevant interval of $S \in [70,75]$.

Ad (b): Davis *et al*. (2010) provide estimates of vehicle gasoline consumption for different vehicle classes based on newer vehicle models. Based on the Davis *et al*. (2010) data we calculate the average miles per gallon for large, medium and small SUVs as displayed in Table A1, column (2) and obtain $\delta g^{Davis2010}/\delta S$ = 0.06101 in the relevant interval of $S \in [70,75]$.

TABLE A1: GASOLINE CONSUMPTION SPEED RELATIONSHIP BASED ON TWO STUDIES

	from West *et al*. (1999) as summarized by Davis (2001) based on nine vehicles of model years 1988–97 sampled from automobiles and light trucks			average of small, medium and large SUVs, from Davis, Diegel and Boundy (2010): Table 4.26		
	(1)			(2)		
Speed	miles per gallon	gallon / (100 miles) $g(S)$	$\delta g/\delta S$	miles per gallon	gallon / (100 miles) $g(S)$	$\delta g/\delta S$
65	29.2	3.4247	0.061337	29.67	3.37	0.0522349
70	26.8	3.7313	0.060183	27.53	3.63	0.0610093
75	24.8	4.0323	n/a	25.40	3.94	

Notes: The entries of the derivative $\delta g/\delta S$ refer to the speed range from the same row to the speed row below. Hence in case of West *et al*. (1999), for speeds between 65 and 70 the derivative of $g^{West99}(S)$ with respect to 100 miles driven is $\delta g \delta S(S \in [65,70]) = 0.061337$.

Calculation of the Standard Error of the Value of Time Coefficient:

Summarizing all parameters in (2) as θ, and after simplifying we obtain

$$\text{VOT} = P^2 \delta g/\delta S \,/\, [1/S(P^2|\theta) - 1/S(P^1|\theta)]$$

Because VOT is a nonlinear function of θ, the standard error of the VOT coefficient is derived via the delta method as

$$\text{std.err(VOT)} = \text{Sqrt}\{\delta\text{VOT}/\delta\theta^{\text{T}}\ \text{Cov}(\theta)\ \delta\text{VOT}/\delta\theta\}.$$

While θ is estimated via least squares, the estimate of the covariance matrix Cov(θ) relies on the covariance structure of the disturbance $\varepsilon_{ih} = Speed_{ih} - f(\mathbf{z}_{ih})$, with $\mathbf{z}_{ih}$. We allow ε_{ih} to be both heteroskedastic and clustered on a weekly level w, such that the expectations

$$\text{E}(\varepsilon_{iwh}\varepsilon_{iwh}|\mathbf{z}) = \sigma^2_{iwh},\ \text{E}(\varepsilon_{wj}\varepsilon_{wk}|\mathbf{z}) = \rho_{wj}\ \forall\ j \neq k, \text{ and } E(\varepsilon_w \varepsilon_{w'}^{\text{T}} \mid \mathbf{z}) = \mathbf{0}\ \ \forall\ w \neq w'.$$

The motivation for selecting this block-diagonal structure is that it accounts for autocorrelation as well as for common shocks that affect multiple sites contemporaneously. The clustered sample covariance matrix estimator is therefore used for θ (Bertrand *et al*. 2004).

Calculation of Benefits from Reducing Speed due to Reduced Fines from Speeding Tickets

In order to calculate the monetary benefit from reducing speed in terms of the reduced probability to obtain a speeding ticket, Δd^{T}, we collect data from the following three sources.

(a) The average annual total number of speeding tickets issued on rural highways in Washington state from 2005-2008 are collected through a public records request to the Washington State Patrol (2011).

(b) Data on average annual total vehicle miles traveled from 2005 to 2008 on rural highways in Washington State are obtained from the Washington State Department of Transportation (2011)[25].

[25] Rural highway VMT from 2005-2008 can be found on pp. 48 in 2010 WSDOT Annual Traffic Report (WSDOT 2011).

(c) The schedule of speeding ticket fines as a function of the vehicle speed is collected from the Washington Courts (2011) which expresses the fines *T(k)* to be traveling at speeds k to $k+5$, given a speed limit of 70 mph. $k \in \mathbb{K}=\{70,75,\ldots 100\}$.

