Step on It: A New Approach to Improving Vehicle Fuel Economy *

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Abstract

We show that new connected vehicle technologies can save substantial fuel and time. These technologies allow vehicles to communicate with surrounding infrastructure, which smooths traffic flows and decreases stops. Using the quasi-random variation when drivers drive routes repeatedly, sometimes "making" more lights, we show that a 10% reduction in stops per mile and idle time per stop reduces fuel consumption by 1.5%, travel time by 4%, and generates $25.5 billion in annual benefits. These benefits arise even in the presence of gasoline taxes because of the variation in fuel economy caused by roadway conditions outside the control of drivers.

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1 Introduction

Climate change is arguably the most critical issue facing global policymakers today. Global temperatures set record highs in 2016 for the third year in a row and 16 of the 17 hottest years ever recorded have occurred since 2000. In the U.S., transportation generates 26% of total greenhouse gas emissions and limiting the emissions from transportation has been a topic of extensive policy debate.[1] In response to these concerns, economists have invested substantial energy in analyzing the efficiency of the two main policy approaches to reducing emissions from transportation: the gasoline tax and fuel economy standards such as Corporate Average Fuel Economy (CAFE) Standards in the U.S.[2] Generally this line of research as favored gasoline taxes because they address three separate dimensions of fuel consumption: the fuel economy of vehicles people buy, the amount that these vehicles are driven, and how aggressively people drive conditional on their vehicle and mileage.

Comparatively little attention has been paid to how technology is radically changing the transportation sector and the effect this will have on fuel consumption. "Connected vehicle technologies" that allow vehicles to communicate with each other (vehicle-to-vehicle or V2V communications) and the surrounding infrastructure (streetlights, crossing signals, etc, termed vehicle-to-infrastructure or V2I communication) are starting to improve stoplight timing and smooth traffic flows, while ride-sharing services such as Uber and Lyft and "self-driving" vehicles foretell a future when autonomous vehicles may eventually make individual vehicle ownership obsolete. In this paper we suggest that the adoption of these technologies can reduce emissions by more than is possible with a gasoline tax alone, exactly because gasoline taxes do not affect the optimization of the transportation *system,* but rather merely provide drivers with the correct incentives conditional on the existing system. In fact, in his seminal 1960 article, Coase uses the exact example of a car stopped at a stoplight with no cross traffic as an example of a situation where Pigovian taxes fail and welfare can be improved only with improvements to the system itself (Coase (1960), p.34).

Why has the economics literature paid so little attention to these transformative technologies when evaluating policies to reduce gasoline consumption?[3] The most straightforward

[1] U.S. EPA, "Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990-2014"

[2] Austin and Dinan (2005), Bento et al. (2009), Fullerton and West (2010), Feng et al. (2013), Anderson and Sallee (2016), Gruenspect (1982), Crandall (1992), Goldberg (1998), Anderson et al. (2011), Jacobsen (2013), Jacobsen and van Benthem (2015), West et al. (2017), among numerous others.

[3] Vehicle-to-infrastructure communication in particular is a technology that will require policy intervention because it requires that streetlights be updated to be able to receive vehicles' signals and that the transporation system have the computing power and software to optimize signals across the entire system. While some vehicle-to-vehicle communication may occur without policy intervention, the major changes from

answer may be that these technologies will lead to out-of-sample changes in the transportation system, and these types of changes are difficult to predict empirically. We leverage a unique data set of real-world driving for a set of drivers in identical vehicles that provides information every one-tenth of a second on speed, acceleration, and fuel consumption, among many other variables. This data allows us to observe the same drivers driving the same routes repeatedly. We use the quasi-experimental variation in the number of stops per mile and the idle time per stop that occurs when a driver "makes" lights on these routes versus "missing" those same lights to estimate the potential fuel and time savings from improving traffic flows via vehicle-to-infrastructure (V2I) communication technology. To our knowledge, our analysis of the potential benefits of V2I communication in real-world driving scenarios is unique. Although engineers have studied the effect of V2I communication in simulated models (e.g. Feng et al. (2015)), we are able to look at a large variety of real-world driving situations and routes and account for how drivers react to these situations in ways which may or may not be rational or optimal.

We find that even for a very conservative estimate of the effect of V2I communication (a 10% reduction in the average number of stops per mile and the average idle time per stop on any given route) fuel consumption would decrease by 1.4% and travel time would decrease by 4%. Even with extreme assumptions about the cost of these technologies, a national investment in V2I communications would generate over $25.4 billion in annual benefits and would recoup its costs in 7 years. If V2I communication has the more substantial impact of reducing the number of stops per mile and the idle time per stop by one standard deviation of the variation we observe for each driver on each route, fuel consumption would be reduced by 5.8% and travel time would be reduced by 16.9%, leading to $106 billion in annual benefits and a payback period of just over one year. These fuel savings are larger than those estimated to be generated by a 25 cent/gallon gasoline tax by Bento et al. (2009). While these fuel and time savings could be offset by increased driving, this increased driving will directly benefit consumers and therefore not reduce the private benefits of the technology. We find that the fuel savings from V2I technologies only disappear with 100% rebound, and the time savings persist even with 100% rebound, which suggests that even with high rebound there will be social gains from reducing the pollution associated with burning fuel.

These impressive improvements are possible because of three critical facts that we are able to document using our high-frequency data: 1) there is substantial variation in the fuel economy achieved on the road by drivers in identical vehicles, 2) this variation comes

these technologies require some policy intervention.

from *where* people drive rather than *how* they drive, and 3) the time costs of driving more efficiently mean that drivers have very little incentive to unilaterally improve fuel economy. We find that, in identical vehicles, the most inefficient driver uses nearly 70% more fuel per mile than the most efficient driver over nearly 6 weeks of driving. This difference is greater than the change in the Corporate Average Fuel Economy standard between 1990 and 2025, and yet we argue that this is a lower-bound on the actual variation in fuel economy across all drivers in identical vehicles since drivers in our sample were all relatively safe drivers who drive a large number of miles in southeast Michigan.

We further show that this variation in fuel consumption is largely determined by characteristics of the roads on which the driver drives rather than the driver's decisions about how aggressively to drive. Fixed effects for driver, day of week, and month, combined with external conditions such as the outside temperature and gasoline prices only explain 18% of the variation in fuel economy across trips. However, when we further control for the number of stops per mile, the idle time per stop, and the road slope, we can explain an additional 55% of the variation in fuel economy across trips (for a total R^2 of 0.73). Finally, adding in controls for acceleration and speed decisions only explains an additional 5% of the variation in fuel economy across trips (for a total R^2 of nearly 0.79). We take this as substantial evidence that the amount of stopping and re-starting required of a driver is substantially more important in determining fuel consumption than the driver's decisions about how aggressively to drive.

While extensive variation in on-road fuel economy and the important role of stops in generating this variation provide a setting where V2I technologies could improve outcomes, our third fact shows why gasoline taxes alone are insufficient in achieving efficient outcomes. Both the policy literature (Barkenbus, 2010) and the EPA's website[4] suggest that accelerating less aggressively and driving more slowly on the highway could substantially reduce fuel consumption. While this may be true, we show that the costs to drivers of these behaviors generally outweigh the private benefits, even under a implausibly high gasoline tax. In constant-speed highway driving, drivers should only slow from 80 to 75 miles per hour if their value of time is less than $7.98 per hour, and in accelerations from a near-stop, drivers should only accelerate less aggressively if their value of time is less than $2.35/hour.[5] In fact, it is only in high-speed acceleration (for instance, from 40-60 miles per hour) that we find it reasonable for most drivers to accelerate less aggressively to conserve fuel. These results

[4] `http://www.fueleconomy.gov/feg/drive.shtml`

[5] All of these calculations use a gasoline price inclusive of any taxes of $3.50/gallon. At lower gasoline prices the values of time would be even smaller.

also help to explain the somewhat conflicting results in the literature: although engineering estimates suggest that more conservative driving should reduce fuel consumption (Hooker (1988), Barkenbus (2010)), gasoline prices do not affect driving behavior (other than through congestion changes) in Los Angeles (Burger and Kaffine (2009)), but do slightly affect the speed of drivers on a rural Washington State freeway where values of time may be substantially lower (Wolff (2014)). These results also suggest that gasoline taxes alone are unlikely to improve on-road fuel economy if drivers behave optimally,[6] and so policies that address the optimization of the transportation system are the most likely to be effective at reducing fuel consumption conditional on the vehicles and mileage driven.

Overall, we believe that our results demonstrate the potential for connected vehicle technologies to substantially reduce both fuel consumption and drivers' travel time. These improvements are in addition to the existing reductions in fuel consumption that come from fuel economy standards and gasoline taxes because they address an additional margin that existing policies cannot: the functioning of the transportation *system,* rather than just drivers' individual optimization. This analysis provides initial evidence that new vehicle-to-infrastructure communication technologies have important implications for both driver welfare and environmental outcomes. We argue that economists should invest additional effort in understanding important complications such as the potential effect of these policies on land use, vehicle miles traveled, and vehicle choice.

The remainder of the paper is organized as follows: Section 2 describes the data on individual driver behavior and fuel use and documents our three facts that suggest the potential for infrastructure policy to reduce fuel consumption above and beyond what traditional environmental policies can achieve. Section 3 presents our models of fuel consumption and travel time over repeated trips. Section 4 uses these models to simulate the effect of V2I technologies on fuel consumption and travel time and conducts back-of-the-envelope cost benefit analyses of the potential pay-off of investing in these technologies. Section 5 discusses the other potential impacts of V2I communication and the longer-run movement to self-driving vehicles, and section 6 concludes.

[6] Of course, policies like a gasoline tax that increase the cost of gasoline may induce drivers to purchase more fuel efficient vehicles, which will reduce fuel consumption.

2 Empirical Facts about Fuel Consumption

2.1 Data

We use a novel engineering dataset containing observations of real-world driving behavior. Between April 2009 and May 2010, the University of Michigan Transportation Research Institute (UMTRI) conducted its Integrated Vehicle-Based Safety Systems (IVBSS) study to test a prototype crash warning system. UMTRI provided 108 drivers with one of 16 identical vehicles to use as their primary vehicle for forty days.[7] Data on nearly 600 variables were collected from vehicle instruments every one-tenth of a second, including fuel consumption, location, speed, radar data on nearby vehicles, and video of both the driver and the road surrounding the vehicle. This high-frequency data provides detailed information about road characteristics and driver behaviors that affect fuel economy.[8]

UMTRI recruited the experimental sample from registered Michigan drivers living in southeast Michigan with no major driving infractions. From respondents to an initial letter, UMTRI selected people who drove more than 12,000 miles per year and who were evenly distributed across gender and age bins. Participants were nominally compensated for their completion of pre- and post-experiment surveys. Drivers received the cars with a full tank of gasoline, but after that they were responsible for additional gasoline purchases.

We observe 6,352 hours of driving over a total distance of nearly 220,000 miles. The average distance traveled is 48 miles per day, which is about 34 percent greater than the national average (FHWA, 2012). Although the data comes from a selected sample, we believe that this selection might bias us towards finding less variation in fuel economy than occurs in the population. Because study participants drove more and had cleaner driving records, they were likely to be more efficient and less aggressive than the average U.S. driver. Knowing that their behavior was being observed could have led participants to drive less aggressively (although the video shows behavior suggesting that drivers quickly forgot about the recording equipment). Finally, UMTRI maintained the vehicles, reducing variation in

[7]There were 117 drivers who entered the study. Nine drivers were removed from the study early because either they were not driving the vehicles enough or they were allowing other people to drive the vehicles. We only use data from the 108 drivers who completed the experiment.

