

The time-of-day travel demand elasticity paradox ^{*}

Cody Nehiba[†]

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Abstract

Travel demand and congestion fluctuate throughout the day, but temporal heterogeneity in travel demand elasticities is often overlooked. I estimate within-day variation in the fuel economy elasticity of travel demand, illustrating the timing of the rebound effect — when higher fuel efficiency standards increase mileage by decreasing per-mile costs. The results present a paradox. Drivers are most elastic during peak demand periods. Mode switching for shorter commute trips in areas with low-cost alternatives drives the heterogeneity, and the pollution benefits from fuel economy standards are more than offset by exacerbated congestion costs due to temporal heterogeneity in the rebound effect.

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[†]Center for Energy Studies, Louisiana State University, Energy, Coast, and Environment Building, 93 S. Quad Dr., Baton Rouge, LA 70803 (e-mail: cnehiba@lsu.edu).

I Introduction

Peak demand periods are often accompanied by high marginal costs due to capacity constraints. Standard theory suggests applying time-varying prices to align incentives, but this solution is not always possible in practice (Vickrey, 1963, 1969). For example, 3.2 *trillion* miles were driven in the United States in 2017¹ — miles that were disproportionately driven during peak travel periods, morning and evening commuting hours.² Such astronomic levels of demand, particularly during peak periods, on roads with finite capacity, led to an equally immense loss of 8.8 billion hours of time to traffic congestion (Schrank et al., 2019). Though travel demand and the external costs of congestion are highly temporal with well-known patterns, most policies affecting travel demand — like vehicle fuel economy standards that uniformly decrease per-mile driving costs by reducing fuel consumption — do not vary across the hour of day.³

Policies that uniformly affect prices across peak and off-peak periods are often levied when implementing time-varying prices would be technologically difficult or politically infeasible. In these cases, the relative demand elasticities across periods can ultimately determine whether the uniform policy helps or harms society. Given the temporally concentrated nature of congestion and lack of congestion tolling, variation in travel demand elasticities between peak and off-peak periods is a first-order policy concern. However, little is known about how demand elasticities vary across the time of day. While it is often hypothesized that drivers are less responsive to fuel costs during peak periods because they are engaging in relatively important trips (e.g., commuting) and fuel costs are a smaller share of total costs (e.g., due to congestion), little empirical evidence is available to support this claim or quantify the magnitude of the potential differential (Knittel and Sandler, 2018; Parry and Small, 2005; Portney et al., 2003; Yang et al., 2020).⁴

¹To put this in perspective, the sun is a mere 92.2 million miles from Earth. US drivers made the equivalent of 17,353.6 round trips to the sun in 2017.

²Other examples range from congestible goods like popular attractions at national parks, which can become very congested during midday hours, to the electricity sector, which experiences peak demand during the afternoon which is associated with high marginal cost of generation and often high external pollution damages due to the generating units used.

³Economists and transportation engineers have long lobbied for road pricing based on real-time congestion, but only a few instances of such policies have been implemented. London, Stockholm, Singapore, Milan, and several other cities have implemented congestion charges, usually in the form of cordon tolls.

⁴One notable exception is Bento et al. (2013) which estimates the effect of fuel prices on highway travel in Los Angeles and Ventura counties in southern California. They find that drivers are less responsive to fuel prices during peak periods, a result that differs from that found in this paper. This discrepancy can likely be attributed to the empirical setting in Bento et al. (2013), highway travel in a car-centric region, which I find to be less responsive

I address this gap in the literature by examining how drivers respond to fuel costs differentially across the hours of the day. I then illustrate the policy importance of the elasticity heterogeneity in the context of the rebound effect from fuel economy standards — a widely studied phenomenon where increasing a good’s energy efficiency leads to increased usage due to lower usage costs. In the context of vehicles, fuel economy standards reduce the per-mile costs of driving and therefore lead to more driving.

In practice, I accomplish this task by separately estimating how travel demand changes in response to fuel economy shocks during peak and off-peak periods. The empirical estimation leverages exogenous variation in fleet fuel economy caused by randomly occurring fluctuations in ambient air temperature and high frequency travel demand data — 1 billion+ hourly vehicle counts from the network of traffic sensors in the US — to estimate how vehicle counts respond to changes in fuel economy. Ambient air temperature, particularly cold weather, plays a large role in real-world fuel economy. Cold weather causes engines to take longer to reach optimal operating temperatures, air to become denser, engine and transmission friction to increase, tire pressure to fall, and numerous other physical and mechanical issues that have deleterious effects on fuel economy. A drop in temperature from 77 to 20 degrees Fahrenheit reduces fuel economy by 15%, and even up to a 24% reduction for short 3- or 4-mile trip (EPA, 2019; Lohse-Busch et al., 2013; Ostrouchov, 1978).

While weather affects both fuel economy and driving patterns, I utilize only deviations from historic average heating degree days (HDD) within a state and month of year for identification. This strategy allows for contemporaneous changes in weather (average temperature, precipitation, snowfall, and snow depth) to be controlled for in the estimation. In other words, deviations from a state’s historic cold-weather induced fuel economy penalty in a month of year are used for identification while also controlling for changes in trip composition caused by contemporaneous weather.⁵ By also including sensor, week, and county-by-month-of-year fixed effects, I control for unobserv-

during peak periods than nonhighway travel and less car-centric areas. Though less likely, it is also possible that their use of OLS to estimate models differentiating between peak and off-peak periods, as opposed to the instrumental variable specifications that correct for the endogeneity of gasoline prices used elsewhere in their paper, contributes to the differing results.

⁵For example, it is possible for a state to have different deviations from historic average month-of-year HDD in April of 2020 and May of 2020, but the same average temperature of 75 degrees. I control for the types of trips taken when the average temperature is 75 degrees, using only the deviation from the historic fuel economy penalty for identification.

able sensor characteristics, macroeconomic fluctuations, and granular changes in seasonal driving patterns. Cumulatively, these measures remove concerns that the results are driven by weather shocks unrelated to fuel economy.

This empirical strategy allows me to provide a detailed analysis of travel demand elasticities that highlights the importance of the peak load while contributing several innovations to the rebound effect literature. First, I loosen many of the empirical assumptions previously used to estimate the rebound effect. Perhaps most importantly, the elasticities I provide are a measure of the rebound effect which directly examines driver response to fuel economy. In contrast, much of the previous literature has examined driver response to fuel prices when estimating the rebound effect of fuel economy standards, assuming that the responses are inversely proportional (Gillingham, 2020; Linn, 2016). Further, I identify these effects using exogenous shocks to real-world fleet fuel efficiency to recover unbiased estimates of driver response to fuel economy. This strategy eliminates concerns about endogenous fuel economy choices and the shifting of vehicle usage in multi-vehicle households. Finally, while previous research has examined how fuel economy standards affect externalities like pollution and automobile collisions, I provide a better understanding of the relationship between the standards and congestion by examining how the rebound effect varies across hours of the day.

The results present a paradox. In contrast to past assumptions, drivers are found to be *more elastic* during peak travel periods.⁶ A 1% increase in fuel economy leads to a 0.43% increase in vehicle counts during peak periods, but only a 0.22% increase during off-peak hours. Drivers are nearly twice as responsive to fuel costs during peak periods. This result is found to be robust to being estimated using OLS, alternative instruments, and even alternative travel demand data sources.⁷

I then explore the mechanisms driving this differential response during peak periods. I begin by determining if the response is truly driven by commuting trips by separately estimating the results for weekdays and weekends, which have significantly different commuting patterns. I find weekends have a larger baseline response to fuel economy but a smaller increase in responsiveness

⁶Peak periods are defined as 05:00–09:59 and 16:00–18:59. I examine robustness to this modeling decision in Appendix Table A2, finding qualitatively similar results regardless of the definition of the peak period.

⁷OLS results are presented in Appendix Table A4. Results using gasoline content regulations as instrumental variables for fuel prices in a subset of counties in the sample are presented in Appendix Table A10. Similar results are also replicated using survey data from the National Household Travel Survey in Appendix Table A9.

during peak periods relative to weekdays. Weekdays see a 0.475% increase in vehicle counts during peak periods and only a 0.19% increase during off-peak periods for each 1% increase in miles per gallon (MPG). Next, I segment the data across highway and nonhighway roads to examine if the heterogeneity is driven by trip characteristics (e.g., nonhighways tend to be used for trips that may be local, shorter, or otherwise more easily switched to other modes of transportation). Highway travel appears to respond differently than travel on other road types. The peak period elasticity differential on nonhighways is 0.31 but only 0.19 for highways. Finally, I assess how variation in commute mode choice and the availability of alternative modes across space affects the results. I find larger peak period response to fuel economy in areas with higher shares of workers commuting by modes other than passenger vehicles — particularly active transportation (bicycling or walking), carpooling, or working from home.

Taken together, these results provide suggestive evidence that shorter (i.e., nonhighway) and weekday commuting trips drive the increase in elasticity during peak periods. Though much of the prior literature has posited that drivers are less elastic during peak periods, the results presented here are perhaps not surprising as these trips are most likely to have low-cost alternatives (e.g., active transportation, carpooling, transit) and potentially require less mental energy to switch modes than off-peak leisure trips.⁸ This theory is further supported by the differential response in counties with high shares of commute trips not made by passenger vehicles, though it is difficult to test the exact extent that active transportation, carpooling, and other adaptations play into the results due to data limitations.