The hourly difference in costs due to a change in speed from $S|P^1$ to $S|P^2$ is

$$\Delta d^T = \frac{\sum_{k\in\{\mathbb{K}\}} T(k) \int_k^{k+5} f^1(S) - f^2(S)dS}{\int_{k_{min}}^{\infty} f^1(S)dS} p(T)$$

where k represents the minimum speed in each 5 mph interval in set $\mathbb{K}$, $f^{\,i}(S)$ is a probability density function of S given the gasoline price P^i, i =1,2, and $p(T)$ is the probability of receiving a ticket. The numerator, representing the weighted average of fines, is divided by the proportion of drivers eligible to receive speeding tickets.

To calculate Δd^T numerically, we match the average PM time period speed bin data from our speed measuring sites to the schedule of fines $T(k)$, creating a weighted average of fines. We initially fit our PM speed histogram to a normal distribution $f^1(S)$ because we only have speeds in discrete 5 mph bins. (For robustness we also fit the data assuming a uniform distribution within each speed bin. The different distributional assumption leads to qualitatively similar results and are available from the authors upon request). To calculate the expected number of drivers potentially obtaining a speeding ticket at $S|P^1 = 70.82$, we match the area under the normal density f^1 to the appropriate 5 mph fine interval and integrate over the sum over the bins of fines. Secondly we recalculate a new normal distribution $f^2(S)$ for the lower speeds $S|P^2 = 70.55$ subtracting 0.27 mph from the normal density mean and calculate the corresponding new weighted average of speeding fines. Finally, to estimate the probability of receiving a speeding ticket per mile traveled $p(T)$, we divide the average annual speeding tickets by the average annual vehicle miles traveled.

Finally, an assumption on which drivers receive speeding tickets affects the set $\mathbb{K}$. Since the ticketing data provided by WSP are not disaggregated by the 5 mph speed brackets, (neither do the data include total revenues from speeding tickets) we need to make an assumption about which vehicles actually receive tickets. In Table A2, in Scenario 1, we first assume that all drivers going above 70 mph receive tickets, with $\mathbb{K} = \{70, 75, \ldots, 100\}$. Next we calculate the benefits under the assumption that $\mathbb{K} = \{75, 80, \ldots 100\}$ hence that only vehicles going above 75 mph will be ticketed. Lastly, in Scenario 3 we assume that $\mathbb{K} = \{80, 85, \ldots 100\}$, hence that only vehicles driving above 80 mph obtain speeding tickets. Since the number of tickets is fixed, increasing the speeds at which tickets are issued also increases the weighted average of fines, as displayed in Table A2.

The columns of Tables A2 display the estimates of the weighted average of fines, speeding costs per hour, the differentials for reduced speed, and the contribution to VOT. The rows display the costs based on the original and new distribution of speeds evaluated at $S|P^1$ and $S|P^2$.

TABLE A2. BENEFITS FROM REDUCING SPEEDING TICKET COSTS

	Weighted Average of Fines	Cost per Hour from Speeding Tickets	Change in Costs from Reduced Speed	Change in VOT from Reduced Speed
	Scenario 1: Cars Ticketed above 70 mph			
High Speed	\$111.22	\$0.101	\$0.003	\$0.62
Low Speed	\$108.08	\$0.098		
	Scenario 2: Cars Ticketed above 75 mph			
High Speed	\$126.39	\$0.115	\$0.005	\$1.17
Low Speed	\$120.47	\$0.109		
	Scenario 3: Cars Ticketed above 80 mph			
High Speed	\$151.29	\$0.137	\$0.010	\$2.10
Low Speed	\$140.69	\$0.128		

Notes: Cost per hour is the expected cost d^T based on the probability of obtaining a ticket. Change in VOT expresses the bias to the VOT estimate if the change in the disamenity Δd^T were omitted. 'High Speed' and 'Low Speed' refer to the speeds of $S|P^1$ = 70.82 and $S|P^2$ = 70.55 mph, respectively.