[8]The original experiment allowed participants to drive the vehicles for 12 days and then turned on the crash warning system. The system incorporated four types of warning: forward collision, lateral drift, lane departure, and curve speed. An underlying concern was that these warnings might startle the drivers or otherwise exacerbate dangerous driving situations. However, the experiment found high acceptance by drivers of the system and little overall change in driver behavior, with the biggest effect being a reduction in unsignalled lane changes (Sayer et al., 2011). We do not make use of the original experimental design in this study, but instead pool the control and treatment periods for each driver.

maintenance issues that might affect fuel economy, such as tire inflation.

Aggregate fuel consumption during the experiment was 4.2 gallons per 100 miles, or 24.1 miles per gallon. The vehicles in the experiment were 2006 and 2007 Honda Accord EX 4-door V6 sedans, which have an EPA-reported fuel economy of 18 miles per gallon for city driving and 26 miles per gallon for highway driving.[9] Although these estimates are reasonable bounds on the fuel economy for most drivers in the sample, 16 percent of drivers achieved an average fuel economy over the 40 days that was better than the highway estimate, while 2 percent of drivers achieved an average fuel economy that was worse than the city estimate (Figure 1).[10] This variation in fuel economy across drivers is striking. The range of 3.43 to 5.77 gallons per 100 miles (17.3 to 29.2 mpg) is equivalent to the difference in EPA average fuel economy between the Toyota Venza (a midsize SUV) and the Toyota Prius (a hybrid car).[11] It is also greater than the change in the Corporate Average Fuel Economy (CAFE) standard between 1990 and 2025 for even the smallest passenger cars.[12]

Table 1 displays summary statistics for important variables in our data, over two different levels of aggregation. Column 1 presents means and standard deviations of the variables for each of the 108 drivers who completed the experiment. Columns 2 and 3 present the means and standard deviations over trips of at least half a mile, with column 2 showing these statistics for all trips and column 3 limiting the sample to only those trips that the same driver took repeatedly. Drivers in our sample average just over 2,000 miles in the 40 days they have the vehicles, for an average driving time of nearly 59 hours.[13] Trips, on the other hand, average 10.5 miles and take 18 minutes, with repeated trips being slightly shorter in both distance and time.

The remaining variables in Table 1 are divided into three general categories: those that

[9]Information obtained from the EPA's fuel economy website at `http://www.fueleconomy.gov`. The methodology for estimating fuel economy was changed for model years 2008 and later. These estimates are based on the new methodology. There is no difference in reported fuel economy between the 2006 and 2007 model years.

[10]LeBlanc et al. (2010) provide summary results about variation in fuel economy from the same dataset used in this paper. The top panel of Figure 1 corresponds to Figure 1 from their paper. They also show the distribution of fuel economy for constant speed highway driving and for acceleration events.

[11]The difference in gasoline consumption between the most and least efficient driver was 2.34 gallons per 100 miles. The EPA fuel economy for the 2015 Toyota Venza and 2015 Toyota Prius are 4.35 and 2.00 gallons per 100 miles, a difference of 2.35 gallons per 100 miles. Fuel economy information from `http://www.fueleconomy.gov/feg/findacar.shtml`.

[12]In 1990, the CAFE standard for passenger cars was 3.64 gallons per 100 miles. By 2025 the standards are expected to tighten to 1.67 gallons per 100 miles for cars with the smallest footprint, a reduction of 1.97 gallons per 100 miles.

[13]The summary statistics for driving distance and time are unweighted averages while the remaining variables are weighted by distance for comparability across columns.

measure driving style, those that describe route characteristics, and those that measure external conditions. Driving style variables include the average speed for all driving and variables that describe the acceleration and deceleration behavior of drivers. Route characteristics include the number of stops per mile driven, the seconds of idle time per stop, and the characteristic road slope per foot, which measures the amount of work that a vehicle needs to do to climb any hills on the route. Finally, we classify outside temperature, air conditioning use, and the gasoline price as conditions that are external to the actual driving decisions. Some of these categorizations are inherently ad hoc, as average speed and acceleration could be argued to be route characteristics, but in general these categories represent groups of variables that are increasingly out of the driver's control.

Drivers in our sample average 36.3 miles per hour while trips over half a mile average 42.6 miles per hour.[14] Additionally, we calculate a measure of speed known as aerodynamic speed, equivalent to the root mean square of speed (because aerodynamic drag is proportional to the square of velocity), which we will use as our speed measure in later analysis. We generate three additional measures of the total change in speed for each driver. Characteristic acceleration is the inertial work required to accelerate the vehicle per foot traveled, and is therefore a measure of the amount of accelerating that a vehicle needs to do over a given distance. As shown in Figure 2, this measure differs from mean acceleration, which is calculated just for the periods in which the vehicle is accelerating. Finally, we calculate the mean deceleration during periods when the vehicle is decelerating to capture hard-braking behavior.

On average, drivers stop 0.66 times per mile, which is similar to the average number of stops per mile over trips and repeat trips. Similarly, the average idle time per stop is similar across drivers, trips, and repeat trips at 25 seconds per stop. Finally, external conditions are also broadly similar across drivers, trips, and repeat trips, with an average outside temperature of between 55.5 and 57.5 degrees Fahrenheit, air conditioning use between 20 and 25% of the time, and a mean gasoline price in Michigan during this period of $2.61.

[14]The faster speed on trips likely stems from the fact that we remove trips with distances less than half a mile from our calculations of trips, since these trips may just involve moving the car to a different spot in a parking lot or other unusual driving behavior. Repeat trips are slightly slower and less fuel efficient than trips on a whole since they remove long-distance driving that people only do occasionally. This pattern of trips being faster and more fuel efficient than overall driving with repeat trips in the middle is repeated throughout Table 1 but is unlikely to affect our major take-aways from the trip-level data.

2.2 Variation in Fuel Economy

In order for new vehicle technologies to reduce fuel consumption, it must be true that not only is there variation in the fuel economy across drivers that could be reduced by these technologies, but also that this variation in fuel economy is coming from the overall functioning of the roadway system and not drivers' individually optimal decision-making. In this section we demonstrate that the drivers in our data achieve substantially different fuel consumption per mile in practice. We are also able to provide some evidence that this variation in fuel consumption is not the result of drivers' individual decision-making in similar contexts but is rather being largely determined by how often the driver needs to slow to a stop and how long she needs to idle at a stop, which are outcomes that new vehicle technologies can directly improve.

While the (weighted) means of the driving variables are fairly similar across columns of Table 1, the amount of variation is impressive. As discussed, there is substantial heterogeneity in fuel economy across drivers, with a mean of 24.10 miles per gallon and a standard deviation (in the average driver fuel economy) of 2.31 mpg, but this variation is small compared to the variation in fuel economy across trips. The average trip has a fuel economy of 25.01 miles per gallon, but the standard deviation is 4.37 miles per gallon. Figure 1 displays this variation in average driver and trip fuel economy graphically, and shows that the variation in fuel economy achieved by nearly identical vehicles on the road is substantially larger than the range between the EPA's highway and city fuel economy estimates (shown as vertical lines in Figure 1).

This huge variation in fuel economy is likely the result of differences in both roadway characteristics like stops per mile, idle time per stop, and roadway slope, and in driving choices like speed, acceleration, and deceleration, all of which also display substantial variation over both drivers and trips (Table 1). For instance, while drivers average just over 36 miles per hour, the standard deviation in average driver speed over the 40 days is nearly 7.7 miles per hour. Similarly, drivers average approximately 42.5 miles per hour over trips, but the standard deviation is 15.7 miles per hour. This variation matches common sense: a long trip on an open freeway will have a high average speed and a relatively high fuel economy while an urban trip to the supermarket in stop-and-go traffic will have a very low average speed and fuel economy. Additionally, it is possible that the variation comes from some drivers having a "lead foot" (driving quickly and accelerating aggressively) while others drive conservatively and achieve higher fuel economy on the same route.

The summary statistics displayed in Table 1 are highly correlated, which makes it difficult to understand which variables have the greatest effect on fuel consumption. To untangle the independent contribution of external conditions, route characteristics, and driving style to fuel use, we regress fuel consumption per mile on z-scores of different driving variables at both the driver and trip level.[15] By looking at the standardized z-scores of the different variables, we can effectively run a "horse race" to understand whether the variation in fuel consumption is being determined by external conditions, route characteristics, or driving styles.

Table 2 shows the results of regressions at both the driver and trip level where we progressively add explanatory variables that are increasingly within the driver's control. The first and fourth columns include only variables that are unrelated to route characteristics or driving style, including outside temperature, air conditioning use, and the gasoline price (for the trip-level regressions, all columns also include fixed effects for month of year, day of week, and driver). We expect higher temperatures to decrease fuel consumption (since cold engines are less efficient) and air conditioning to increase fuel consumption. We expect gasoline prices to decrease fuel consumption as drivers have more incentive to conserve fuel and there are fewer other vehicles on the road to lead to congested, stop-and-go driving, although this effect will be somewhat offset by increases in aggressive driving that are limited when there are more vehicles on the road. The combination of these two effects means that gasoline prices may not have a substantial effect on fuel consumption.

The second and fifth columns of Table 2 add route characteristics such as the number of stops per mile, the idle time per stop, and the road slope. Additional stops per mile mean that the driver needs to decelerate and then accelerate again, which will increase fuel consumption. Longer idle time per stop similarly increases fuel consumption per mile. Hills require the vehicle to do more work to travel the same distance, and therefore will also increase fuel consumption.

Finally, the third and sixth columns of Table 2 add variables that describe the driver's driving style such as speed, total amount of acceleration (characteristic acceleration), mean rate of acceleration and deceleration, and the interaction between the amount of acceleration and deceleration and the mean rate of each. A higher average speed is associated with lower fuel consumption, but the relationship is non-linear, so we include a quadratic term in characteristic speed.[16] The total amount of acceleration required (characteristic acceleration)

[15] Fuel consumption (gallons per 100 miles) is linear in fuel use while fuel economy (miles per gallon) is non-linear, which makes fuel consumption the correct variable to analyze in a linear regression model.

[16] The strong negative correlation between average speed and average fuel economy was noted by Evans (1979), based on field experiments of drivers in urban traffic.

will increase fuel consumption per mile. As previously noted, both characteristic speed and acceleration could be considered route characteristics rather than driving style variables since they will obviously vary greatly based on where a driver drives rather than just a driver's "aggressiveness." Mean acceleration may increase or decrease fuel consumption since accelerating more aggressively means that the driver needs to accelerate for less time in order to reach the same cruising speed. For this reason we include both mean acceleration (and deceleration) and the interaction between mean acceleration and characteristic acceleration.