Finally, because the elasticity I estimate is a novel measure of the rebound effect, I evaluate the change in external pollution and congestion costs from a change in fuel economy standards after accounting for this time-dependent rebound effect. Because large shares of the rebound effect occur during peak travel periods (when demand is more responsive to fuel economy), fuel efficiency policies (e.g., the Corporate Average Fuel Economy Standards in the US) exacerbate the congestion externality to such an extent that their pollution benefits are more than offset by increases in congestion. A 1.5% increase in fleet fuel economy, the annual increase mandated under current standards, produces \$460 million/year in pollution benefits. However, the standard also induces

⁸For example, learning what transit line or bike lanes to use to get to work eliminates 10 car trips per week while learning how to get to the grocery store, movie theater, a friend's house, or your favorite restaurant via alternative modes likely has higher average mental costs per trip.

\$1,215 million/year in congestion costs, leading to a net loss of \$755 million/year. Further, in a counterfactual analysis which erroneously assumes the peak period is more inelastic, these results are reversed.⁹ This counterfactual finds pollution benefits exceed congestion damages, creating a net gain of \$538 million/year — highlighting that variation in elasticities can be enough to reverse policy recommendations.

The remainder of the paper is organized as follows. Section II provides background information on travel demand and congestion, the relationship between weather and fuel economy, and the rebound effect. Sections III and IV describe the data and empirical strategy used in the analysis. The results from this analysis are provided in section V, and section VI illustrates the importance of the heterogeneity in travel demand elasticities across the hours of the day in the context of the rebound effect from fuel economy standards. Section VII concludes.

II Background

A *Travel Demand and Congestion*

Though they vary in size and shape across regions, travel demand peaks generally correspond with the timing of economic activity. Travel by urban passenger vehicles exhibits a strong bimodal distribution across the day with peaks in the morning and evening, while travel by rural passenger vehicles tends to increase throughout the day, beginning at 05:00 and exhibiting a single peak in the evening (FHWA, 2014).

Regardless of the timing of these peak periods, they are capable of straining infrastructure and causing congestion. Because of these infrastructure limitations, congestion increases nonlinearly with travel demand. When there are few vehicles on the road, adding another vehicle may decrease speeds slightly or leave them unaffected; however, as the number of vehicles increases, the marginal effect of adding a vehicle on average speed becomes larger. Once the capacity of the road is reached hypercongestion and gridlocked traffic can occur.

This nonlinear relationship suggests that the marginal external costs of congestion are not uniform across the hours of the day. Adding another vehicle to the road during a hypercongested

⁹This exercise is identical to the one described above except the counterfactual policy analysis replaces the peak period elasticity estimated in this paper with a more inelastic parameter.

period will lead to more congestion than adding the same vehicle when there are prevailing free-flow speeds. Reductions in driving during peak demand periods can provide significant welfare improvements while reductions in driving during off-peak periods are relatively inconsequential.

The private costs of driving also rise with congestion due to increases in per-mile time costs — slower speeds increase travel times. Private costs due to congestion during peak periods should factor into an agent’s decision to drive. This means that as congestion worsens and a driver’s time costs increase, fuel costs, which are a function of vehicle efficiency, become a smaller share of a trip’s total costs. This logic, combined with the notion that most trips made during peak periods are commute trips and therefore relatively important, has led economists to assume that drivers will be less responsive to fuel costs (and therefore fuel economy) during peak periods (Knittel and Sandler, 2018; Parry and Small, 2005; Portney et al., 2003; Yang et al., 2020).

This assumption has been scarcely tested in the empirical literature with the exception of Bento et al. (2013) which do indeed find that drivers are less responsive to fuel prices during peak periods. Their results potentially differ from those presented in this paper for several reasons. Most importantly, Bento et al. (2013)’s data covers only highway roads in Los Angeles and Ventura County. My results suggest that nonhighway roads drive the differential response in peak period elasticities. Further, I find that areas with high shares of commute trips performed by passenger vehicle do not have a differential peak period effect, and southern California travel is notoriously dominated by passenger vehicles. Finally, though Bento et al. (2013) employ an instrumental variables strategy to correct for the endogenous relationship between fuel prices and traffic counts in parts of their analysis, they use OLS when examining the differences between peak and off-peak periods, which may further mute the differential effects.

B *Weather and Fuel Economy*

I use the relationship between ambient air temperature and fuel efficiency to identify the effects of fuel economy on vehicle counts. The transportation engineering literature has established that cold weather lowers vehicle fuel efficiency through multiple channels for both mechanical and physical reasons. Low temperatures cause engines to take longer to reach optimal operating temperatures. Air becomes denser as temperatures fall, increasing aerodynamic drag on vehicles. Cold

temperatures reduce tire pressure which increases resistance. Engine and transmission friction increases due to cold engine oil and driveline fluids. Battery performance decreases with temperature which makes it more difficult for alternators to keep the battery charged. Other weather-related concerns including the use of four-wheel drive, slower driving speeds, loss of traction from icy or snow-covered roads, and the use of heated seats may further decrease fuel economy (EPA, 2019; Lohse-Busch et al., 2013; Ostrouchov, 1978). These effects are nontrivial — in city driving fuel economy has been estimated to drop by 15% at 20 degrees Fahrenheit relative to fuel economy at 77 degrees (EPA, 2019). Further, this fuel economy penalty can be as large as a 24% reduction for short 3- or 4-mile trips.

The identification strategy utilizes fluctuations in vehicle fuel economy caused by cold weather, but weather plays a significant role in when and where individuals drive. As will be described in more detail in section IV, I mitigate concerns that weather shocks unrelated to fuel economy drive the results by using anomalous variations in heating degree days (HDD) as an instrument for average fuel efficiency. These anomalous HDD are deviations from the historical average HDD for that state and month of year from a baseline period of 1901 to 2000. This strategy allows me to isolate the identifying variation to historic deviations within a state and month of year while also controlling for contemporaneous weather.

While excessively hot weather may also impact fuel economy, I rely on HDD for identification. This is because the main pathway that warm weather reduces fuel economy is through the use of air conditioning. While it is rare for new vehicles to not come with an air conditioner not all individuals uniformly use their air conditioners during warm weather.¹⁰ In contrast, it is impossible for individuals to avoid many of the deleterious effects of cold weather on fuel economy. While they may wish to avoid the additional drag cold air causes on their vehicle, drivers cannot alter air density.

C The Rebound Effect

Energy efficiency programs are a common tool used to correct market failures associated with energy usage. These programs are designed to address externalities and internalities including myopic consumers, firm underinvestment in energy efficiency research, or air pollution. These

¹⁰Notable exceptions include some trim models of Jeep Wranglers, Renegades, and Patriots.

programs aim to reduce energy usage by improving the efficiency of our automobiles, major appliances, and even buildings. Improving a good's energy efficiency also lowers its usage costs which in turn leads agents to increase their utilization of the good. This increase in use caused by higher efficiency is a widely studied phenomenon known as the "rebound effect" (Gillingham et al., 2015; Jevons, 1865; Small and Van Dender, 2007). The rebound effect has been examined in numerous settings ranging from air conditioners to automobiles. In the context of fuel economy standards for automobiles, most studies have found relatively small rebound effects — most elasticity estimates fall between 0.1 and 0.4.¹¹

The most frequently employed empirical strategy to estimate the rebound effect is to estimate the fuel price elasticity of driving using either survey data or odometer readings (Gillingham, 2020; Linn, 2016). As discussed in Linn (2016), these elasticity estimates, often referred to as a measure of the direct rebound effect, tend to rely on at least one of the following assumptions: (1) the choice of fuel economy is not correlated with other attributes of vehicles or households, (2) households with multiple vehicles do not adjust usage intensity based on fuel costs, and (3) the effects of fuel prices and fuel economy are inversely proportional. Assumption (3) is perhaps most critical as relatively few studies have directly estimated the effect of fuel economy on travel demand.¹² Recent literature has also explored how the fuel price elasticity of driving varies across dimensions. These studies have furthered our understanding of the welfare and distributional consequences of energy policy by examining heterogeneity in fuel price elasticities across vehicles, consumer demographics, and regions (Barla et al., 2015; Gillingham and Munk-Nielsen, 2019; Knittel and Sandler, 2018; Nehiba, 2019; Spiller et al., 2017).

I make several contributions to the rebound effect literature. First, I propose a novel empirical strategy to estimate the rebound effect that loosens the assumptions listed above. Instrumenting for fuel economy using anomalous HDD eliminates concerns that fuel economy choice is endogenous — drivers cannot control the weather. Because the instrument affects fleet fuel economy and the dependent variable is vehicle counts at traffic sensors as opposed to any one vehicle's fuel economy and vehicle miles traveled (VMT), multi-vehicle households changing between vehicles will not bias the results. This new strategy also provides one of the few direct estimates of the effect of fuel

¹¹ See Gillingham (2020) or Gillingham et al. (2016) for reviews of recent estimates of the direct rebound effect of the Corporate Average Fuel Economy Standards.