Calculation of Benefits from Reducing Speed due to Reduced Accidents

This section describes the data and methodology to calculate $\Delta d^{A} = \Delta d^{A,PD} + n\ (\Delta d^{A,H} + \Delta d^{A,F})$ which monetizes the benefits associated with the decreased risk of accidents at the speed decrease from $S|P^1$=70.82 to $S|P^2$=70.55. To calculate the change in accident rates (accidents per vehicle miles traveled) as a function of speed, the formulas by Cameron and Elvik (2010) and Ashenfelter and Greenstone (2004) require that we first determine a 'baseline' accident rate which represents the conditions at our highway sites. All baseline numbers will be superscripted by B.

The benefits from decreased fatalities are calculated by

$$\Delta d^{A,F} = 70.82 \left(\frac{\hat{F}^{B}(S|P^{1}) - \hat{F}^{CE}(S|P^{2})}{\widehat{VMT}^{B}}\right) Cost^{F} \tag{A1}$$

(a) $\hat{F}^{B}(S|P^{1})$ is our estimate of the baseline number of fatalities, which we calculate as the average annual number of fatal vehicle crashes under ideal conditions on all U.S. rural highways from 4:00-6:00 PM for the years 2005 to 2008. The data are obtained from the National Highway Traffic Safety Administration' Fatality Analysis Reporting System (FARS) (2005-2008)[26]. In our calculations we use the U.S. national fatalities because there are too few fatalities in Washington State alone to obtain a reliable state level estimate of the fatality rate.

(b) $\widehat{VMT}^{B}$ is the estimated number of vehicle miles traveled under the same restrictions used to calculate $\hat{F}^{B}(S|P^{1})$. We calculate $\widehat{VMT}^{B}$ as

$$\widehat{VMT}^{B} = VMT^{R,US} * \Sigma total^{AD,PM}/total$$

[26] In the FARS dataset using the crash outcomes from 2005 to 2008 we control for the outcomes (displayed in parenthesis) of the following variables: Atmospheric Conditions (no rain, clear visibility), Construction Zone (no), Crash Hour (4pm-6pm), Day of Week (Monday to Friday), Holiday (no), Number of Travel Lanes (2 and higher), Relation to Junction (non- junction present), Roadway Alignment (Straight), Roadway Function Class (Rural-Principal Arterial-Interstate, Rural-Principal Arterial-Other, Rural-Other), Roadway Profile (Level), Roadway Surface Condition (dry), Route Signing (Interstate, U.S. Highway, State Highway), Speed Limit (60 to 95), and Trafficway Flow (Divided Highway, Median Strip(With Traffic Barrier, One Way Trafficway). Furthermore, for all variables we also include the outcomes: "blank", "unknown", "Other".

whereby *(i)* $VMT^{R,US}$ is the average annual vehicle-miles travelled for all rural highways in the U.S. from 2005-2008, which we obtained from the Federal Highway Administration (2005-2008) and (*ii*) $\Sigma total^{AD,PM}/total = 0.068$ is the proportion of vehicles passing the double loop detectors under ideal driving conditions as calculated by our conditions A. to D. in the PM timeperiod as a percentage of to the total vehicles passing the loop detectors at any condition from 2005 to 2008.[27]

(c) $\hat{F}^{CE}(S|P^2)$ is the predicted number of accidents conditional on $S|P^2$. $\hat{F}^{CE}(S|P^2)$ is calculated using the formula in Cameron and Elvik (2010) $\hat{F}^{CE}(S|P^2) = \hat{F}^B(S|P^1) * \left(\frac{S|P^2}{S|P^1}\right)^{\beta^F}$ where β^F is the power parameter for rural highway fatal collisions obtained from column one of Table 8 on p. 1913 of Cameron and Elvik (2010).

(d) $\Delta d^{A,H}$ and $\Delta d^{A,PD}$ are calculated in principle the same way as $\Delta d^{A,F}$ substituting the appropriate power parameter, β^H and β^{PD} respectively, again using the first column of Table 8 in Cameron and Elvik (2010). The following additional adjustments are necessary. Since we were not able to directly collect $\hat{H}^B(S|P^1)$ and $\widehat{PD}^B(S|P^1)$ we estimate these as,

$$\frac{\hat{H}^B(S|P^1)}{\widehat{VMT^B}} = \frac{H^{R,WA}}{VMT^{R,WA}} * \left(\frac{\frac{\hat{F}^B(S|P^1)}{\widehat{VMT^B}}}{\frac{F^{R,WA}}{VMT^{R,WA}}}\right)$$

where $\frac{H^{R,WA}}{VMT^{R,WA}}$, and $\frac{F^{R,WA}}{VMT^{R,WA}}$ are the average annual accident rates of injuries and fatalities on Washington State's rural highways obtained from the Washington