The results in Table 2 show that external conditions such as outside temperature, air conditioning use, gasoline price, and month, day of week, and driver fixed effects (for the trip-level regressions) explain relatively little of the variation in fuel consumption across drivers and trips. The R^2s in the first and fourth columns for drivers and trips are 0.09 and 0.18 respectively and the coefficient estimates are moderate. Adding route characteristics in the second columns drastically increases the R^2 to 0.82 and 0.73 respectively. Additionally, the coefficients on number of stops per mile and idle time per stop in the second and fifth columns are large and very statistically significant, especially in the trip-level regressions. When driving style variables are added to the regressions in the third and sixth columns, the R^2s increase somewhat to 0.90 and 0.77 for drivers and trips respectively. The coefficients on driving style generally have the expected signs, but, with the exception of characteristic speed and acceleration, are relatively small in magnitude. Additionally, it is worth noting that when the driving style variables are added to the regression the coefficient on the number of stops per mile decreases somewhat but the coefficient on idle time per stop remains constant. This makes intuitive sense given that characteristic acceleration is picking up the amount of acceleration required of the vehicle per mile, which is likely one of the major ways in which number of stops per mile increases fuel consumption, but this should have no effect on the fuel consumed while idling.

Overall, the coefficients on the number of stops per mile and idle time per stop are large relative tot he other coefficients and only the aerodynamic speed coefficients rival their magnitude in the trip-level regressions. In combination with the R^2s across regressions, this leads us to our second major descriptive result from this data: *where* people drive is more important in determining fuel consumption than *how* people drive. By this we mean that routes with many stops or where drivers need to wait for a long time at a given stop use substantially more fuel than smoother-flowing routes, and that this effect is much larger than the effect of a particular driver having a "lead foot" and accelerating aggressively out of a stop.

The implication of this result is that, conditional on driving a particular route, reducing the number of times that a driver needs to stop and the amount of time she idles at each stop is likely to reduce fuel consumption substantially more than changing her acceleration decisions conditional on route characteristics. These route characteristics are generally outside of a driver's control and are only likely to be affected by policies that coordinate traffic flows such as vehicle-to-infrastructure (V2I) communication technologies. Before we turn to evaluating the potential benefits of V2I technologies, we briefly look at the incentives for drivers to unilaterally reduce fuel consumption by "hyper-miling" or driving less aggressively in order to conserve fuel. These incentives are critical to understanding the unique benefits of V2I technologies because traditional policies that may improve on-road fuel economy such as gasoline taxes generally rely upon drivers responding to increased prices by driving more efficiently.

2.3 Incentives to Unilaterally Improve Fuel Economy

We have shown that there is substantial variation in fuel economy across drivers, but this still leaves open the possibility that an optimal Pigovian gasoline tax would properly internalize the externalities of fuel consumption and substantially improve on-road fuel consumption.[17] Before we move on to understanding the potential for vehicle-to-infrastructure communication technologies to reduce drivers' fuel consumption and travel time, we show that higher gasoline taxes are unlikely to change driving behavior for most drivers. While Barkenbus (2010) and the EPA's website[18] suggest that accelerating less aggressively and driving more slowly on the highway could substantially reduce fuel consumption, we find that the time costs of this type of efficient driving are higher than the fuel savings for most drivers, even at a high gasoline price. This suggests that a gasoline tax, while potentially effective at getting drivers into more efficient vehicles or convincing them to drive less, are unlikely to convince drivers to drive more efficiently, which means that alternative policies such as infrastructure investment for connected vehicles may be worthwhile even in the presence of an optimal gasoline tax.

Conditional on a driver needing to drive a given route, the driver still has many choices about how aggressively to drive. There are three main outcomes that a driver may take into consideration when deciding whether to drive quickly or accelerate and decelerate aggres-

[17] Parry and Small (2005) argue that the optimal U.S. gasoline tax would be just over $1/gallon, whereas the current federal gasoline tax is only 18.4 cents per gallon and state taxes bring the average tax to just under 50 cents/gallon.

[18] `http://www.fueleconomy.gov/feg/drive.shtml`

sively. Driving quickly (and perhaps aggressively) could benefit the driver by saving time in getting to her destination, but it would likely cost additional fuel consumption, some reduction in safety, and increase in wear-and-tear. This leads to a rather simple model of driving decisions:

$$\max_{\mathbf{s}} U_{irt} = D_{irt} - \nu_i h(\mathbf{s}|x_{rt}) - p_t f(\mathbf{s}|x_{rt}) - c(\mathbf{s}|x_{rt}) \tag{1}$$

where U_{irt} is the utility that driver i gets from completing route r on day t, $\mathbf{s} = \{s_1, ..., s_T\}$ is the the speed path the driver uses to complete that route, and D_{irt} is the benefit that the driver gets from completing the trip, which is assumed to be large such that drivers always choose to complete the trip. Furthermore, ν_i is driver i's value of time, $h(\mathbf{s}|x_{rt})$ is the time it takes to complete a route at a given speed, $\mathbf{s}$, given the characteristics of the route such as pavement quality and road grade, x_{rt}. p_t is the price of gasoline, which is assumed to be constant across routes but vary over days, and $f(\mathbf{s}|x_{rt})$ is the fuel consumed on a route given the driver's choice of speed and the route characteristics. Finally $c(\mathbf{s}|x_{rt})$ are additional costs such as safety and vehicle depreciation.

Since we do not observe a large enough sample to get a good measure of the safety or vehicle depreciation effects of aggressive driving, we focus on the trade-off between fuel consumption and time savings and ask the question: "Given the effect of different driving behaviors on travel time and fuel consumption that we observe in the data, how high would the driver's value of time need to be to make the driver indifferent between driving more aggressively and more conservatively?" In particular, we focus on a few controlled examples of situations where a driver needs to decide on a speed-trajectory, $\mathbf{s}$, and where we can use our data to effectively measure how fuel consumption changed with a speed trajectory, $f'(\mathbf{s}|x_{rt})$, so that we can solve the first-order condition for $\nu_i = p_t f'(\mathbf{s}|x_{rt})/{-h'(\mathbf{s}|x_{rt})}$, the value of time that makes a driver indifferent between different speed trajectories ($h'(\mathbf{s}|x_{rt})$ is the change in travel time with respect to the speed trajectory, which is straightforward to calculate directly from alternative speed paths). In particular, we find the values of time that make a driver indifferent between driving faster and slower on a flat freeway and the values of time that make a driver indifferent between accelerating more and less aggressively both at low and high initial speeds. The basic idea is that for any driver with a value of time greater than the reported value, it will be utility maximizing to drive with the faster or more aggressive speed trajectory, while for any driver with a value of time less than the reported value, it will be utility maximizing to drive with the slower or less aggressive speed trajectory. Safety and depreciation considerations may further limit aggressive driving, but these constraints will not be affected by changing gasoline prices or taxes. While these three situations are in no way exhaustive of all of the potential driving decisions that a driver must make over the course of a trip, they are instructive as to the overall incentives that drivers have to drive more aggressively.

In Appendix A we present a theoretical structure of a physical model of fuel consumption based on Saerens et al. (2010) and Hellström et al. (2009) that we then use to estimate $f(\mathbf{s}|x_{rt})$ and calculate $h(\mathbf{s}|x_{rt})$ in Appendix B. Appendix B also presents detailed descriptions of our empirical model's fit to the data for the three scenarios in which we estimate the value of time required to make a driver indifferent between the more and less aggressive speed trajectory.

Constant Speed Highway Driving

In table 3, we calculate the cost of driving 100 miles at different speeds in terms of fuel consumption, fuel cost (at an intentionally high value of $3.50 per gallon), and time, and then use these numbers to calculate the cost of time in dollars per hour that makes the driver indifferent between driving that speed or 5 mph slower if the safety and depreciation costs are zero. At speeds below 50 mph, increasing speed actually decreases fuel use, so all drivers would prefer to drive faster. Above 50 mph, increasing speed by 5 mph is optimal if the driver's value of time net of non-fuel costs is quite low: 22 cents for the increase to 55 mph, $5.80 for the increase from 65 mph to 70 mph, and $7.98 for the increase from 75 mph to 80 mph. These values are well below the value of time for most American workers, which averaged $10.97/hour in 2009. Even for speed increases above 80 mph, many drivers will find that their values of time net of safety are above the $11.28/hour cost of increasing to 85 mph. This suggests that individuals, left to their own devices, have very little direct monetary incentive to decrease their freeway speed to the fuel-economy-maximizing level.[19]

Acceleration Events

Our empirical model of fuel consumption during acceleration events leads to two important take-aways. First, accelerating aggressively (up to 4.5 ft/s^2) uses substantially less fuel during the acceleration phase than accelerating very slowly, although this fuel savings diminishes with acceleration. This is because, although the fuel consumption at any second is higher at higher acceleration rates, the time spent accelerating up to 40 miles per hour is much

[19]Of course, this ignores the fact that driving faster could put the driver at an increased risk of receiving a speeding ticket. Since this is largely related to the safety cost of driving we consider it to be part of the safety cost of increased speed and abstract from it here.

shorter with more aggressive acceleration. The second point is that this fuel savings is offset by the fact that the top cruising speed of 40 miles per hour is reached in a shorter distance, so the vehicle needs to drive at a constant speed of 40 miles per hour for a longer distance. The combined effect is that accelerating more aggressively uses slightly more fuel than accelerating less aggressively, but the difference is very small.[20]

Of course, accelerating at a slower rate means that it takes substantially longer to cover a quarter mile than accelerating quickly. Table 4 shows, for different acceleration rates, the fuel consumption, fuel cost and time for accelerating from 3 to 40 miles per hour (top panel) and for accelerating from 40 to 60 miles per hour over a half mile (bottom panel). Table 4 also shows the minimum value of time net of non-fuel costs that would be required to make accelerating at that level preferable to accelerating one level more slowly. For accelerations from a near-stop, the minimum value of time net of non-fuel costs never exceeds $2.35, which means that drivers would need to have an extraordinarily low value of time or be extremely safety- and depreciation- conscious for accelerating conservatively to be preferable to more aggressive acceleration. This calculation changes for accelerations to highway speeds, where lower rates of acceleration are, in fact, optimal. At these speeds, higher rates of acceleration use relatively more fuel over a fixed distance, both because the engine is less efficient when accelerating in a higher gear, and because longer time is spent driving at the higher speed for which fuel consumption is higher (as shown in Table 3). Furthermore, at faster speeds the time savings from higher acceleration are smaller. Combined, these results suggest that drivers have little incentive to accelerate less aggressively in low-speed, urban driving, or to drive more slowly on the highway, and that the only real avenue for improving fuel economy through behavior change is to accelerate less aggressively at high speeds or to reduce the amount of speed changes in "constant speed" highway driving (for instance, by using cruise control). Both sets of results assume that the driver is not constrained by congested roads and can drive freely after the acceleration event, allowing the decreased time during the acceleration event to translate into a decrease in the total trip time.

[20]Akcelik and Biggs (1987) derive optimal acceleration rates, for different final speeds, to minimize fuel consumption during the acceleration period. They find that a hard initial acceleration minimizes fuel use. Hooker (1988) notes that this objective is different to minimizing fuel consumption for driving over a fixed distance with an initial acceleration then cruising at a constant speed. His conclusion was similar to our result: "When the object is to accelerate from rest to cruising speed and then to cruise for some distance while achieving a fixed overall average speed, fuel economy is not very sensitive to the rate of acceleration."

Lessons

From our comparison of the time cost of driving efficiently to the fuel savings, we find that few drivers have an incentive to unilaterally drive in a way that improves fuel economy, especially in low-speed or urban driving.[21] It may be that the safety benefits of driving efficiently prevent more drivers from engaging in aggressive driving behavior, but the fuel expenditure savings alone do not seem to be enough to offset the time costs of conservative driving. This likely helps to explain why the economics literature has found mixed evidence as to whether drivers respond to increased gasoline prices by driving more slowly (e.g. Burger and Kaffine (2009) and Wolff (2014)): fuel costs are not what is limiting drivers' speed in most driving scenarios. This is likely to be increasingly true as vehicles' fuel economy improves over time.