¹² Notable exceptions include Gillingham (2011), Greene (2012), and West et al. (2017).

economy on miles traveled — as opposed to assuming that drivers respond symmetrically to fuel price and fuel economy changes. Further, I examine how the rebound effect varies with the time of the day. While expansive literatures have examined heterogeneity in the rebound effect and how fuel economy standards may affect other transportation externalities like vehicle collisions and transportation emissions, few have examined the relationship between fuel economy standards and congestion beyond measuring a change in miles driven.

III Data Sources and Summary Statistics

A *Traffic Sensors*

Travel demand data come from the network of traffic sensors across the United States. State transportation agencies collect traffic volume data through traffic counting programs and report these data to the US Department of Transportation’s Federal Highway Administration (FHWA). The state agencies and the Federal Highway Administration utilize these data for a variety of purposes ranging from creating estimates of vehicle miles traveled to identifying areas in need of infrastructure improvements.

The sensors report traffic flows, the number of vehicles that travel over the sensor each hour. Each sensor is identified as a single traffic lane, so hourly vehicle flows can be matched to a particular road, travel direction, and individual lane on the road segment. In total, the data set contains over a billion hourly observations, and provides remarkably rich spatial and temporal information on when and where individuals drive.

I aggregate these hourly traffic sensor observations to hour-of-day-by-week averages prior to analysis — each traffic sensor has 24 observations, one for each hour of the day, for each week in the sample.¹³ For example, the average hourly count at a sensor between 01:00 and 01:59 in week 1 of 2016, 02:00 and 02:59 in week 1 of 2016, or 13:00 and 13:59 in week 32 of 2015. The final data set contains 104.6 million observations covering 24,709 individual traffic sensors in 1,879 counties between 2013 and 2018 in the US.

¹³I aggregate the data for weekdays and weekends separately for the analysis in Table 3. I.e., each traffic sensor has 48 observations in Table 3, one for each hour of the day during weekdays and one for each hour of the day during the weekend days, for each week in the sample.

Finally, the traffic sensors occasionally experience outages. Sensors experiencing errors may report implausibly large traffic counts. These traffic counts are dropped if (1) the state altered the data to identify an erroneous count (e.g., changed value to 99999) or (2) the counts exceed 5,000 vehicles per hour.¹⁴

B *Weather Data*

I obtain weather data from two data sets provided by the National Oceanic and Atmospheric Administration (NOAA). Weather controls including average temperature, precipitation, snowfall, and snow depth come from NOAA's Global Historical Climatology Network data set, which provides daily station-level data. Past literature has outlined best practices for utilizing these data and suggests that missing weather data should be imputed prior to analysis (Auffhammer et al., 2013). I follow this suggestion, and impute the missing observations using linear regressions and data from the nearest active neighboring weather station. The data are then averaged to the county-by-week level and the precipitation, snowfall, and snow depth variables are censored at zero.¹⁵

Data on anomalous heating degree days, measured at the state-by-month level, are obtained from NOAA's Climate at a Glance data set. Anomalous HDD measures the deviation in HDD within a state and month from the average HDD in that state and month of the year between 1901 and 2000. In other words, the difference between a state's contemporaneous HDD this month and their historical average HDD for that month.

C *Fuel Economy Data*

I construct a measure of state-level fuel economy using data on monthly vehicle miles traveled (VMT) from the FHWA and gallons of gasoline sold in each state from the EIA. Dividing miles driven by gallons sold provides average fleet fuel economy for each state and month. There are several concerns with this measure of fuel economy that should be noted.

First, this measure ignores miles traveled by vehicles not powered by gasoline. This includes

¹⁴The FHWA states that under ideal circumstances (no weaving, no trucks, and constant free-flow speed) traffic flows can reach average 2,850 vehicles per hour (FHWA, 2018) though a somewhat larger maximum value is chosen here to allow for possible extremes.

¹⁵Because the data are imputed, these variables can have values less than zero (e.g., precipitation of -.3 mm), but it is not possible to have negative precipitation, snowfall, etc. The variables are therefore censored at zero.

diesel, electric, and alternative (e.g., liquefied natural gas or propane) fuel vehicles. This means that the measure of MPG will likely be higher than the true fleet fuel economy in the state. Second, not all fuel sold in a state is used within that state — vehicles are mobile and not bound by state borders. Finally, the variables used in constructing this measure are themselves estimates.

These issues can largely be controlled for using location fixed effects. This removes the average MPG of a state’s vehicle fleet and the portion of VMT that comes from non-gasoline vehicles. While the fleet composition does change over time, the relatively short duration of the sample (2013-2018), slow retirement of vehicles, and low uptake of non-gasoline vehicles mitigates this concern. Likewise, location fixed effects remove the average amount of fuel sold in a state that is not used within that state, and it is unlikely that weather plays a major role in this factor. Finally, any variation in measurement error in the VMT and gallons sold variables between states should also be differenced out by location fixed effects, and time fixed effects should mitigate any concerns that this measurement error changes over the sample.

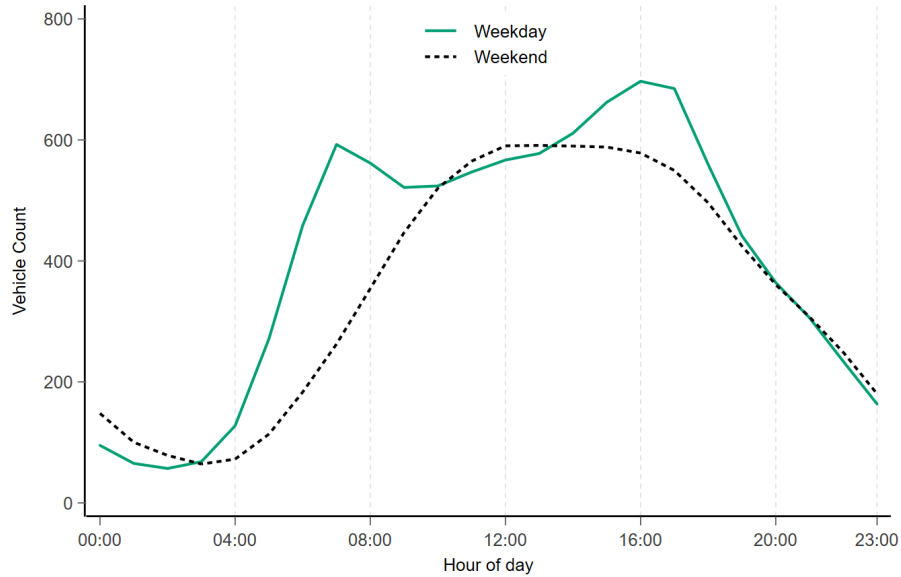
D *Other Data*

Several other control variables are used in the analysis. Unemployment data at the county-by-month level are provided by the Bureau of Labor Statistics’ Local Area Unemployment Statistics database. Annual county population estimates are obtained from the Census Bureau. State-level gasoline tax data come from the Federal Highway Administration. Gasoline price data are web scraped from Gasbuddy.com, a crowd sourcing website that provides users with local retail station prices. Fuel prices are aggregated to the state-by-week level.

Finally, I obtain commuting mode shares for each county from the Census Transportation Planning Products (CTPP). These commute mode share values are five-year estimates covering 2012-2016, so only a single value is available for each mode and county.¹⁶ In some cases, I aggregate commuting modes into easier-to-interpret bins for analysis. For example, the CTPP data have separate bins for carpooling that break down the number of individuals in the carpool. Instead of examining these granular measures of carpooling, I sum each bin to determine the total share of commute trips done by carpool regardless of the number of participants in the carpool. Similarly, I

¹⁶The previous five-year estimates cover 2006-2010 and more recent estimates are not available.

Figure 1: Hourly Vehicle Counts Throughout the Day



Notes: Figure depicts the average hourly vehicle counts for sensors across the hour of the day in the sample. Averages are calculated separately for weekdays (Monday–Friday) and weekends (Saturday and Sunday).

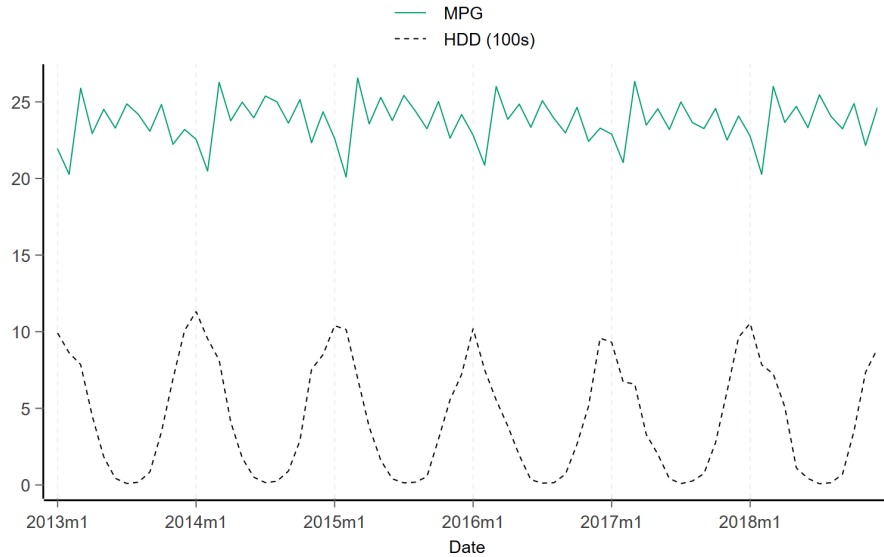
create an active transportation (bicycling plus walking), non-passenger vehicle (all modes besides passenger vehicle), and transit (all bus and rail modes) bins.