[27] The unconditional aggregate fatality rate $F^{R,WA}/VMT^{R,WA}$ for Washington State (WA) for all rural (R) highways can be obtained from the 2009 Washington State Collision Data Summary, p.25 produced by Washington State Department of Transportation (2010). Using this published fatality rate is not appropriate however for our baseline fatality rate because our study controls for the most ideal driving conditions analyzing 'safe' sites under the best possible weather and driving conditions.

State Department of Transportation (2010). The final term, $\left(\frac{\frac{\widehat{F}^B(S|P^1)}{\widehat{VMT}^B}}{\frac{F^{R,WA}}{VMT^{R,WA}}}\right)$, is the proportion of the ideal rural interstate PM fatality rate to the aggregate Washington rural interstate rate. To calculate the baseline property damage rate $\frac{\widehat{PD}^B(S|P^1)}{\widehat{VMT}^B}$, we simply replace $\frac{H^{R,WA}}{VMT^{R,WA}}$ with $\frac{PD^{R,WA}}{VMT^{R,WA}}$, also obtained from Washington State Department of Transportation (2010).

(e) $Cost^j$ represent the monetary costs per accident type j = *F, H, PD,* which we obtain from AASHTO (2010)[28].

(f) Finally, the pre-factor of 70.82 of equation (A1) translates the benefits from reduced accidents per mile into the benefits from driving per hour at the baseline speed of 70.82 mph.

Since the $\Delta d^{A,F}$ is a high proportion of the total cost of Δd^{A}, for robustness we also use the study by Ashenfelter and Greenstone (2004) to estimate the predicted fatalities at the lower speed as,

$$\widehat{F}^{AG}(S|P^2) = \widehat{F}^B(S|P^1)\big(1 + .14(S|P^2 - S|P^1)\big)$$

where .14 is the increase in fatalities for every mph increase in speed as determined in Ashenfelter and Greenstone (2004).

As an additional robustness check we employ different estimates for $Cost^F$, commonly referred to as Value of Statistical life, from the Department of Transportation (DOT 2009) and Ashenfelter and Greenstone (2004). Throughout all the specifications for VSL the non-fatality costs, $Cost^{PD}$ and $Cost^H$, remain constant as determined by AASHTO (2010).

[28] Estimates for $Cost^{PD}$, $Cost^H$, and $Cost^F$ can be found on pp. 190 in column 3 of table 5-17 of AASHTO (2010).

TABLE A3: TRAFFIC ACCIDENT BENEFITS

Panel (a) Per Hour Traffic Accident Benefits from Reducing Speed by .27 mph

		Value of Statistical Life Estimate by		
		DOT	AASHTO	A&G
Speed-Fatality Parameter Estimate by	Cameron & Elvic	$0.007	$0.006	$0.004
	Ashenfelter & Greenstone	$0.013	$0.011	$0.006

Panel (b): Contribution to the VOT in Dollars from Reducing Speed by .27 mph

		Value of Statistical Life Estimate by		
		DOT	AASHTO	A&G
Speed-Fatality Parameter Estimate by	Cameron & Elvic	$1.72	$1.50	$1.00
	Ashenfelter & Greenstone	$3.33	$2.79	$1.58

Notes: Panel (a) displays Δd^A in dollars and Panel (b) Δd^A / $[t(S|P^2)$- $t(S|P^1)]$ in dollars based on various scenarios. In the rows we display the sources of studies we draw the speed-fatality coefficients from and in the columns the sources of the different assumptions on the VSL. The property and injury benefits are derived from AASHTO (2010) and Cameron and Elvik (2010) for all fields. Benefits are calculated as the difference in accident damages over a 70.82 mile trip when an individual drivers speed is reduced from 70.82 mph to 70.55 mph. In 2008 dollars, the VSL is $5,800,000, $4,655,771.01 and $2,065.835.64 for the DOT (2009), AASHTO (2010) and the Ashenfelter and Greenstone (2004) VSL study, respectively.