The lack of incentive for drivers to unilaterally conserve fuel also has substantial policy implications. While a gasoline tax will encourage drivers to purchase more fuel efficient vehicles and drive *less,* it is unlikely to encourage drivers to drive more *efficiently.* This means that improving on-road fuel economy is likely to only occur by changing the amount that drivers need to stop and restart or the variation in driving speed generated by congested driving, which is exactly what new vehicle communication technologies are poised to do.

3 The Effect of Traffic Flow on Travel Time and Fuel Use

The basic idea behind vehicle-to-infrastructure communication technology is simple: if street lights know how many cars are coming from different directions, then they can adjust their timing in real-time in order to get as many vehicles through each intersection as quickly and safely as possible. When an entire system of street lights is connected, then this optimization can occur across many intersections simultaneously and the number of stops that vehicles need to make and the amount of time that vehicles need to idle at each stop can be substantially reduced (Feng et al. (2015)). The question remains, however, whether this optimization of traffic signals would actually have a substantial effect on overall fuel consumption and travel time.

[21] One important caveat is that our analysis is only applicable to our model of cars (Honda Accords). It is possible that drivers' incentives to conserve fuel are different in other vehicles.

3.1 Empirical Approach

In order to understand how this type of technology could affect fuel consumption and travel time in a real-world driving situation, we make use of the fact that there are many routes in our data that the same driver takes repeatedly. On these routes, sometimes the driver will "make" more lights and have a relatively smooth trip and sometimes she will "miss" the lights and need to stop frequently or for long periods of time. This quasi-random variation in the number of stops and idle time per stop on a given route may affect many other things about a trip including the amount of accelerating a driver needs to do, the rate at which she accelerates and decelerates, the speed she travels between stops, and the amount of fuel she uses. We use this variation to think about the effect of V2I communication that would increase the number of lights that drivers "make" and decrease idle time per stop.[22]

In order to identify routes that a driver takes repeatedly, we identify the exact longitude and latitude of the start and end points of each trip and use these to identify addresses for the trip's origin and destination. Routes are considered to be the same if they have the same origin and destination and their total distance does not vary by more than 25% from the median distance for that driver to travel between that origin and destination. While our base regressions include any route that a given driver takes more than once, we also conducted our analysis with only those routes that a driver takes at least 5 or 10 times and the results are fundamentally unchanged.

We regress both fuel consumption per mile and travel time per mile for a given driver, i, on a particular route, r, taken on a particular trip, t, on a set of controls including route fixed effects, γ_r, month fixed effects, γ_t, external conditions, X_t, trip characteristic variables, R_{irt}:

$$y_{irt} = \gamma_r + \gamma_t + X_{irt}\beta_1 + R_{irt}\beta_2 + \varepsilon_{irt} \tag{2}$$

The vector R_{irt} includes the number of stops per mile and the idle time per stop, which are our primary independent variables of interest. In our primary specification, we do not

[22] Currently, installed traffic signals are outdated and generally not optimized for system performance. The Federal Highway Association estimates that 75% of traffic signals could perform better if their timing was adjusted or coordinated with adjacent signals. `https://www.fhwa.dot.gov/publications/publicroads/02janfeb/timing.cfm` Further, the National Transportation Operations Coalition's 2012 National Traffic Signal Report Card gives the U.S. "C"s for Traffic Signal Operations and Signal Timing Practices, saying that "Traffic signal timing performance is not regularly measured in connection with objectives... (and) may force motorists to stop at multiple adjacent intersections and result in travel delays when settings are not updated."

control for driving style variables because we want to allow driving style to vary with the number of stops and the idle time per stop, but we also show regression results where we hold driving style variables constant. The identification of β_2 therefore comes from differences in fuel consumption and travel time for the same route depending on whether the driver makes more lights or idles for longer during stops, controlling for monthly differences, and differences in external factors such as temperature, air conditioning use, and gasoline prices.[23]

In order for β_2 to measure the causal effect of randomly making an additional light or stopping for less time per light on fuel consumption and travel time, it must be the case that other things that affect these outcomes but are not controlled for in our regression, ε_{irt}, are not also correlated with whether the driver "makes" lights. The primary concern here is that lights are timed so that drivers will make more lights when traffic is flowing smoothly and that congestion will disrupt these patterns and lead a driver to make fewer lights or wait longer at lights while simultaneously directly increasing fuel consumption and travel time. To the extent that V2I technologies will smooth traffic flows and reduce fuel consumption from congested driving, not controlling for congestion beyond its appearance in the number of stops or idle time per stop in our regressions may actually be ideal: it will load the effect of congestion on our independent variables of interest. However, we also have information on the distance between our vehicles and the vehicle in front of them: to the extent that congested conditions lead drivers to follow other vehicles more closely, this variable should pick up the direct effect of congestion. Our results are effectively unchanged when we include either the average following distance, the average change in following distance (closing rate), or both in our regressions.

3.2 Results

Table 5 shows the results of the regressions in equation 2. For each dependent variable, we show the regression results both not including and including the driving style variables, although our preferred specifications will not hold these variables constant. Column 1 of Table 5 shows that the number of stops per mile substantially increases fuel consumption per mile: the coefficient suggests that doubling the number of stops per mile from 0.69 to 1.38 would increase fuel consumption by 0.37 gallons per 100 miles, or nearly 8.5%. This is equivalent to reducing fuel economy from 23.1 miles per gallon to 21.3 miles per gallon. Similarly, doubling idle time per stop from 25.15 seconds to 50.3 seconds would increase fuel

[23] Additionally, we tried including day of week fixed effects but they did not change the results or improve the fit of our regressions.

consumption by 0.54 gallons per 100 miles, or 12.5% (equivalent to reducing fuel economy from 23.1 mpg to 20.6 mpg). As expected from our previous regressions, characteristic slope increases fuel consumption, outside temperature decreases fuel consumption, and air conditioning use increases fuel consumption. The average gasoline price does not have a statistically significant effect on fuel consumption.[24]

In column 2 of Table 5 we control for the driving style variables. These variables all enter with the expected signs, and, as expected, the coefficient on the number of stops per mile decreases slightly when we control for the speed, acceleration, and deceleration variables, and the overall R^2 for the regression does not change by much.

Columns 3 and 4 of Table 5 repeat the same regressions but with seconds of travel time per mile as the dependent variable. Again here, the number of stops per mile, idle time per mile, and road slope increase travel time, but, intuitively, the external variables of outside temperature, air conditioning use, and recent gasoline price do not have a statistically significant effect on travel time like they did on fuel consumption. When we control for the driving style variables they generally enter with the expected signs and the coefficient on the number of stops per mile again attenuates slightly but remains large and statistically significant. Finally, the R^2s for these regressions are extremely large (by social science standards): these variables explain over 80% of the variation in the dependent variables in all four regressions, which does limit the scope for omitted variables to bias our estimates of the effect of stops and idling on fuel consumption and travel time (Altonji et al., 2005).

4 Simulating the Effect of Vehicle-to-Infrastructure Communication

To understand the potential for vehicle-to-infrastructure communication to reduce fuel consumption and travel times, we simulate the effect of two different potential reductions in stops per mile, idle time per mile, or both. A rather conservative assumption is that V2I communication would decrease the number of stops per mile or the idle time per stop by 10%. A more optimistic assumption is that V2I technology decreases stops per mile, idle time per stop, or both by one standard deviation of the variation we observe on a given

[24] We tried including both the current average gasoline price as well as the gasoline price the last time the driver stopped to purchase gasoline as determined using the methodology described in Langer and McRae (2014) and neither variable nor their difference statistically significantly affected fuel consumption or driving time.

route.[25] To simulate these outcomes, we assume that, on each route driven repeatedly in our sample, V2I technologies decrease either stops per mile, idle time per stop, or both by the given amount and then compare the predicted fuel use under these alternative outcomes to the predicted fuel use and travel time for the current route.

Table 6 presents the results of these simulations. A 10% decrease in only stops per mile is predicted to decrease total fuel consumption in our repeated-routes sample by 1% and total travel time by 2.59%. Assuming the average gasoline price of $2.61/gallon, an average value of time of $10.97/hour, and an average non-gasoline, non-time cost of driving an additional mile of $0.285,[26] this leads to a combined decrease in the cost of driving a mile of 1.54%. If V2I technologies were to only decrease idle time per stop by 10% on every route (while leaving the number of stops the same), fuel consumption would decrease by 0.44%, travel time by 1.42%, and the total average cost of driving a mile by 2.37%. To put these numbers in perspective, Langer et al. (2017) find that it would take a 31.2 cent per gallon gasoline tax to decrease fuel consumption by 1%, holding the current vehicle fleet constant.

The lower panel of Table 6 shows the effect of changing stops per mile, idle time per stop, or both by one standard deviation of the variation observed for a particular driver on a particular route in our data. A one standard deviation decrease in the stops per mile on each route would decrease total fuel consumption by 2.71%, total travel time by 7.03% and the total average cost of driving by 3.61%. If, instead, V2I technologies decreased idle time per stop by one standard deviation on each route, fuel consumption would decrease by 3.05%, travel time would decrease by 9.88%, and the total cost of driving would decrease by 4.94%. Finally, if V2I technology was able to decrease both the number of stops per mile and the idle time per stop by one standard deviation, fuel consumption would decrease by 5.76%, travel time would decrease by a whopping 16.91%, and the total cost of driving would drop by 8.55%. This effect on fuel consumption is larger than the effect of a 25 cent per gallon gasoline tax estimated by Bento et al. (2009), which combines the effect of the gasoline tax on mileage with the long-run change in the vehicle mix induced by the tax. Additionally, these fuel savings come with a benefit to drivers of decreased travel times rather than the

[25] This may also be a conservative assumption if entire networks of streetlights are connected using modern traffic management software.

[26] The non-gasoline, non-time cost of driving a mile is derived from AAA (`http://exchange.aaa.com/wp-content/uploads/2012/04/Your-Driving-Costs-2009.pdf`) and incorporates maintenance, tires, depreciation, and marginal insurance costs. We follow Bento et al. (2009) and assume that 15% of annual insurance costs are allocated per-mile. We use $2.61/gallon of gasoline rather than the higher $3.50/gallon because $2.61 was the actual average gasoline price during our sample period. The $3.50/gallon used in the analysis of the incentive to drive efficiently is intentionally high in order to show that drivers' incentives to conserve fuel are low even under a substantially higher gasoline tax.

cost of paying a tax to the government.

While a one percentage point decrease in fuel consumption or a 2.5 percentage point decrease in travel time may seem minimal, it is important to put these simulation results in the context of the sheer volume of driving in the United States. In 2009, the United States used 3.28 billion barrels or 138 billion gallons of finished motor gasoline to drive nearly 3 trillion miles.[27] Conservatively assuming that V2I technology would only affect urban mileage and that fuel economy is identical for urban and rural mileage (as is true in Langer et al. (2017)), our simulation results imply that a 10% decrease in only the number of stops per mile would decrease annual fuel consumption by over 920 million gallons of gasoline worth $2.4 billion at the average gasoline price in our sample of of $2.61/gallon. If both stops per mile and idle time per mile decreased by one standard deviation on each route, fuel consumption would decrease by 5.31 billion gallons of gasoline per year worth $13.8 billion.