E Summary Statistics

Figure 1 depicts the average vehicle count for each hour of the day. The figure differentiates between weekday and weekend counts. The weekday counts exhibit a dual-hump shape with peaks in the morning and evening. Counts are low in the early morning hours and begin to rise sharply around 05:00 before reaching an initial peak between 07:00 and 08:00. Counts decrease slightly after the morning commuting times before rising to a second evening peak that persists across two hours, 16:00–17:00 and 17:00–18:00, before falling at night. The evening peak of approximately 700/vehicles/hour/lane is higher than the 600/vehicles/hour/lane morning peak, similar to the pattern for urban and rural cars in FHWA (2014).

Weekends exhibit a starkly different pattern of traffic flows throughout the day. Not surprisingly, slightly more driving occurs during the early morning and late-night hours on the weekends.

Figure 2: Fuel Economy and Cold Weather



Notes: Figure depicts monthly average fleet fuel economy in miles per gallon and heating degree days (100s) across all states in the sample.

Drivers also take to the roads somewhat later in the morning before flows peak around noon. This peak persists for several hours before traffic flows start to decrease at around 17:00. While the traffic flows on weekends can approach the levels of flows during the weekday-morning peak, the changes in flows on the weekend appear to be much more gradual.

Figure 2 aggregates the state-level fuel economy and HDD variables to monthly national averages. The figure provides visual evidence of the effect of cold weather on fleet fuel economy. As one would expect, heating degree days peak each winter and fall to near zero during the warm summer months. While fuel economy exhibits more variability, it sharply decreases in the cold winter months. Fuel economy is also generally at or near its highest levels during the summer. Fleet fuel economy gradually increases during the sample, driven at least in part by the Corporate Average Fuel Economy Standards in the US.

Further descriptive statistics are available in Appendix Table A1.

IV Empirical Setting

A Driver Response to Fuel Economy Shocks

I now estimate how drivers respond to fuel economy shocks. In the baseline specification, the sample consists of hour-of-day-by-week observations from the universe of traffic sensors, and the dependent variable is the log of hourly vehicle counts. The model for sensor i in county j and state s is¹⁷

$$\ln(V_{ijsh}) = \omega + \eta \cdot \ln(MPG_{st}) + \psi \cdot X_{ijsh} + \mu_i + \rho_t + \varepsilon_{ijsh} \quad (1)$$

where h denotes the hour of the day and t denotes the week of the sample. X is a matrix of control variables, μ contains sensor fixed effects, and ρ contains time fixed effects. The relationship between fleet fuel economy and vehicles counts, η , is the coefficient of interest. Standard errors are clustered at the county level throughout the analysis.¹⁸

X controls for various factors like weather and economic conditions that may both influence fleet fuel economy and driving behavior. In the preferred specification, I include county-by-week controls for temperature, precipitation, snowfall, and snow depth as well as controlling for county-by-month unemployment rate, county-by-year population, and state-by-week gasoline prices and gasoline taxes.¹⁹

Vehicle fuel economy is a choice made by drivers, making a region's fuel economy endogenous. For example, a driver with a long commute may sort into a more fuel-efficient vehicle. While a single atomistic driver would likely have a miniscule effect on the estimates, this behavior will lead to a correlation between fuel economy and unobservable local characteristics if a region on average has long commutes and therefore more fuel-efficient vehicles. The sensor fixed effects control for the average fleet fuel economy in an area, but unobservables that affect fuel economy like the fleet composition itself, vehicle usage intensity, policies, and preferences vary over time across regions.

To overcome this endogeneity issue, I leverage exogenous variation in fleet fuel economy caused by randomly occurring fluctuations in ambient air temperature. Cold temperature shocks

¹⁷I use sensor-level data to better facilitate an exploration of the mechanisms driving the results.

¹⁸Robustness to alternative error clustering is examined in Appendix Table A11.

¹⁹The results are robust to including additional control variables (e.g., GDP, income). See Appendix Table A12 for these results.

are well known to affect automobile performance for various reasons (air is denser at colder temperatures, vehicles take longer to reach optimal operating temperatures, tire pressure decreases can lead to more rolling resistance, etc.). As was discussed in section II, temperature plays a significant role in fuel economy that drivers cannot control — a change in temperature from 77 to 20 degrees Fahrenheit can reduce MPG by 15%.

While cold temperature can reduce a vehicle’s fuel efficiency, it is also correlated with driving behavior. Individuals are likely to change their leisure activities in response to the weather. You will find far more people driving to the beach when it is 77 degrees out than when it is 20 degrees out, and that difference is not likely due to the change in fuel economy between temperatures. This correlation must be controlled for empirically to ensure that the instrument meets the exogeneity requirement of instrumental variables (IV). As a solution, I propose the use of anomalous heating degree days as an instrument for fuel economy as opposed to contemporaneous HDD. These anomalous heating degree days are deviations from a state’s historic HDD, based on data from 1901 to 2000, during a given month of the year. Utilizing abnormal and unexpected fluctuations in HDD allows for the effect of county-level weather controls including average temperature, precipitation, snowfall, and snow depth on driving behavior to be controlled for in all specifications. Further, the estimates are robust to the exclusion of various months of the year that may be more susceptible to changes in driving behavior due to weather.²⁰

The use of a state-level anomalous HDD instrument means that only deviations from a state’s historic average HDD within a month of year identify the effects while the contemporaneous county-level weather variables control for temperature driven travel patterns. For example, a state may have different anomalous HDD in April of 2020 and May of 2020, but it is possible for a county within the state to have an average temperature of 75 in both the last week of April and first week of May. In this case, I use the deviations from historic average temperature, and therefore deviations from historic weather-induced fuel economy effects, for identification while also controlling for the types of trips drivers take when the average temperature is 75. The coarser measurement of the instrument at the state-by-month level also alleviates concerns drivers may put off some types of trips due to weather conditions.

Further, I include a wide set of fixed effects in the model. As mentioned above, traffic sensor

²⁰See Appendix Table A3.

fixed effects control for factors like average fleet fuel economy and traffic load across the sample. Week fixed effects control for macroeconomic trends that may broadly affect both fuel economy and driving behavior. County-by-month-of-year fixed effects granularly control for the typical types of trips being made in a county during a particular time of the year.

I therefore estimate the model using instrumental variables with a first-stage regression

$$\ln(MPG_{st}) = \tau + \delta \cdot (\text{Anom. HDD}_{st}) + \phi \cdot X_{ijsh} + \mu_i + \rho_t + v_{ijsh} \quad (2)$$

where Anom. HDD is the measure of anomalous heating degree days within that state and month.

B *Differential Response during Peak Periods*

I next explore how driver response to fuel economy shocks varies across the time of day. This is accomplished with a relatively simple extension of the empirical model described in equations (1) and (2) — including an interaction term of the fuel economy variable and an indicator variable equal to one during peak hours. The model is

$$\ln(v_{ijsh}) = \omega + \lambda \cdot (\ln(MPG_{st}) \times P_h) + \eta \cdot \ln(MPG_{st}) + \alpha \cdot P_h + \psi \cdot X_{ijsh} + \mu_i + \rho_t + \varepsilon_{ijsh} \quad (3)$$

where P is equal to one if the hour is between 05:00 and 09:59 or 16:00 and 18:59. While the intensity and duration of peak periods varies across locations, they generally occur between these hours. The results are robust to varying definitions of peak, as illustrated in Appendix Table A2. The variable of interest is now $(\ln(MPG_{st}) \times P_h)$, which estimates how fleet fuel economy differentially affects vehicle counts during peak periods. The fixed effects are also allowed to vary across the hours of day. For example, Peak×Sensor and Peak×Week fixed effects are included that separately control for time invariant sensor characteristics that may differ between peak and off-peak periods and macroeconomic shocks that may differentially affect peak and off-peak traffic, respectively. Allowing the fixed effects to vary across periods is important because ultimately the greatest threat to identification in this setting is a factor differentially biasing the effects of fuel economy across peak and off-peak periods.