Table A3 shows the full range of benefits for Δd^A for a 0.27 mph decrease in speed per hour. The columns of Table A3 display how safety benefits change depending on the estimate of the VSL used by the Department of Transportation (DOT 2009), AASHTO (2010) and the VSL estimate by Ashenfelter and Greenstone (2004) (abbreviated by A&G). The rows represent the study from which we obtain the predicted number of fatalities, $\hat{F}(S|P^2)$.

Bias from Omitting the Second Order Effects $d(S)$ in a Dichotomous Choice Setting

In order to explore the potential bias from omitted elements of $d(S)$ in discrete choice settings, 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 the toll lane of the California SR-91 in Los Angeles the traffic fee amounts \$3.85[29]. For details we refer to the 'Brooking revealed preference' setup in Small *et al*. (2005). We assume VOT to be 50% of the 2008 LA gross wage rate of \$22.88, obtained from the Bureau of Labor Statistics (2008). Because we do not have the individual data on time savings in the Brooking setting, we calculate speed differentials from Bento *et al*. (2011). This study analyzes traffic on HOV and main lanes for different time periods from 2004-2007 on the I-10 in California. Since Small *et al*. (2005) study the morning commute, we get an estimate of the morning rush hour minute per miles by Bento *et al.* (2011, Table 1), which translates into speeds of 46.11 mph and 36.54 mph for the HOV lane and main lane respectively. This translates into time savings of 15.27 minutes for the 44.8 mile long highway commute. In this setting, the procedure for calculating Δd^A is in principle the same as explained earlier in this paper, predicting new fatalities using $\hat{F}^{CE}(S|P^2)$ and utilizing the VSL from the AASHTO (2010). To calculate the appropriate baseline rate $\hat{F}^B(S|P^1)$ we query the FARS system for highway crashes in California from 2004-2007 (National Highway Traffic Safety Administration, 2004-2007) and estimate $\widehat{VMT}^B$ through collecting the annual highway VMT from the California State Department of Transportation Public Road Data reports (2004-2007)[30]. The gas expenditure saving, $P\Delta g$, is calculated by using the data of $g^{\text{West}}(S)$ approximated by a quadratic functional form. To calculate the psychological costs of being in a traffic jam, Δd^{Jam}, we assume that $\Delta d^A(S) = -\Delta d^A(Var(S))$, so the increased accident cost due to higher speeds in the HOT lane perfectly offset the decrease in accident cost due to reduced congestion. This allows us to back out the bias of Δd^{Jam} as

$$\frac{\Delta d^{Jam}}{t(S|main\ lane) - t(S|toll\ lane)} = VOT - \frac{Toll + P\Delta g}{t(S|main\ lane) - t(S|toll\ lane)}.$$

[29] The schedule of toll fees is collected from Orange County Transportation Authority (2011). We calculate the average toll of \$3.85 by matching the hourly toll schedule from 4:00am to 9:00am on weekdays to the proportion of drivers in the sample in Small *et al.* (2005) that travel at each hourly interval.

[30] These VMT can be found in Table 1 in all editions of the report under the category State Highway Annual Vehicle Miles Traveled on pp. 4 – 8 depending on the year (California State Department of Transportation 2004-2007).