The economic benefit of the implied time savings are even more substantial than the fuel savings. Using the average speed in our repeat-trips sample of 39.49 miles per hour, drivers spent 50 billion hours driving urban miles in 2009. At the average value of time in 2009 of $10.97/hour, this means that a 10% decrease in stops per mile would save $14.2 billion per year in travel time and a one standard deviation decrease in both stops per mile and idle time per stop would save $92.8 billion per year.

It is worth comparing these numbers to rough estimates of the potential cost of implementing V2I technologies nationally. According to industry sources, technology to have signals respond to traffic flows would cost $10,000-15,000 per intersection plus less than $1 million per city for traffic management software. The National Transportation Operations' Coalition's 2012 National Traffic Signal Report Card suggests that a reasonable estimate of the number of signalized intersections is one per every 1,000 people, or approximately 319,000 signalized intersections across the U.S. As a high-end estimate, assuming that each of the 19,492 municipal governments across the U.S. each pays $1 million per system plus $15,000 per signalized intersection, the total cost of updating infrastructure to serve V2I needs is $24.28 billion.

Vehicles would also need communication technology for V2I communication. The US Department of Transportation has already conducted a Preliminary Regulatory Impact Analysis (PRIA) for requiring all new vehicles to contain technology to communicate with each other

[27] Annual finished motor gasoline supplied from the U.S. Energy Information Administration and roadway vehicle-miles traveled from the Bureau of Transportation Statistics' National Transportation Statistics publication.

(National Highway Traffic Safety Administration (2016)). The technology required for V2V communication is similar to that required for V2I communication, so we assume that the marginal cost of vehicle-based V2I technology above and beyond V2V technology is somewhere between 0 and the highest cost of V2V technology reported in the PRIA of $350 per vehicle. Again, taking the upper bound and assuming that V2I technology is installed on the entire fleet of 260 million registered vehicles in the US, the cost of V2I technology for vehicles would be $91 billion, for a combined infrastructure and vehicle cost of $115.3 billion.[28]

Given these high-end assumptions on the potential cost of V2I technology, we can compare the cost to the benefits we simulated. If V2I technology only decreases stops per mile by 10%, the annual benefits would be $16.61 billion and the investment in V2I technology would pay off in 13 years with a discount rate of 10%. With a 5% discount rate the investment pays off in 9 years. If, on the other hand, V2I communication decreases stops per mile and idle time per stop by one standard deviation then the investment pays off early in the second year. Additionally, it is worth noting that, unlike gasoline taxes or fuel economy standards, most drivers have a unilateral incentive to purchase vehicles with V2I capabilities if traffic signals are updated with the technology because then the signal will respond to the driver's presence and decrease the driver's personal fuel consumption and travel time. The benefits of this unilateral adoption are obvious to any driver who has ever been stopped at a stop light with no other vehicle in sight and wished that the light could just sense her presence and allow her through the intersection.[29] For a driver who drives 15,000 miles per year and otherwise has the average characteristics in our data (e.g. fuel economy, speed, percent urban driving, value of time, and fuel costs), a 10% decrease in stops per mile is worth $82.89/year and is worth the $350 investment in 6 years. For the same driver a one standard deviation decrease in both stops per mile and idle time per stop is worth $532.90/year and so the investment pays off in the first year.

The Impact of Rebound

From an environmental standpoint, one major concern with the substantial impact of V2I technologies is that the decrease in travel costs will encourage drivers to drive more, thereby

[28]The additional vehicle technology required for V2I technology once vehicles are required to have V2V technology would likely be quite minimal, thus arguing for a vehicle cost much closer to $0. However, we take the extremely conservative approach of assuming that the marginal cost of V2I technology for vehicles is the full $350.

[29]We thank Frank Provenzano at Econolite for this well-understood example of the benefits of unilateral V2I technology adoption by drivers.

reducing the fuel savings and therefore externality benefits of the technology. Table 7 replicates the first two columns of Table 6, accounting for 10%, 50%, and 100% rebound, where 100% rebound means that for every 1% decrease in the cost of driving a mile, total (affected) vehicle mileage increases by 1%. The wide range of rebound values presented here reflect the substantial amount of uncertainty about the correct value to use for the elasticity of vehicle miles traveled with respect to travel cost. Duranton and Turner (2011) suggest that reducing travel costs by improving roadway capacity has a 100% long-run rebound, while estimates of the elasticity of driving with respect to changes in fuel costs stemming from CAFE standards are quite modest (West et al., 2017). While it is important to understand how the quantity of driving will respond to V2I technologies, the variation in our data does not capture this effect and the welfare benefits of V2I technologies are measured with the zero rebound numbers presented above since drivers will only increase the amount of driving if the utility from this change is at least as great as the cost savings generated by V2I technologies.

Table 7 shows that, for all but complete rebound, V2I communications are likely to decrease fuel consumption, and that even at 100% rebound, the total amount of time spent driving decreases. Table 7 shows that even with 50% rebound (an elasticity of driving of -0.5) a 10% decrease in both stops per mile and idle time per stop decreases fuel consumption by 0.43% and total travel time by 3.03%. Amazingly, even with 50% rebound, a one standard deviation decrease in stops per mile and idle time per stop decreases fuel consumption by 1.95% and total travel time by 13.61%. One lesson from Table 7 is that investment in V2I technology might be best focused on reducing fuel consumption if it is paired with policies that decrease rebound, such as an appropriate internalization of the externalities of urban sprawl (Langer et al. (2008)).

5 Discussion and Long-term Technological Change

We have shown that there are large potential benefits of V2I communication even if the technology only reduces the number of stops per mile and the amount of idling per stop by 10% on each route. But there are other potential benefits of the technology that are not accounted for in our analysis.

Increasingly, vehicles are equipped with "start-stop" technology that turns the engine off when the vehicle is stopped and then restarts the engine when the driver pushes the accelerator. However, adoption of this technology has been somewhat limited by the fact that drivers don't like the lag that accompanies needing the engine to restart before the vehicle can move after a stop, and there is some evidence that many drivers disable the technology even if it is installed on their vehicle (Taub (2016), Martinez (2014)). However, V2I technology would potentially allow stoplights to communicate with vehicles so that the engine can restart *before the stoplight changes to green,* thus eliminating the lag when the driver pushes the accelerator and practically eliminating the wasted fuel that occurs when the vehicle's engine is running at a stoplight. Automakers estimate that start-stop technology can save up to 10% of total fuel consumption in urban driving (Martinez (2014)), although in our data idling, while accounting for over 16% of the time driving, only uses 5.2% of the total fuel consumed driving. This suggests that this technology could have a large effect on fuel consumption, but perhaps not quite as large as automakers suggest. However, because fuel costs are a relatively small component of the overall cost of driving and start-stop technology doesn't affect the time cost of driving, this fuel savings would likely not lead to substantial rebound in the total amount of driving and therefore could improve the fuel consumption benefits of V2I communication even at high levels of rebound.

Another benefit of V2I technology that we do not incorporate is the safety improvements that could be generated by stoplights responding to the presence of vehicles. If stoplights can reduce the amount of time drivers spend stopped at red lights, then they can also reduce the incentive for drivers to run red lights or speed up to "catch" lights. Further, by smoothing traffic flows, V2I technologies could reduce accidents that result from stop-and-go driving. Given that we do not observe any accidents in our data, it is impossible for us to estimate the effect of smoother traffic flows on accident rates, but the safety benefits from both V2I technology and V2V technology (which can warn drivers about other vehicles in blind spots or coming quickly into difficult intersections) are one of the major arguments put forward by engineers and government policymakers for these technologies (e.g. Olia et al. (2016) and National Highway Traffic Safety Administration (2016)).

Finally, it is important to understand our results in the context of the longer-term technological change that is anticipated in transportation. Most major automakers are investing in self-driving vehicle technology that will likely partially or fully take over driving decisions from humans. GM in particular envisions a future where vehicles don't need to stop at lights at all and massive computing power allows vehicles to travel through intersections at full speed without accidents. While this would drastically change the fuel consumption per mile, both by reducing stops and idling and by increasing safety and therefore decreasing the need for heavy safety equipment on each vehicle, this would also completely transform the driving experience. If the driver does not need to be engaged in driving, then "driving" could be a time for other activities (e.g. work, entertainment, or socializing), which would strikingly decrease the cost of commuting. This transformation further highlights how rebound and the potential for these new technologies to increase the total vehicle miles traveled will substantially impact whether these technologies are beneficial or detrimental for overall fuel consumption. Again, these considerations are beyond what we can analyze in this paper, but are critical for understanding the future of fuel consumption and the role of policy in shaping that future.

6 Conclusion

Taken together, our results show that investment in new vehicle communication technologies have the potential to substantially reduce both fuel consumption and travel times. These benefits accrue above-and-beyond what is possible with a Piguvian gasoline tax because they increase the optimization of the entire transportation *system,* and because the time-cost to drivers of unilaterally improving their fuel economy is high relative to the fuel savings, even with a high gasoline tax. We therefore argue that infrastructure investments that allow for the widespread adoption of V2I technologies are likely justified on both environmental and private welfare grounds (in addition to potentially improving driving safety).

While we find these results very encouraging in a policy environment where investment in new technologies may be more politically palatable than increases in gasoline taxes or fuel economy standards, we still view this work as a first-step in a more thorough analysis of the long-run potential impact of vehicle communication technologies on the transportation system. In particular, understanding how new vehicle technologies will affect the total mileage driven and the extent of rebound will be critical for whether the benefits of these technologies accrue in terms of private benefits to drivers (with potential increases in external costs) or in terms of overall increases in social welfare.

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Table 1: Descriptive Statistics: Means with Standard Deviations in Parentheses

	Drivers	All Trips	Repeat Trips
Distance (Miles)	2033.29	10.51	8.17
	(957.58)	(16.99)	(10.50)
Time (Hours)	58.82	0.30	0.25
	(24.58)	(0.31)	(0.22)
Miles per Gallon	24.10	25.01	24.16
	(2.31)	(4.37)	(4.31)
Fuel Consumption (Gallons per 100 Miles)	4.19	4.16	4.32
	(0.43)	(1.05)	(1.13)
Driving Style Variables			
Speed (Miles per Hour)	36.31	42.59	39.49
	(7.69)	(15.71)	(14.14)
Aerodynamic Speed (ft/s)	83.40	81.62	77.77
	(9.66)	(20.03)	(19.32)
Characteristic Acceleration (ft/s^2)	0.45	0.45	0.49
	(0.12)	(0.21)	(0.20)
Mean Acceleration (ft/s^2)	2.81	2.67	2.79
	(0.24)	(0.48)	(0.45)
Mean Deceleration (ft/s^2)	-2.92	-2.77	-2.90
	(0.25)	(0.50)	(0.47)
Route Characteristic Variables			
Stops per Mile	0.66	0.63	0.69
	(0.34)	(0.81)	(0.79)
Idle Time per Stop (Seconds)	25.13	25.70	25.15
	(11.84)	(36.63)	(41.80)
Characteristic slope	0.05	0.05	0.05
	(0.01)	(0.16)	(0.31)
External Conditions			
Outside Temperature (Degrees Fahrenheit)	57.50	56.90	55.44
	(17.06)	(17.26)	(18.63)
Air Conditioning (Percent of Time)	0.24	0.23	0.21
	(0.18)	(0.24)	(0.24)
MI Gas Price (Dollars)	2.61	2.61	2.61
	(0.12)	(0.15)	(0.16)
N	108	20,839	7,178

Note: The first two variables are unweighted averages over drivers or trips. Additional variable means and standard deviations are weighted by the total distance driven by the driver or the trip distance.