Here, both MPG and the interaction of MPG and the peak period will be endogenous, necessitating a second instrument and two first-stage regressions. An obvious candidate instrument is

the interaction of anomalous HDD and peak period. The first stage now consists of the following equations

$$\ln(MPG_{st}) = \tau + \pi \cdot (\text{Anom. HDD}_{st}) + \delta \cdot (\text{Anom. HDD}_{st} \times P_h) + \iota \cdot P_h + \phi \cdot X_{ijst} + \mu_i + \rho_t + v_{ijst} \quad (4)$$

$$\ln(MPG_{st}) \times P_h = \beta + \zeta \cdot (\text{Anom. HDD}_{st}) + \theta \cdot (\text{Anom. HDD}_{st} \times P_h) + \nu \cdot P_h + \kappa \cdot X_{ijst} + \mu_i + \rho_t + v_{ijst} \quad (5)$$

V Results

This section provides results from estimating the models described in section IV. I begin by estimating the aggregate driver response to fuel economy shocks before decomposing the effects between peak and off-peak periods. Finally, potential mechanisms driving the difference in elasticities across the time of day are explored by examining various subsections of the data and variation in commuting modes across regions.

A *Aggregate Response to Fuel Economy Shocks*

I present results from estimating the instrumental variables models described in equations (1) and (2) in Table 1. Panel A provides first-stage estimates of the effects of anomalous HDD on the log of MPG. Panel B provides the second-stage estimates of the effect of the predicted changes in MPG on the log of hourly traffic counts. Fixed effects included vary across columns. Each regression includes controls for average temperature, precipitation, snowfall, snow depth, gasoline prices, gasoline taxes, unemployment rate, and population. Standard errors are clustered at the county level.

Anomalous HDD are a statistically significant predictor of fleet fuel economy, and the Kleibergen-Paap F-statistic of the excluded instruments exceeds 300 in every regression. As expected, abnormally cold weather reduces fleet fuel economy. One thousand anomalous HDD in a month reduces fleet fuel economy by approximately 1% — a result that is consistent across specifications. This

relatively small effect may be caused by the empirical strategy's tight focus, which eliminates much of the potential variation; however, the empirical strategy does provide enough identifying information to produce a relevant instrument as evidenced by the statistical significance and large F-statistics.

The effect of fleet fuel economy on traffic counts importantly depends on the fixed effects included in the model. When State×Month-of-Year (MOY) fixed effects are included, the elasticity is approximately 0.09 and statistically insignificant at conventional levels. In contrast, the elasticity triples in size and becomes statistically significant when County×MOY fixed effects are included. These results provide suggestive evidence that traffic counts increase by 1–3% when fuel economy increases by 10%. In other words, a rebound effect of 10-30%.

These estimates are similar in magnitude to previous estimates of the rebound effect. For example, Gillingham et al. (2015), Leung (2015), Langer et al. (2017), and Hymel et al. (2010) all estimate rebound effects around the lower range of these estimates, 10%. Hymel and Small (2015), Linn (2016), Liu et al. (2014), and Bento et al. (2009) estimate rebound effects up to 40%, though most estimates are closer to 20%. Of particular interest in this setting is Linn (2016) which, like this paper, loosens many of the empirical assumptions made in the previous literature and estimates a rebound effect between 20% and 40%.

Table 1: Aggregate Effect of Fuel Economy on Traffic Counts

| | (1) | (2) | (3) | (4) |
|--|----------------------|----------------------|----------------------|----------------------|
| <i>Panel A: ln(MPG) first stage</i> | | | | |
| Anom. HDD | -0.089*** (0.005) | -0.089*** (0.005) | -0.089*** (0.005) | -0.089*** (0.005) |
| <i>Panel B: ln(Traffic Count) second stage</i> | | | | |
| ln(MPG) | 0.090 (0.114) | 0.292*** (0.094) | 0.093 (0.114) | 0.296*** (0.094) |
| Observations | 104,575,134 | 104,575,134 | 104,575,134 | 104,575,134 |
| F-stat of Excluded Instruments | 304.145 | 361.99 | 304.062 | 361.88 |
| Sensor FE | Yes | Yes | No | No |
| Week FE | Yes | Yes | No | No |
| State×MOY FE | Yes | No | No | No |
| County×MOY FE | No | Yes | No | No |
| Peak×Sensor FE | No | No | Yes | Yes |
| Peak×Week FE | No | No | Yes | Yes |
| Peak×State×MOY FE | No | No | Yes | No |
| Peak×County×MOY FE | No | No | No | Yes |

Notes: Standard errors are clustered at the county level. Every regression controls for average temperature, precipitation, snow, snow depth, gasoline prices, gasoline taxes, unemployment rate, and population. ln(MPG) is fleet average fuel economy in miles per gallon. Anomalous HDD are deviations in historic average HDD in a state-month-of-year from a baseline of 1901–2000 measured in 1000s. Peak is an indicator variable equal to one if the hour of the day is between 05:00 and 09:59 or 16:00 and 18:59. *** Statistically significant at the 1% level; ** 5% level; * 10% level.

Though not reported, the control variable coefficients generally have the predicted sign, effects of reasonable magnitude, and are statistically significant. However, when only State×MOY fixed effects are included the gasoline price and gasoline tax controls have a positive and significant effect — likely due to the endogeneity between fuel prices and traffic counts biasing the coefficient upward. The effects become smaller in magnitude, though still positive, and statistically insignificant when County×MOY fixed effects are included, suggesting that these more granular fixed effects to some extent correct for the endogeneity.

B Evidence of Differential Response during Peak Periods

Next, Table 2 examines if the rebound effect varies between peak and off-peak periods by estimating the system described in equations (3), (4), and (5). Panel A presents the first-stage estimates of anomalous HDD and the interaction of anomalous HDD and a peak indicator on the

Table 2: Differential Effect of Fuel Economy during Peak Periods

| | (1) | (2) |
|--|----------------------|----------------------|
| <i>Panel A: ln(MPG) first stage</i> | | |
| Anom. HDD | -0.089*** (0.005) | -0.089*** (0.005) |
| Anom. HDD×Peak | -0.000 (0.000) | -0.000 (0.000) |
| <i>Panel B: ln(MPG)×Peak first stage</i> | | |
| Anom. HDD | -0.003*** (0.001) | -0.004*** (0.001) |
| Anom. HDD×Peak | -0.080*** (0.006) | -0.079*** (0.006) |
| <i>Panel C: ln(Traffic Count) second stage</i> | | |
| ln(MPG) | 0.016 (0.115) | 0.217** (0.094) |
| ln(MPG)×Peak | 0.203*** (0.052) | 0.210*** (0.052) |
| Observations | 104,575,134 | 104,575,134 |
| F-stat of Excluded Instruments | 102.385 | 98.731 |
| Peak×Sensor FE | Yes | Yes |
| Peak×Week FE | Yes | Yes |
| Peak×State×MOY FE | Yes | No |
| Peak×County×MOY FE | No | Yes |

Notes: Standard errors are clustered at the county level. Every regression controls for average temperature, precipitation, snow, snow depth, gasoline prices, gasoline taxes, unemployment rate, and population. ln(MPG) is fleet average fuel economy in miles per gallon. Anomalous HDD are deviations in historic average HDD in a state-month-of-year from a baseline of 1901–2000 measured in 1000s. Peak is an indicator variable equal to one if the hour of the day is between 05:00 and 09:59 or 16:00 and 18:59. *** Statistically significant at the 1% level; ** 5% level; * 10% level.

log of MPG. Similarly, Panel B presents the first stage with dependent variable being the interaction of the log of MPG and an indicator for peak hours. Panel C presents the second-stage results. Control variables again include average temperature, precipitation, snowfall, snow depth, gasoline prices, gasoline taxes, unemployment rate, and population, and standard errors are clustered at the county level.

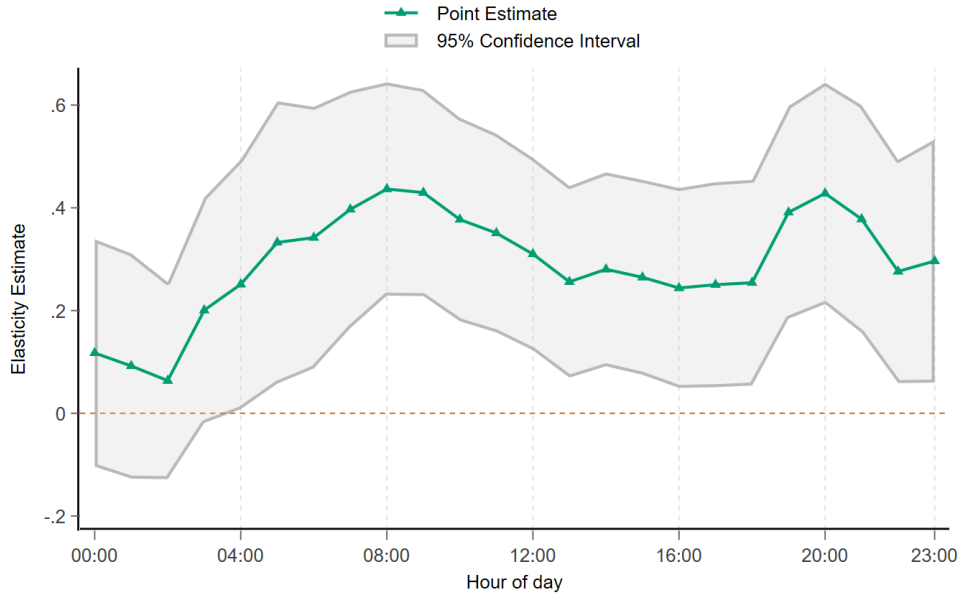
The instruments have the predicted sign and are statistically significant in each regression with the exception of the Anom. HDD×Peak variable in Panel A. This statistical insignificance is not particularly surprising as the interaction of anomalous HDD and peak is not expected to provide any further identifying variation when the dependent variable is not also interacted with the peak period indicator. The Kleibergen-Paap F-statistics of the excluded instruments are near 100 for both regressions.