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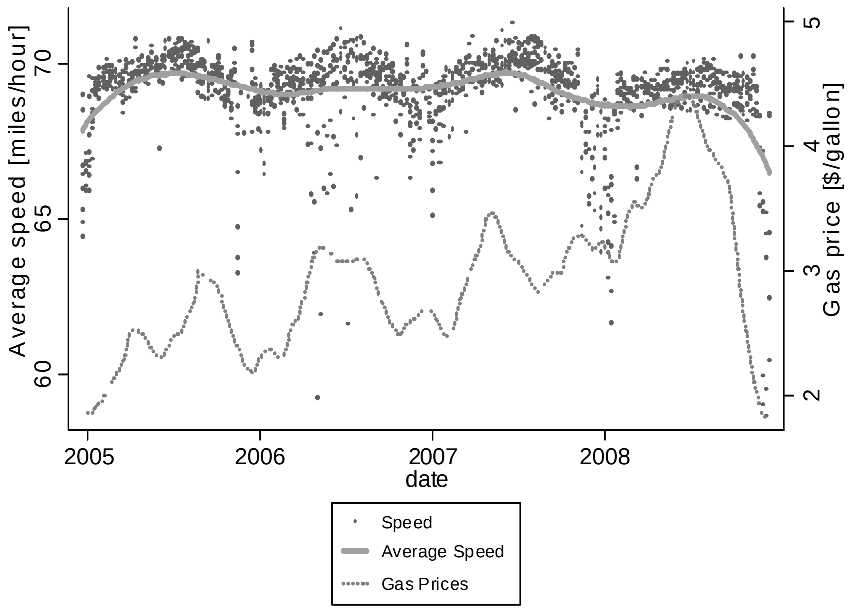
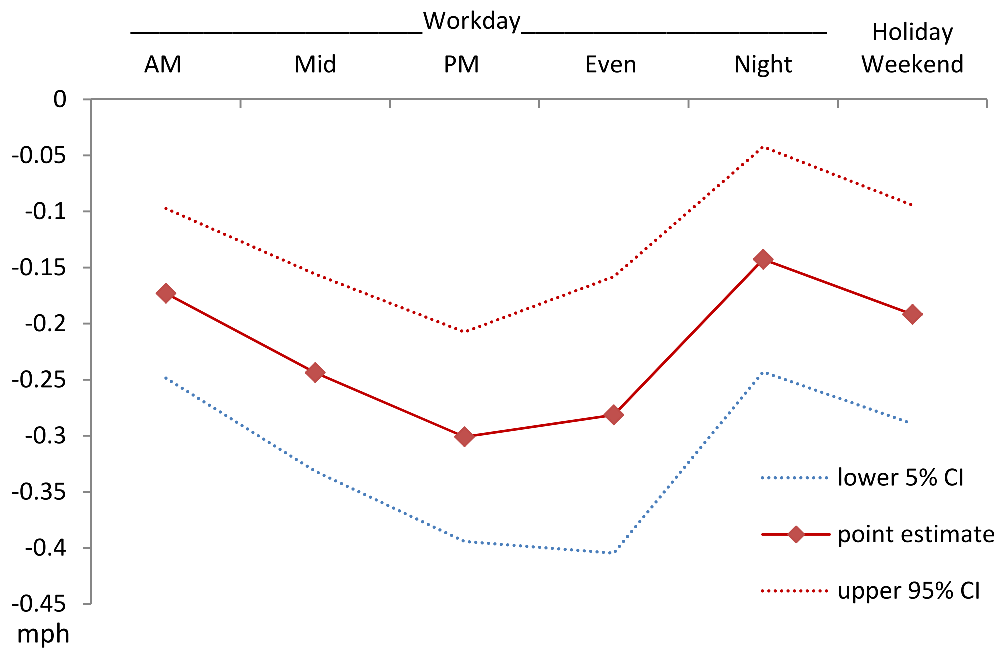
FIGURE I: AVERAGE SPEED PER WEEK AND GAS PRICES, 2005 TO 2008



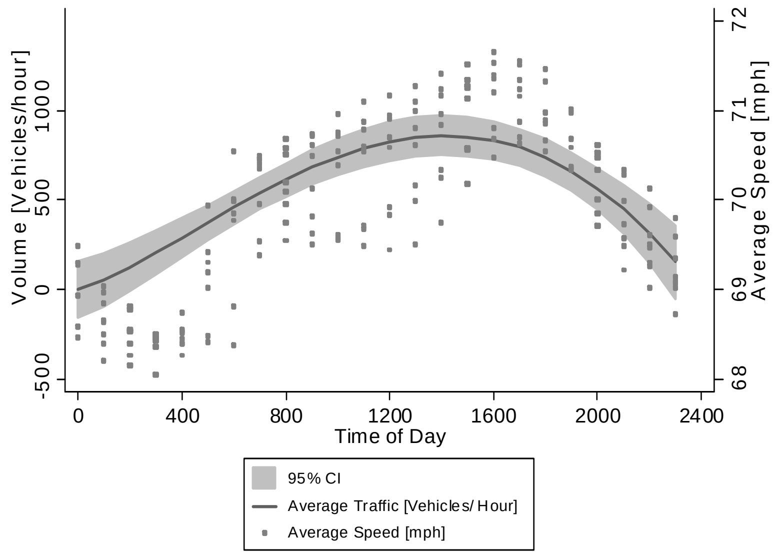
Notes: The bold grey line displays average speed estimated by the locally weighted scatterplot smoothing method with bandwidth of 0.3. Each dot represents the average weekly speed by highway location.