Table 2: Variation in Fuel Economy with Driving Conditions

	Drivers			Trips		
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Outside Temperature	-0.055	-0.175***	-0.134***	-0.079***	-0.247***	-0.252***
	(0.073)	(0.029)	(0.022)	(0.021)	(0.013)	(0.012)
Air Conditioning Use	-0.082	0.109***	0.091***	0.254***	0.188***	0.191***
	(0.064)	(0.030)	(0.023)	(0.014)	(0.008)	(0.007)
Gas Price	-0.047	-0.024	-0.013	0.044***	0.015*	-0.001
	(0.029)	(0.020)	(0.014)	(0.014)	(0.008)	(0.007)
Stops per Mile		0.264***	0.129***		2.8615***	1.692***
		(0.026)	(0.032)		(0.0233)	(0.034)
Idle Time per Stop		0.140***	0.159***		0.266***	0.276***
		(0.024)	(0.021)		(0.0178)	(0.018)
Characteristic Slope		0.027	0.023		0.0864**	0.092***
		(0.024)	(0.017)		(0.0349)	(0.034)
Char. Acceleration			0.184***			0.361***
			(0.031)			(0.011)
Aerodynamic Speed			-0.328*			-1.419***
			(0.169)			(0.055)
Aerodynamic Speed^2			0.400**			1.423***
			(0.165)			(0.056)
Mean Acceleration			-0.019			0.025***
			(0.034)			(0.008)
Mean Deceleration			-0.035			-0.037***
			(0.026)			(0.008)
Mean Acceleration			0.046**			0.004
* Char. Acceleration			(0.022)			(0.006)
Mean Deceleration			0.040*			-0.023***
* Char. Acceleration			(0.023)			(0.006)
Month	No	No	No	Yes	Yes	Yes
Day of Week FEs	No	No	No	Yes	Yes	Yes
Driver FEs	No	No	No	Yes	Yes	Yes
N	108	108	108	20839	20839	20839
R^2	0.0880	0.8152	0.9067	0.1827	0.7341	0.7855

Note: All independent variables have been converted to z-scores within drivers or trips.

Table 3: Fuel cost and value of time for constant-speed highway driving

	Constant speed (mph)							
	50	55	60	65	70	75	80	85
Cost per 100 miles								
Fuel consumption (gal)	2.86	2.87	2.95	3.10	3.28	3.47	3.66	3.90
Fuel cost ($)	10.02	10.06	10.34	10.84	11.48	12.14	12.81	13.64
Time (minutes)	120.0	109.1	100.0	92.3	85.7	80.0	75.0	70.6
Effect of increasing speed								
Δ Fuel cost ($)	.	0.04	0.28	0.50	0.64	0.67	0.66	0.83
Δ Time (minutes)	.	-10.9	-9.1	-7.7	-6.6	-5.7	-5.0	-4.4
Cost of time ($/hour)	.	0.22	1.84	3.91	5.80	7.01	7.98	11.28

Note: The first block shows the fuel consumption, fuel cost, and time taken to drive 100 miles at constant speeds. Fuel cost assumes a gasoline price of $3.50 per gallon. The second block shows the effect of increasing speed from the previous column by 5 mph. For example, increasing speed from 70 to 75 mph will increase the fuel cost by $0.67 but reduce the trip time by 5.7 minutes.

Table 4: Fuel cost and value of time for acceleration events

	Acceleration (ft/s^2)					
	1.5	3.0	4.5	6.0	7.5	9.0
3–40 mph over 0.25 miles						
Fuel consumption (fl. oz)	2.28	2.21	2.20	2.21	2.22	2.23
Fuel cost (cents)	6.23	6.04	6.02	6.04	6.07	6.11
Time (seconds)	39.2	30.9	28.1	26.7	25.8	25.3
Δ Fuel cost (cents)	.	-0.19	-0.03	0.02	0.03	0.04
Δ Time (seconds)	.	-8.4	-2.8	-1.4	-0.8	-0.6
Cost of time ($/hour)	.	-0.81	-0.33	0.46	1.41	2.35
40–60 mph over 0.5 miles						
Fuel consumption (fl. oz)	3.11	3.23	3.34	3.45	3.57	3.68
Fuel cost (cents)	8.50	8.83	9.14	9.45	9.77	10.05
Time (seconds)	33.2	31.6	31.1	30.8	30.6	30.5
Δ Fuel cost (cents)	.	0.33	0.31	0.31	0.32	0.29
Δ Time (seconds)	.	-1.6	-0.6	-0.3	-0.2	-0.1
Cost of time ($/hour)	.	7.32	20.32	40.87	71.62	94.29

Note: Each block shows the simulated fuel consumption and time to drive a fixed distance, beginning with an initial acceleration period. Gasoline consumption is reported in fluid ounces (1 gallon = 128 fluid ounces). Fuel cost assumes a gasoline price of $3.50 per gallon. Each column illustrates the effect of a different value of acceleration during the acceleration period.

Table 5: Determinants of Fuel Consumption and Travel Time

	Fuel Consumption (Gallons per 100 Miles)		Travel Time (Seconds per Mile)	
Stops per Mile	0.6236***	0.5127***	0.6741***	0.6242***
	(0.0342)	(0.0370)	(0.0422)	(0.0420)
Idle Time per Stop	0.0076***	0.0077***	0.0102***	0.0099***
	(0.0012)	(0.0012)	(0.0015)	(0.0015)
Characteristic Slope	0.0832***	0.0891***	0.0887***	0.0826***
	(0.0177)	(0.024)	(0.0258)	(0.0245)
Outside Temperature	-0.0136***	-0.0142***	9.32e-5	0.0011
	(0.0013)	(0.029)	(0.0010)	(0.0009)
Air Conditioning Use	0.6892***	0.6867***	0.0402	0.0110
	(0.0567)	(0.0583)	(0.0409)	(0.0367)
Gas Price	-0.0498	-0.0764	-0.0522	-0.0496
	(0.0843)	(0.0885)	(0.0691)	(0.0653)
Aerodynamic Speed		2.87e-10***		3.63e-10***
		(8.16e-11)		(9.92e-11)
Aerodynamic Speed^2		-2.67e-5*		-1.57e-4***
		(1.38e-5)		(1.42e-5)
Char. Acceleration		1.5778***		2.1064***
		(0.5487)		(0.4377)
Mean Acceleration		0.0042		0.0424
		(0.0974)		(0.0909)
Mean Deceleration		-0.0252		-0.1269
		(0.0892)		(0.0817)
Mean Acceleration		-0.0154		-0.2367
* Char. Acceleration		(0.1603)		(0.1599)
Mean Deceleration		-0.0279		0.4359***
* Char. Acceleration		(0.1517)		(0.1426)
Month FEs	Yes	Yes	Yes	Yes
Route FEs	Yes	Yes	Yes	Yes
R^2	0.8708	0.8801	0.8392	0.8524

Note: Each regression is on the 7,178 trips that drivers take repeatedly and are over 0.5 miles.

Table 6: Simulation Results

	% change in fuel	% change in time	% change in cost
10% Decrease in:			
Stops per Mile	-1.00	-2.59	-1.33
Idle Time per Stop	-0.44	-1.42	-0.71
Both	-1.44	-4.01	-2.04
1 SD Decrease in:			
Stops per Mile	-2.71	-7.03	-3.61
Idle Time per Stop	-3.05	-9.88	-4.94
Both	-5.76	-16.91	-8.55

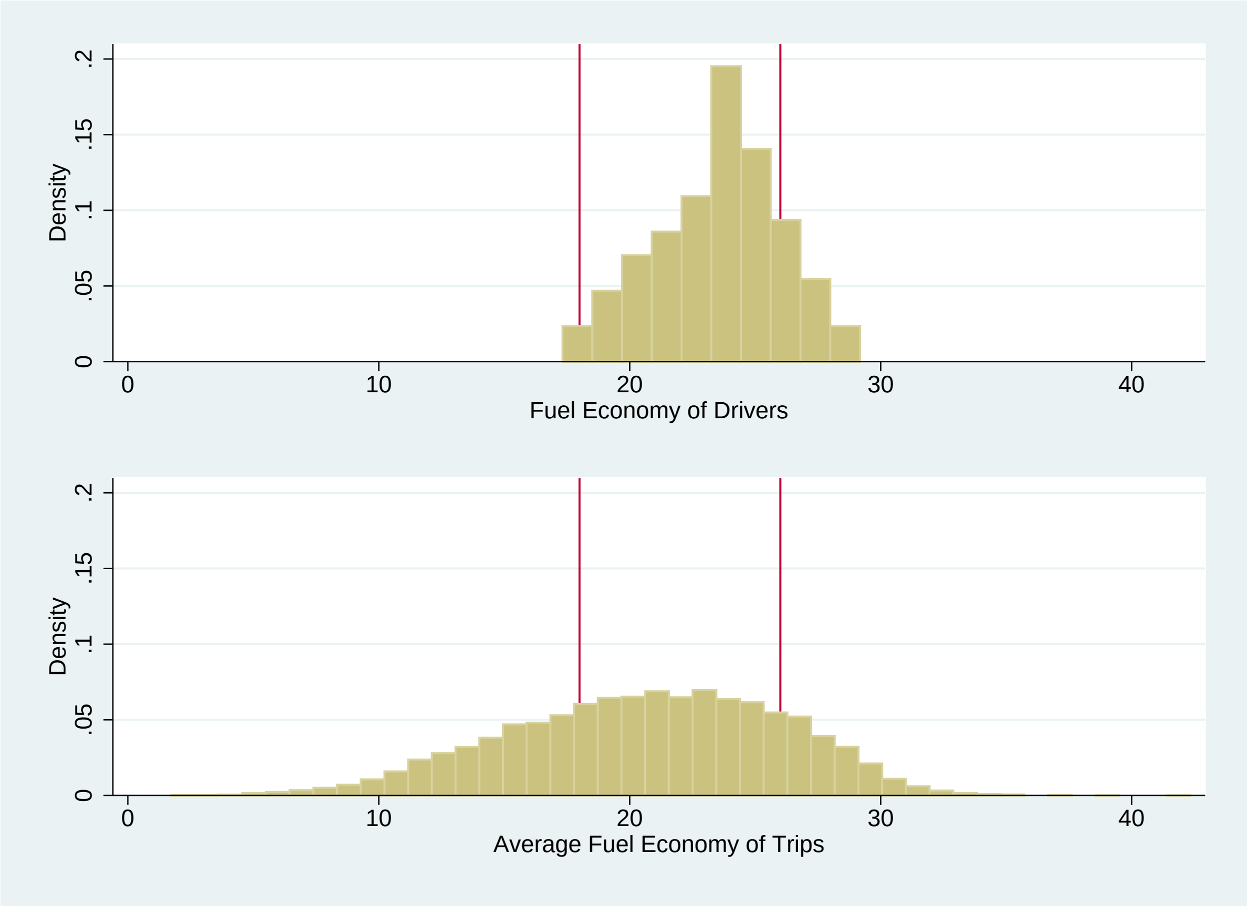
Note: Eliminating the variation in stops per mile and idle time per stop by assuming that all trips on a route have the minimum of both stops per mile and idle time per stop generates results similar to reducing both variables by one standard deviation.