In Panel C, the second-stage estimates of the effect of $\ln(\text{MPG})$ are smaller in magnitude than those estimated in Table 1 and are again only significant when $\text{County} \times \text{MOY FE}$ are included in the regression. In contrast, the variable of interest, $\ln(\text{MPG}) \times \text{Peak}$, is positive, statistically significant, and consistent in magnitude in both regressions. This positive and statistically significant effect suggests that a 10% increase in MPG increases traffic counts by 2% more during peak periods relative to off-peak periods. A disproportionately large amount of the rebound effect occurs during peak periods. This result also explains the smaller coefficients of $\ln(\text{MPG})$ relative to the aggregate effects estimated in Table 1. The preferred specification in column (2) suggests that the effect of fuel economy on traffic counts approximately doubles from 0.22 to 0.43 during peak periods with an average effect — from column (4) of Table 1 — of 0.296.

I further examine the robustness of this result in Appendix Tables A4, A5, A6, A9, and A10. Table A4 estimates the model using OLS finding a similar result — drivers are nearly twice as responsive to fuel economy during peak periods. While the magnitude of the rebound effect decreases, the size of the peak differential remains relatively constant and statistically significant. Table A5 provides reduced form estimates showing that drivers respond differentially to anomalous HDD during peak periods. In Table A6, I find that the results are robust to varying definitions of the HDD instrument and weather controls. Table A9 examines if a similar peak period differential can be found using another travel demand data set. I estimate a differential response of trip lengths to fuel costs during peak periods using survey data from the National Household Travel Survey. Drivers are again found to be more responsive to fuel costs during peak periods. Finally, in Table A10, I estimate a differential response of traffic counts to fuel costs during peak periods using an alternative identification strategy — instrumenting for fuel prices using gasoline content regulations as is done in Nehiba (2019).

Finally, the heterogeneity in the rebound effect can be seen clearly in Figure 3, which estimates a separate model for each hour of the day and plots the individual elasticity estimates with a 95% confidence interval. Two clear humps emerge in the morning and evening. Elasticities are near zero and statistically insignificant in the early morning hours before rising to an overall daily peak between 08:00 and 09:00. The estimates then decrease in the middle of the day before rising to a shorter-lived peak in the evening. Interestingly, the evening elasticity peak is several hours later

Figure 3: Hourly Estimates of the Fuel Economy Elasticity of Traffic Counts



Notes: Figure depicts point estimates and 95% confidence intervals from 24 separate IV regressions. Dependent variable is the log of traffic counts and the variable of interest is the log of MPG. $\ln(\text{MPG})$ is instrumented for using Anomalous HDD. Every regression controls for average temperature, precipitation, snow, snow depth, gasoline prices, gasoline taxes, unemployment rate, and population. Every regression includes sensor, week, and County \times MOY fixed effects. Standard errors are clustered at the county level.

than the evening travel demand peak. I examine if the effects of fuel economy standards on traffic counts vary across the morning and evening peaks in Appendix Table A7. I find that the evening-peak effect is larger in magnitude, but the morning-peak effect remains economically relevant and statistically significant.

C Mechanisms Driving Differential Response

The estimates presented in Table 2 present a paradox. The prior literature has consistently posited that travel demand is less elastic during peak periods because the trips are more important and fuel costs are a smaller share of total costs (Knittel and Sandler, 2018; Parry and Small, 2005; Portney et al., 2003; Yang et al., 2020). Further, Bento et al. (2013) explicitly estimates that drivers on highways in southern California are less responsive to fuel costs during peak periods. In this section, I will explore several possible explanations for these results.

Weekdays and Weekends

Peak periods are generally associated with high priority morning and evening commutes. As a first step to understanding why drivers respond to fuel efficiency and fuel costs to a greater extent during peak periods, I separately estimate the effects of fuel economy during peak and off-peak periods for weekdays and weekends. Columns (1) and (2) of Table 3 provide estimates for only weekdays while (3) and (4) provide estimates for only weekends.

The first-stage results in Panels A and B are similar to those seen in Table 2 and have Kleibergen-Paap F-statistics ranging from 83 to 156; however, the second-stage results diverge between weekdays and weekends. The effect of $\ln(\text{MPG})$ becomes slightly smaller in magnitude for weekdays and much larger for weekends. In contrast, the effect of $\ln(\text{MPG}) \times \text{Peak}$ becomes larger in magnitude during weekdays and much smaller for weekends, relative to the estimates in Table 2. Further, the effects of $\ln(\text{MPG}) \times \text{Peak}$ on traffic counts on weekends are estimated with less precision.

These results indicate a clear divide in elasticities between weekdays and weekends, particularly during peak periods. Drivers are more elastic during off-peak periods on weekends than weekdays. Evidence for a peak period differential becomes weaker during weekends and stronger when focusing solely on weekdays. Cumulatively, these estimates suggest that commute trips largely drive the differential elasticities between peak and off-peak periods. Several characteristics of carpooling and public transit that make these options specifically lower-cost alternatives for commute trips may contribute to this pattern. First, carpool and public transit generally operate to bring workers to employment centers. Second, public transportation systems often operate at a higher frequency during commute hours. Third, there are lower average mental costs associated with mode switching for a commute trip relative to leisure trips which tend to be more idiosyncratic. For example, an individual switching her commute mode from car to rail only needs to look up transit directions once to remove 10 car trips per week, but each leisure trip switched may require its own route planning.

Table 3: Weekday and Weekend Estimates of Fuel Economy Elasticities

| | (1) | (2) | (3) | (4) |
|--|----------------------|----------------------|----------------------|----------------------|
| | Weekdays | | Weekends | |
| <i>Panel A: ln(MPG) first stage</i> | | | | |
| Anom. HDD | -0.088*** (0.005) | -0.087*** (0.005) | -0.086*** (0.005) | -0.086*** (0.005) |
| Anom. HDD×Peak | -0.000 (0.000) | -0.000 (0.000) | -0.000*** (0.000) | -0.000** (0.000) |
| <i>Panel B: ln(MPG)×Peak first stage</i> | | | | |
| Anom. HDD | -0.003*** (0.001) | -0.003*** (0.001) | -0.004*** (0.000) | -0.004*** (0.001) |
| Anom. HDD×Peak | -0.079*** (0.006) | -0.079*** (0.006) | -0.076*** (0.006) | -0.075*** (0.006) |
| <i>Panel C: ln(Traffic Count) second stage</i> | | | | |
| ln(MPG) | -0.039 (0.112) | 0.192** (0.094) | 0.153 (0.133) | 0.330*** (0.114) |
| ln(MPG)×Peak | 0.268*** (0.057) | 0.283*** (0.058) | 0.113* (0.060) | 0.123** (0.060) |
| Observations | 103,776,439 | 103,776,439 | 101,100,836 | 101,100,836 |
| F-stat of Excluded Instruments | 99.012 | 156.016 | 86.648 | 83.353 |
| Peak×Sensor FE | Yes | Yes | Yes | Yes |
| Peak×Week FE | Yes | Yes | Yes | Yes |
| Peak×State×MOY FE | Yes | No | Yes | No |
| Peak×County×MOY FE | No | Yes | No | Yes |

Notes: Weekends are Saturday and Sunday. Weekdays are Monday–Friday. Standard errors are clustered at the county level. Every regression controls for average temperature, precipitation, snow, snow depth, gasoline prices, gasoline taxes, unemployment rate, and population. ln(MPG) is fleet average fuel economy in miles per gallon. Anomalous HDD are deviations in historic average HDD in a state-month-of-year from a baseline of 1901–2000 measured in 1000s. Peak is an indicator variable equal to one if the hour of the day is between 05:00 and 09:59 or 16:00 and 18:59. *** Statistically significant at the 1% level; ** 5% level; * 10% level.

Highways and nonhighways

Table 4 examines how the results vary depending on the road type. I divide the traffic sensors into two groups, highway and nonhighway, based on functional class codes provided by the FHWA. A majority of the sensors are located on highways, with 85.2 million highway observations relative to the 19.4 million nonhighway observations. Though the functional class codes provide additional road-type information, I avoid further segmentation of the data due to the relatively small number of sensors in more precisely coded nonhighway classifications.

Columns (1) and (2) of Table 4 estimate the model using only observations from nonhighway

sensors, while columns (3) and (4) use only highway sensors. For nonhighways, fuel economy only has a statistically significant impact on traffic counts during peak periods, and this effect is larger in magnitude than that estimated in Table 2. In contrast, the results from the highway-only regressions are similar to those in Table 2 with a slightly larger $\ln(\text{MPG})$ effect and somewhat diminished peak differential.