FIGURE II: 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. Timeperiods as defined in footnote 10.

FIGURE III: 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.

TABLE I: SPEED DATA SITE LOCATIONS

Site	WSDOT 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: Description of the sites of the WSDOT speed data. Details see the Appendix.

TABLE II: 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.

TABLE III: 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	1,429	1,429	1,429	1,428	1,428	1,428
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.

TABLE IV: DATA REMOVED FOR REGRESSIONS

	All Day		PM period	
	(1)	(2)	(3)	(4)
Data	Observations	%	Observations	%
Rain	30617	13.5%	1754	13.7%
Temperature ≤ 32	29967	13.2%	892	6.9%
Visibility < 10	28674	12.6%	1117	8.7%
Average Speed<67	33326	14.7%	294	2.3%
Total observations removed	82409	36.3%	3003	23.4%

Note: The sum over the observations removed by each variable do not add to the 'total observations removed'.

TABLE V: HOURLY VEHICLE SPEED REGRESSIONS

Panel A: Basic Models

COEFFICIENT	(1) Basic Model (Month, Site & Year fixed effects)	(2) Basic Model & Hour Fixed Effects	(3) Basic Model & Hour & 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***	-1.1636***
		(0.0222)	(0.0324)
Hour 8:00		-1.0112***	-1.1080***
		(0.0201)	(0.0318)
Hour 9:00		-0.9508***	-1.0449***
		(0.0209)	(0.0322)
Hour 10:00		-0.8824***	-0.6043***
		(0.0187)	(0.0243)
Hour 11:00		-0.7951***	-0.5160***
		(0.0183)	(0.0246)
Hour 12:00		-0.6975***	-0.4193***
		(0.0170)	(0.0231)
Hour 13:00		-0.5820***	-0.2956***
		(0.0158)	(0.0235)
Hour 14:00		-0.4040***	-0.1194***
		(0.0155)	(0.0239)
Hour 15:00		-0.1628***	0.1205***
		(0.0133)	(0.0232)
Hour 17:00		-0.0153	-0.0171
		(0.0190)	(0.0186)
Hour 18:00		-0.1767***	-0.0162
		(0.0348)	(0.0375)
Hour 19:00		-0.5164***	-0.3513***
		(0.0412)	(0.0424)
Hour 20:00		-0.9375***	-0.7764***
		(0.0347)	(0.0361)
Hour 21:00		-1.3618***	-1.2065***
		(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

Notes: Robust standard errors in parentheses clustered by week. All regressions include month, site and year fixed effects (Basic Model). *** p<0.01, ** p<0.05, * p<0.1

TABLE V: HOURLY VEHICLE SPEED REGRESSIONS–CONTINUED

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 & unemployment, income	(4) Interacted Fixed Effects Model Gas price effect unpooled over Timeblocks & unemployment, income
Gas price	-0.1950*** (0.0329)	-0.2724*** (0.0490)	-0.2206*** (0.0318)	-0.3009*** (0.0477)
Gas price x "AM"		0.1233*** (0.0467)		0.1279*** (0.0465)
Gas price x "Midday"		0.0622 (0.0404)		0.0572 (0.0401)
Gas price x "Evening"		0.0133 (0.0448)		0.0195 (0.0449)
Gas price x "Night"		0.1435** (0.0623)		0.1582** (0.0623)
Gas price x "Non-workday"		0.1059 (0.0689)		0.1091 (0.0671)
Unemployment			-0.1986*** (0.0361)	-0.1993*** (0.0362)
Income			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	0.65	0.65	0.65	0.65

Notes: 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 10. Robust standard errors in parenthesis clustered by week. *** p<0.01, ** p<0.05, * p<0.1.

TABLE VI: 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 & income
Gas price	-0.2874*** (0.0528)	-0.2491*** (0.0488)	-0.2701*** (0.0483)
Unemployment			-0.1514*** (0.0547)
Income			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	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<0.01, ** p<0.05, * p<0.1.