Table 7: Simulation Results Allowing For Rebound

	10% rebound		50% rebound		100% rebound	
	% change in fuel	% change in time	% change in fuel	% change in time	% change in fuel	% change in time
10% Decrease in:						
Stops per Mile	-0.87	-2.46	-0.34	-1.95	0.32	-1.30
Idle Time per Stop	-0.37	-1.35	-0.08	-1.07	0.27	-0.72
Both	-1.24	-3.82	-0.43	-3.03	0.57	-2.06
1 SD Decrease in:						
Stops per Mile	-2.57	-6.94	-1.17	-5.60	0.58	-3.93
Idle Time per Stop	-2.78	-9.67	-0.87	-7.89	1.52	-5.67
Both	-5.17	-16.44	-1.95	-13.61	2.07	-10.07

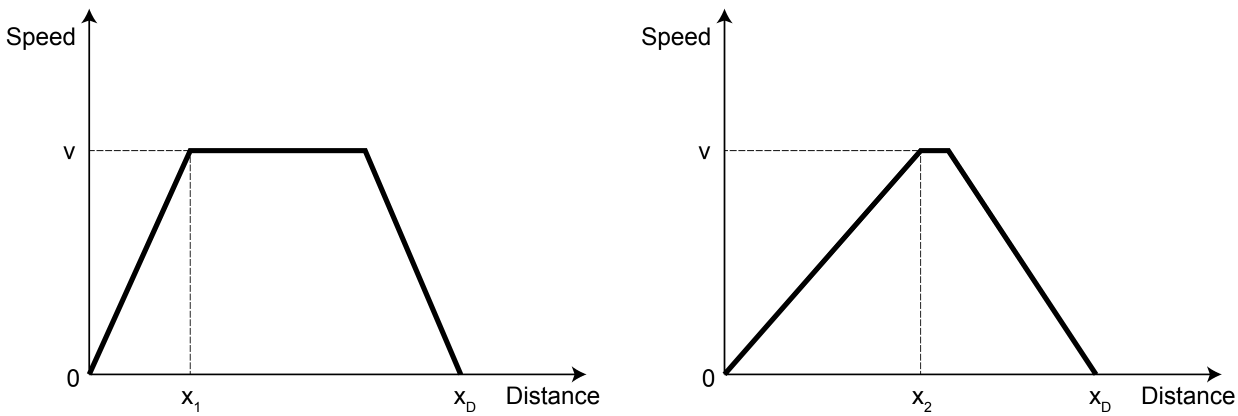
Note: 10%, 50%, and 100% rebound represent elasticities of driving of -0.1, -0.5, and -1 respectively.

Figure 1: Distribution of mean fuel economy across drivers and trips



Note: Distribution of average driver fuel economy and average trip fuel economy in our sample. Vertical bars indicate the EPA's fuel economy rating for city (18 mpg) and highway (26 mpg) driving.

Figure 2: Definition of characteristic and mean acceleration



Note: The two panels show the speed profiles for two trips over the same distance x_D. In both trips, the drivers accelerate from 0 to speed v, travel at constant speed v, then decelerate to 0. The characteristic acceleration does not depend on x_1 or x_2 and is identical for the two panels: v^2/x_D. However, the mean acceleration for the left panel is about twice as large as the right panel: v^2/x_1 compared to v^2/x_2.

A Physical model of fuel consumption

The theoretical structure of the physical model is developed from Saerens et al. (2010) and Hellström et al. (2009).[30] Unlike these papers in the engineering literature, we use our observed data on fuel consumption to econometrically estimate the parameters of the model for our particular vehicle type.[31]

Instantaneous fuel flow $\dot{m}$ is a modeled as a non-linear function of the engine rotation speed ω and the engine torque T_e.[32] Both of these can be written as a function of vehicle speed and acceleration. First, conditional on gear, engine rotation speed is a linear function of the vehicle speed, as in Equation (3):

$$\omega = v\left(\frac{i_g}{R_w}\right) \tag{3}$$

In this equation R_w is the wheel radius and i_g is the combined transmission and final drive conversion ratio for the chosen gear g.

The vehicle driveline transmits the engine torque into a friction force on the wheels of the vehicle, F_w, as in Equation (4):

$$T_e = \frac{R_w}{i_g \eta} F_w \tag{4}$$

The power transmission efficiency, η, is assumed to be constant.

The equation of motion for the vehicle is then given by Equation (5):

$$F_w = ma + F_a(v) + F_r(\alpha) + F_N(\alpha) \tag{5}$$

[30] Other papers that apply mathematical programming techniques to a simplified vehicle model in order to derive fuel-minimizing driving behavior include Schwarzkopf and Leipnik (1977), Chang and Morlok (2005) and Saerens et al. (2009).

[31] In a similar approach, Hooker (1988) uses a statistical model to simulate fuel consumption for 15 types of vehicle. Fuel consumption measurements are from dynamometer testing in a laboratory. These are matched to observations of engine speed and load during driving on a track. Ahn et al. (2002) also use a combination of laboratory measurements and field driving tests to develop models of vehicle fuel consumption and emissions. In contrast to this approach, we use simultaneous observations of speed, acceleration and fuel consumption from driving on real roads.

[32] This is the approach used by Saerens et al. (2010). An alternative is to model fuel flow as a function of the fueling level (determined by the driver using the accelerator pedal) and the engine speed (Hellström et al., 2009). This requires an additional equation to relate the engine torque, fueling level and engine speed.

In this equation m is the mass of the vehicle. $F_a(v)$ is the aerodynamic resistance, which is proportional to the square of the velocity of the vehicle.[33] $F_r(\alpha)$ is the rolling resistance of the vehicle, which is proportional to the cosine of the roadway slope, α. $F_N(\alpha)$, the gravitational force, is proportional to the sine of the road slope.

Combining Equations (4) and (5) allows us to write engine torque as a function (conditional on gear) of acceleration, the square of velocity, and the slope of the road. Although it is possible to estimate the entire model conditional on observed gear, for our counterfactual analysis we wish to abstract away from modeling gear changes by the automatic transmission. Instead we assume that gear changes are instantaneous and that i_g is itself a function of speed.

The final stylized expression for instantaneous fuel flow is given by Equation (6):

$$\dot{m} = f(\omega, T_e) = f(\omega(v, i_g(v)), T_e(v, a, \alpha, i_g(v))) \tag{6}$$

Saerens et al. (2010) use a polynomial approximation for this function, including the interaction of cubic terms in ω and quadratic terms in T_e.

B Empirical Implementation

We estimate a flexible version of the physical model from Appendix A to understand how drivers' choices of speed and acceleration affect their fuel consumption. Equation (6) shows that the rate of fuel use is a nonlinear function of speed, acceleration, and road grade. We approximate this function using the interation of sixth-order polynomials in speed, second-order polynomials in positive and negative acceleration, and road grade. Combining all of these components with our second-by-second data gives us our estimation equation:

$$y_t = \alpha + \sum_{i=0}^{6} v_t^i \left[\sum_{j=0}^{2} \beta_{ij0}(a_t^+)^j + \sum_{k=0} \beta_{i0k}(a_t^-)^k + \delta_i \alpha_t \right] + \gamma \mathbf{z_t} + \varepsilon_t \tag{7}$$

In Equation (7), y_t is the fuel use for a given second of driving in our sample, as measured in gallons per 100 miles. v_t is the mean speed during the second-of-sample t, a_t^+ is the mean acceleration in feet per second squared if this is positive (and zero otherwise), a_t^- is the mean

[33] Other components of air resistance are the frontal surface of the vehicle, the vehicle drag coefficient, and density of air. These are assumed to be constant.

acceleration in feet per second squared if this is negative (and zero otherwise), and α_t is the mean road grade measured in radians. z_t contains other explanatory variables that are not interacted with the polynomial in speed: the outside temperature in degrees Fahrenheit and a measure for the use of the air conditioner.

Because the dependent variable of equation (7) is fuel use measured in gallons per 100 miles, this variable approaches infinity for extremely low speeds or idling. For this reason, we estimate a separate model for fuel consumption at zero or very low speeds (less than 3 mph). This low-speed model is identical to equation (7) except that the dependent variable is measured in gallons per hour.

Table 8 shows the results for equation (7), estimated for all observations with speed above 3 mph. Column 1 shows the results for a quadratic in speed and excluding all acceleration terms, while Column 2 adds linear terms in acceleration, with positive and negative acceleration entering separately. Column 3 adds the interaction of the linear terms in acceleration and speed and Column 4 shows a selection of coefficients from the full set of estimation results, including the full interactions between a sixth-order polynomial in speed and a second-order polynomials in the two acceleration terms.

The full model in column 4 fits the data extremely well and substantially better than other models, with an R^2 of 0.928. The largest increase in R^2 comes from adding the linear acceleration terms to the model, suggesting that acceleration is critically important in understanding fuel use, even controlling for speed. This means that speed sensor data will be substantially weaker at understanding on-road fuel use than the panel data that we use in this study.

The coefficient estimates are fairly consistent across models at least in terms of sign. Increased speed decreases fuel use, but at a decreasing rate. Positive acceleration increases fuel use substantially across all of the models in table 8, and negative acceleration decreases fuel use in the full model in column 4. The interactions between acceleration and speed show that his effect is largest at low speeds and diminishes at higher speeds. Uphills increase fuel use and downhills decrease fuel use, as shown by the positive coefficient on the sine of road grade, and air conditioner use always increases fuel use. Higher outdoor temperatures generally decrease fuel use, as the engine runs more efficiently at higher temperatures.[34]

[34]Table 9 shows the same set of estimation results, but on observations at speeds less than 3 mph and a dependent variable of gallons per hour. In this speed range, increasing speed increases fuel use per second, but at a decreasing rate (although in each second the vehicle is covering a greater distance). Positive acceleration again increases fuel use and negative acceleration decreases fuel use, but this relationship is strongly tied to the speed of the vehicle as the interaction term is large and negative for positive acceleration interacted with speed and large and positive for negative acceleration interacted with speed. As before, air conditioner use

Table 8: Estimates for fuel consumption in gallons per 100 miles, at speeds above 3 miles per hour

	(1)	(2)	(3)	(4)
Speed (ft/s)	-0.33	-0.26	-0.21	-1.46
	(0.000)	(0.000)	(0.000)	(0.018)
Speed squared (ft^2/s^2)	0.00	0.00	0.00	0.05
	(0.000)	(0.000)	(0.000)	(0.001)
Acceleration > 0 (ft/s^2)		3.05	3.79	4.13
		(0.001)	(0.002)	(0.110)
Acceleration < 0 (ft/s^2)		0.54	0.04	-1.29
		(0.000)	(0.001)	(0.052)
(Acceleration > 0) $\times$ speed			-0.02	0.08
			(0.000)	(0.019)
(Acceleration < 0) $\times$ speed			0.01	0.24
			(0.000)	(0.010)
Sin of road grade	11.90	17.98	17.51	4.26
	(0.095)	(0.084)	(0.082)	(0.546)
Air conditioner (0–1)	0.83	0.76	0.75	0.74
	(0.003)	(0.001)	(0.001)	(0.001)
Outside temperature (°F)	-0.01	-0.01	-0.01	-0.01
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	15.95	11.47	9.94	19.55
	(0.008)	(0.005)	(0.005)	(0.098)
Higher order interactions	N	N	N	Y
Minimum fuel speed (mph)	56.2	51.9	50.1	51.6
Minimum fuel usage (gal/100mi)	2.37	1.48	2.08	2.86
Observations	18,333,541	18,333,541	18,333,541	18,333,541
Adjusted R^2	0.306	0.854	0.866	0.928

Note: Each observation is the fuel consumption, in gallons per 100 miles, during one second of driving at a speed greater than 3 mph. The regression in the fourth column includes the full set of interactions between a sixth-order polynomial in speed and second-order polynomials in positive and negative acceleration as well as the sine of the road grade. The speed that minimizes fuel usage per mile, assuming zero acceleration and zero grade, is shown at the bottom of the table, along with the fuel consumption at this speed. Robust standard errors are shown in parentheses.