Table 4: Variation in Fuel Economy Elasticities between Road Types

| | (1) | (2) | (3) | (4) |
|---|----------------------|----------------------|----------------------|----------------------|
| | | Nonhighways | | Highways |
| <i>Panel A: $\ln(\text{MPG})$ first stage</i> | | | | |
| Anom. HDD | -0.085*** (0.005) | -0.084*** (0.004) | -0.089*** (0.006) | -0.090*** (0.005) |
| Anom. HDD \times Peak | -0.000 (0.000) | -0.000 (0.000) | 0.000 (0.000) | 0.000 (0.000) |
| <i>Panel B: $\ln(\text{MPG})\times\text{Peak}$ first stage</i> | | | | |
| Anom. HDD | -0.001*** (0.001) | -0.001** (0.001) | -0.004*** (0.001) | -0.004*** (0.001) |
| Anom. HDD \times Peak | -0.081*** (0.005) | -0.080*** (0.005) | -0.079*** (0.006) | -0.079*** (0.006) |
| <i>Panel C: $\ln(\text{Traffic Count})$ second stage</i> | | | | |
| $\ln(\text{MPG})$ | -0.133 (0.156) | 0.026 (0.133) | 0.051 (0.127) | 0.245** (0.104) |
| $\ln(\text{MPG})\times\text{Peak}$ | 0.317*** (0.086) | 0.312*** (0.087) | 0.183*** (0.057) | 0.186*** (0.057) |
| Observations | 19,384,238 | 19,384,238 | 85,190,896 | 85,190,896 |
| F-stat of Excluded Instruments | 154.649 | 179.554 | 80.057 | 76.979 |
| Peak \times Sensor FE | Yes | Yes | Yes | Yes |
| Peak \times Week FE | Yes | Yes | Yes | Yes |
| Peak \times State \times MOY FE | Yes | No | Yes | No |
| Peak \times County \times MOY FE | No | Yes | No | Yes |

Notes: Highways are roads with FHWA classifications of “Interstate” or “Principal Arterial - Other Freeways and Expressways.” Nonhighways include road classifications “Minor Collector,” “Major Collector,” “Minor Arterial,” and “Principal Arterial - Other.” Standard errors are clustered at the county level. Every regression controls for average temperature, precipitation, snow, snow depth, gasoline prices, gasoline taxes, unemployment rate, and population. $\ln(\text{MPG})$ is fleet average fuel economy in miles per gallon. Anomalous HDD are deviations in historic average HDD in a state-month-of-year from a baseline of 1901–2000 measured in 1000s. Peak is an indicator variable equal to one if the hour of the day is between 05:00 and 09:59 or 16:00 and 18:59. *** Statistically significant at the 1% level; ** 5% level; * 10% level.

While both road classifications exhibit a stronger response to fuel economy during peak periods, this differential effect is more pronounced for nonhighway trips. This discrepancy can partially explain why the results presented in this paper differ from those in Bento et al. (2013), which

finds drivers are less responsive to fuel costs during peak periods. Bento et al. (2013)'s empirical analysis used only highway data from Los Angeles and Ventura counties in southern California, which may have muted the effects of fuel prices during peak periods.

The more pronounced effect for nonhighway roads also provides suggestive evidence that shorter trips or those in denser areas are more likely to be affected by fuel economy changes. Intuitively, these trips may have higher quality substitutes. For example, it is likely easier to switch a relatively short trip from car to public transit than it is a 25-mile trip taken by highway. Similarly, shorter trips are more likely to be performed using active transportation modes. This may be especially true if the trip does not require crossing or traveling on/near a highway as these large roadways significantly reduce an area's "walkability" and safety for active transportation modes, which contribute to individuals' mode choice decisions (Liao et al., 2020).²¹

Commuting Modes

Finally, I examine how fuel economy differentially affects areas depending on their commuting mode choices. Unfortunately, granular panel data on commuting mode choices across the sample do not exist. In lieu of these data, I segment the data based on a county being above or below the US median share of a particular commuting mode based on cross-sectional data from the Census Transportation Planning Products. Splitting the data in this manner should highlight whether having a high share of a commuting mode is associated with higher peak period elasticities.

Table 5 presents the results from five separate commuting mode choices. Each mode choice has two regressions — one including counties that have above the US median share of commuters selecting that mode and a second containing counties with below the median share of commuters selecting that mode. Columns (1)–(2) present results for above and below median share of commuters selecting any mode besides a privately owned passenger vehicle (e.g., public transit, active transit, etc.). Columns (3)–(4) present results for public transit, (5)–(6) active transportation modes (walking and bicycling), (7)–(8) carpooling, and (9)–(10) work from home (no commute necessary).

The first-stage results are qualitatively similar across regressions and to those presented in ear-

²¹Factors like "Too much traffic" and "Road was too wide" are frequently considered when determining a community's walkability. See the National Highway Traffic Safety Administration's walkability checklist <https://www.nhtsa.gov/sites/nhtsa.dot.gov/files/walkingchecklist.pdf>.

lier specifications. However, a significant amount of variation exists in the second-stage estimates. Counties that have a higher share of commuters selecting modes other than private passenger vehicles drive the results (columns (1) and (2)). Counties above the median in this metric exhibit statistically significant effects for $\ln(\text{MPG})$ and $\ln(\text{MPG}) \times \text{Peak}$, with both effects being larger in magnitude than those estimated in Table 2. In fact, the model fails to estimate a statistically effect of fuel economy regardless of time of day in counties below the median in this metric. The statistical insignificance in counties with high shares of commute trips performed with passenger vehicles may also explain the difference in conclusions between this paper and Bento et al. (2013), which again examines only southern California — an area widely known for its propensity for personal vehicles.

Interestingly, the differential effect of fuel economy during peak periods is not driven by counties with high shares of transit ridership. Though a statistically significant differential effect exists in counties with above median transit share, the effect is larger in counties below the median. This result persists when I estimate the model separately for bus transit and rail transit, as can be seen in Appendix Table A8. In contrast, active transportation (columns (5) and (6)), carpooling (columns (7) and (8)), and working from home (columns (9) and (10)) all appear to be important for the differential rebound effect during peak periods. Counties with higher shares of each of these mode choices exhibit larger effects of $\ln(\text{MPG}) \times \text{Peak}$ than their below median counterparts.

While public transit is undoubtedly valuable in reducing congestion, it appears drivers are more likely to switch to other commute modes like active transportation or carpooling during peak periods when fuel costs increase. These results again suggest that shorter (nonhighway) commute trips may be the easiest trips for drivers to eliminate or mode switch, leading to more elastic demand during peak periods.

Table 5: Results by Commuting Mode Share

| Commute mode: | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|--|-----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|
| | Non-passenger vehicle | | Transit | | Active | | Carpool | | Work from home | |
| | Above Median | Below Median | Above Median | Below Median | Above Median | Below Median | Above Median | Below Median | Above Median | Below Median |
| <i>Panel A: ln(MPG) first stage</i> | | | | | | | | | | |
| Anom. HDD | -0.087*** (0.006) | -0.100*** (0.009) | -0.085*** (0.006) | -0.102*** (0.005) | -0.099*** (0.006) | -0.072*** (0.007) | -0.080*** (0.004) | -0.105*** (0.007) | -0.092*** (0.005) | -0.095*** (0.008) |
| Anom. HDD×Peak | -0.000 (0.000) | 0.000 (0.000) | -0.000 (0.000) | 0.000 (0.000) | -0.000 (0.000) | 0.000* (0.000) | -0.000** (0.000) | 0.000 (0.000) | -0.000 (0.000) | 0.000 (0.000) |
| <i>Panel B: ln(MPG)×Peak first stage</i> | | | | | | | | | | |
| Anom. HDD | -0.004*** (0.001) | 0.001 (0.001) | -0.004*** (0.001) | -0.001 (0.001) | -0.005*** (0.001) | -0.003* (0.001) | -0.004*** (0.001) | -0.004*** (0.001) | -0.003*** (0.001) | -0.002 (0.002) |
| Anom. HDD×Peak | -0.075*** (0.008) | -0.102*** (0.010) | -0.073*** (0.007) | -0.099*** (0.006) | -0.087*** (0.008) | -0.065*** (0.009) | -0.070*** (0.005) | -0.094*** (0.008) | -0.083*** (0.006) | -0.089*** (0.010) |
| <i>Panel C: ln(Traffic Count) second stage</i> | | | | | | | | | | |
| ln(MPG) | 0.247** (0.125) | 0.102 (0.131) | 0.193* (0.107) | 0.278* (0.148) | 0.220** (0.094) | 0.274 (0.193) | 0.533*** (0.149) | -0.012 (0.114) | 0.165 (0.138) | 0.252** (0.108) |
| ln(MPG) × Peak | 0.281*** (0.074) | 0.032 (0.068) | 0.177** (0.069) | 0.302*** (0.052) | 0.240*** (0.062) | 0.146 (0.113) | 0.312*** (0.082) | 0.203*** (0.066) | 0.288*** (0.077) | 0.121** (0.060) |
| Observations | 70,736,445 | 33,838,689 | 79,119,171 | 25,455,963 | 56,547,306 | 48,027,828 | 44,905,563 | 59,669,571 | 59,821,979 | 44,753,155 |
| F-stat of Excluded Instruments | 47.038 | 66.905 | 52.615 | 182.219 | 57.675 | 27.339 | 84.404 | 62.759 | 139.801 | 64.814 |
| Peak×Sensor FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Peak×Week FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Peak×County×MOY FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

Notes: Commuting mode shares come from the Census Transportation Planning Products. Non-passenger vehicle includes all modes besides consumer-owned passenger vehicles. Transit includes all bus and rail modes. Active includes walking and bicycling. Standard errors are clustered at the county level. Every regression controls for average temperature, precipitation, snow, snow depth, gasoline prices, gasoline taxes, unemployment rate, and population. ln(MPG) is fleet average fuel economy in miles per gallon. Anomalous HDD are deviations in historic average HDD in a state-month-of-year from a baseline of 1901–2000 measured in 1000s. Peak is an indicator variable equal to one if the hour of the day is between 05:00 and 09:59 or 16:00 and 18:59. *** Statistically significant at the 1% level; ** 5% level; * 10% level.