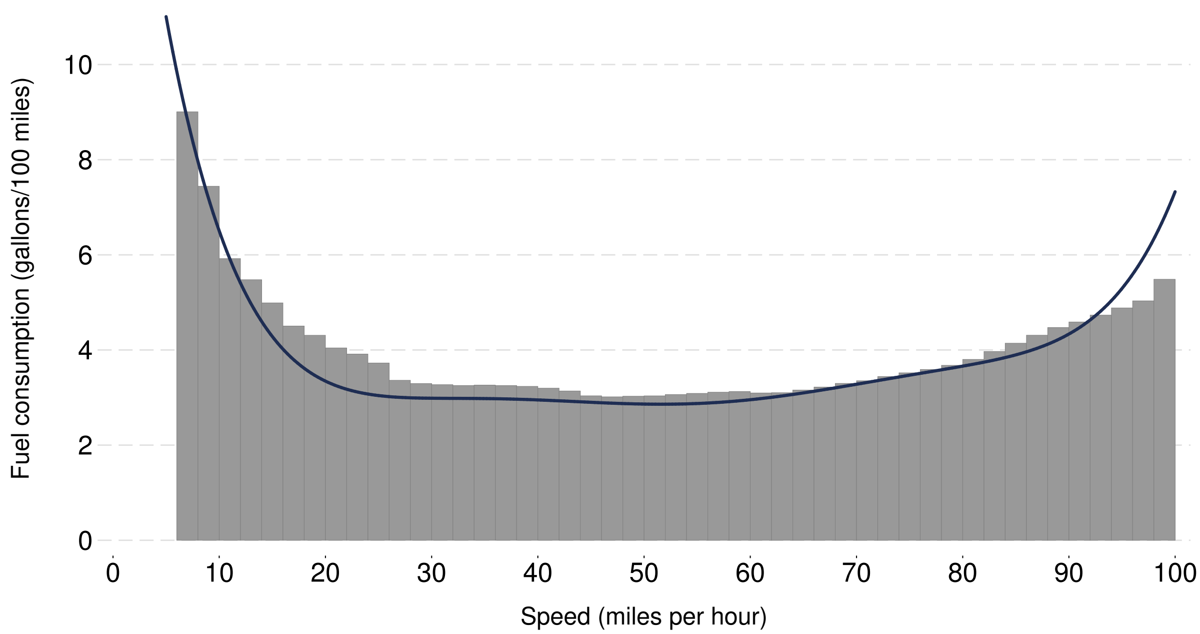
Table 9: Estimates for fuel consumption in gallons per hour, at speeds below 3 miles per hour

	(1)	(2)	(3)	(4)
Speed (ft/s)	0.09	-0.01	0.01	0.34
	(0.000)	(0.000)	(0.000)	(0.034)
Speed squared (ft^2/s^2)	-0.01	0.01	-0.00	-0.65
	(0.000)	(0.000)	(0.000)	(0.090)
Acceleration > 0 (ft/s^2)		0.13	0.06	0.05
		(0.000)	(0.000)	(0.008)
Acceleration < 0 (ft/s^2)		-0.02	-0.04	-0.09
		(0.000)	(0.000)	(0.003)
(Acceleration > 0) $\times$ speed			0.03	-0.47
			(0.000)	(0.084)
(Acceleration < 0) $\times$ speed			0.01	0.48
			(0.000)	(0.035)
Air conditioner (0–1)	0.11	0.11	0.11	0.11
	(0.000)	(0.000)	(0.000)	(0.000)
Outside temperature (°F)	-0.00	-0.00	-0.00	-0.00
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.54	0.54	0.54	0.54
	(0.000)	(0.000)	(0.000)	(0.000)
Higher order interactions	N	N	N	Y
Observations	4,532,054	4,532,054	4,532,054	4,532,054
Adjusted R^2	0.152	0.297	0.309	0.318

Note: Each observation is the fuel consumption, in gallons per hour, during one second of idling or driving at a speed less than 3 mph. The regression in the fourth column includes the full set of interactions between a sixth-order polynomial in speed and second-order polynomials in positive and negative acceleration. Robust standard errors are shown in parentheses.

The implied minimum constant-speed fuel use occurs 51.6 miles per hour for the full model, at which point the vehicle is using 2.86 gallons per 100 miles. Figure 3 makes this relationship clear by showing both the observed and predicted fuel economy for constant speed driving at different speeds over 2 mile per hour speed bins. The gray bars are the observed fuel economy in our data over all one-second observations in our data where acceleration is zero and the vehicle is driving on level road. The black line is the fitted relationship using the coefficients from column 4 of table 8, with acceleration and grade set to zero and all other non-speed terms set to their mean values in the sample. The model fits the data very well over the range of normal driving speeds and shows that there is a substantial improvement in fuel use as speed increases from very low speeds (and therefore inefficient low gears) and a more gradual increase in fuel use at speeds over 60 miles per hour. Both the predicted curve and the observed fuel use are very flat over the range from 30 to 70 miles per hour.

Figure 3: Observed and Predicted Relationship between Fuel Consumption and Speed



Notes: The gray bars show the mean fuel consumption for level driving at constant speed (defined as the absolute value of the grade less than 1 degree and the absolute value of acceleration less than 1 ft/s^2), using 2 mph speed bins. The function plot shows the predicted relationship between speed and fuel consumption, assuming zero acceleration and zero grade, based on the estimates in Table 8.

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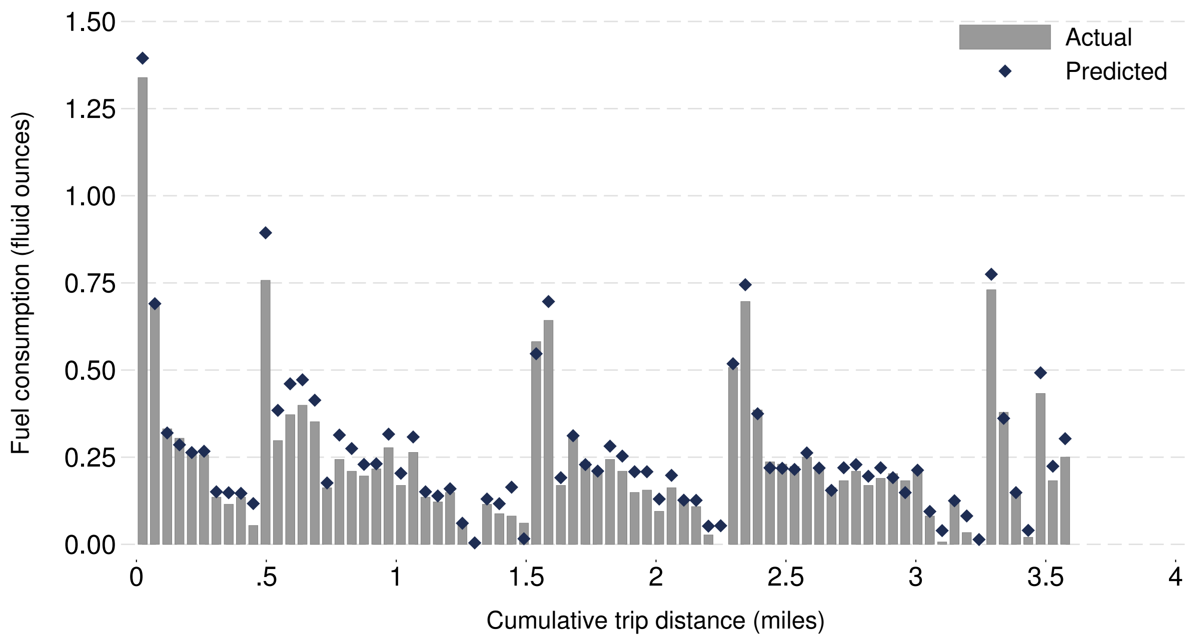
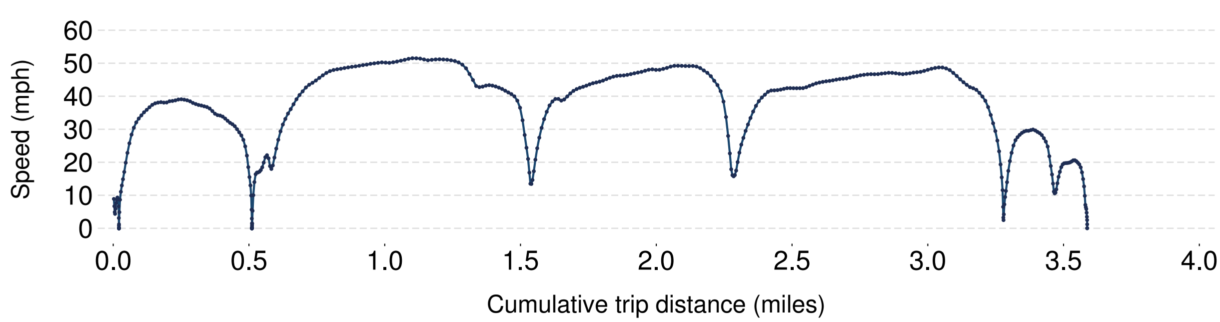
increases fuel use and higher outside temperatures decrease fuel use. This model does not fit the data nearly as well as it fits the higher-speed data, with the R^2 only reaching 0.318 for the full model in column 4.

We have seen that the model fits constant speed driving quite well, as evidenced by figure 3. We conduct an additional check of model fit by taking a single trip and looking at the predicted and observed fuel use given the characteristics of the trip.

Figure 4 shows the observed and predicted fuel use over a short trip of just under 4 miles. The top panel of figure 4 shows the actual fuel use in 250 foot bins with the gray bars. The black diamonds display the predicted fuel use in that 250 foot bin using the characteristics of this particular trip. The bottom panel of figure 4 shows the speed in miles per hour over the trip. The obvious first take-away is that the model predicts the variation in fuel consumption over the trip extremely well. The black diamonds are generally very close to the tops of the gray bars, although there are occasionally some small differences. The second thing to notice about figure 4 is that fuel consumption is much higher during acceleration events. The fuel consumption when the vehicle is accelerating is substantially higher than the fuel consumption when the speed is either constant or decreasing.

Figure 4: Observed and predicted fuel consumption and observed speed for a single trip





Note: The top figure shows the fuel consumption during one particular trip. The gray bars show the actual fuel consumption for each 250 foot segment of the trip. The diamond markers show the predicted fuel consumption based on the estimates in Table 8. The vertical axis shows fuel consumption in fluid ounces for the 250 foot segment. The bottom figure shows the trace of speed (in miles per hour) for the same trip.