VI Implications for Fuel Economy Standards

I now apply the results from the previous section to an analysis of fuel economy standards in the US. I simplify the analysis by omitting many of the practical implementation issues surrounding the Corporate Average Fuel Economy Standards and focusing solely on the effects of an exogenous shock to fuel economy on driving. Concerns that CAFE standards may affect vehicle weight and therefore collision severity (Bento et al., 2017), alter used vehicle prices and scrappage decisions (Jacobsen and van Benthem, 2015), are regressive (Davis and Knittel, 2019), and other issues raised in the vast literature on fuel efficiency standards will not factor into the calculations.

The policy analysis estimates how the rebound effect from a uniform 1.5% MPG increase in fleet fuel economy, the annual increase in CAFE standard fuel economy stringency required for new vehicles in model years 2021 through 2026 by the Safer Affordable Fuel-Efficient (SAFE)

Vehicles Rule²², would affect pollution and congestion if applied to the entire fleet. Given the limitations, this is not a direct or complete analysis of CAFE standards, but rather an illustration of how accounting for time-of-day heterogeneity in the rebound effect impacts the costs and benefits of fuel efficiency standards more broadly.

The analysis requires several parameters beyond the peak and off-peak elasticities estimated in Table 2. Local pollution damages from Muller and Mendelsohn (2012) and global pollution damages from the Interagency Working Group on Social Cost of Greenhouse Gases can be converted to damages per gallon of gasoline consumed using EPA estimates of per-gallon emissions of nitrogen oxides, particulate matter (both particles less than 10 microns and less than 2.5 microns), volatile organic compounds, and carbon. Unfortunately, estimates of US average marginal external congestion costs per mile that vary by the time of day are not available in the literature. In light of this limitation, I take a conservative approach to congestion costs. I use inflation adjusted lower and upper bounds of US average marginal external costs of congestion from FHWA (2000) for off-peak and peak per-mile congestion costs, respectively. Peak period congestion costs are valued at \$0.164 per mile while off-peak costs are \$0.012 per mile. While there certainly exists a large amount of heterogeneity in costs across regions, these costs seem reasonable and comparable to other averaged estimates in magnitude and the dispersion between peak and off-peak is similar to that seen in studies estimating costs in single locations (Parry et al., 2005; Parry, 2005; Parry and Small, 2009). Finally, I use values of light-duty vehicle VMT and average fuel economy in 2019 from the Bureau of Transportation Statistics.

Table 6 presents results from two policy simulations. Panel B examines the change in pollution and congestion externalities from a 1.5% increase in fleet fuel economy when accounting for the heterogeneity in the timing of the rebound effect estimated in this paper. The peak period elasticity is 0.427, while the off-peak elasticity is significantly smaller at 0.217. In contrast, Panel C assumes, like much of the previous literature, that drivers are inelastic during peak periods. I simply reverse the sign of the peak differential estimated in Table 2 to examine how external costs may change under such a scenario. Panel C therefore assumes that peak elasticity is 0.007, while the off-peak elasticity is identical to Panel B at 0.217.

²²The SAFE rule, passed in March of 2020, replaced more stringent (approximately 5%/year) annual fuel economy increases for these model years from a previous 2012 rule. See <https://www.nhtsa.gov/corporate-average-fuel-economy/safe> for more information on CAFE and SAFE.

Table 6: Policy Analysis

Panel A: Baseline Simulation Parameters

| | |
|---|-----------|
| Peak congestion costs per mile ^a | \$0.164 |
| Off-peak congestion costs per mile ^a | \$0.012 |
| Pollution costs per gallon ^b | \$0.492 |
| Light-duty vehicle VMT (millions) ^c | 2,254,309 |
| Light-duty vehicle fuel economy ^d | 24.2 |

Panel B: Effects of 1.5% Increase in MPG Accounting for Elastic Peak Period

| | |
|--|---------------|
| Off-Peak Elasticity | 0.217 |
| Peak Elasticity | 0.427 |
| Δ VMT (millions) | 10,850 |
| Pollution Damages (millions) | -\$460 |
| Congestion Damages (millions) | +\$1,215 |
| Net Δ External Damages (millions) | +\$755 |

Panel C: Effects of 1.5% Increase in MPG Assuming Inelastic Peak Period

| | |
|--|---------------|
| Off-Peak Elasticity | 0.217 |
| Peak Elasticity | 0.007 |
| Δ VMT (millions) | 3,826 |
| Pollution Damages (millions) | -\$601 |
| Congestion Damages (millions) | +\$63 |
| Net Δ External Damages (millions) | -\$538 |

Notes:

^a <https://www.fhwa.dot.gov/policy/hcas/addendum.cfm>;

^b Muller and Mendelsohn (2012) and IWG (2016)

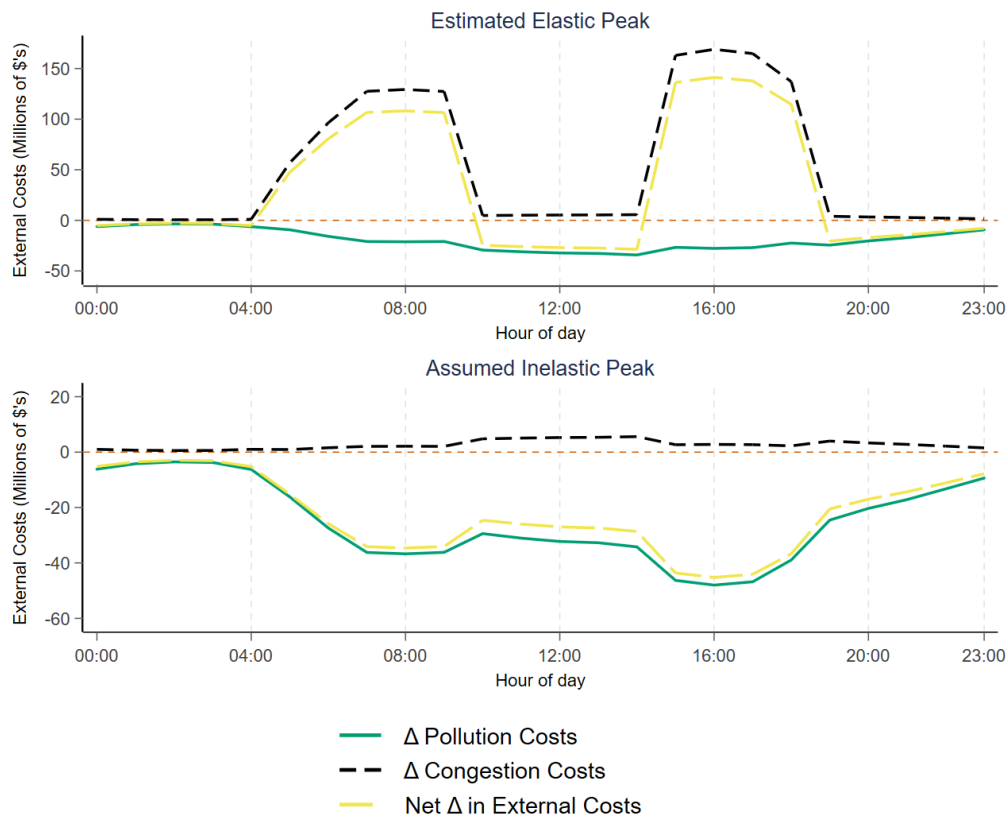
^c <https://www.bts.gov/content/us-vehicle-miles>

^d <https://www.bts.gov/content/average-fuel-efficiency-us-light-duty-vehicles>

Panel B estimates a total increase in VMT of 10,850 million miles due to the rebound effect. This VMT increase equates to just 33 miles per capita annually, or an individual reducing their daily VMT by less than a tenth of a mile. The improved fuel efficiency leads to a reduction in pollution valued at \$460 million/year due to reduced fuel consumption. However, because the increase in VMT occurs mostly during peak periods, the increase in fuel economy increases congestion by \$1,215 million/year, leading to a net increase in external costs of \$755 million/year. In other words, the pollution benefits are more than offset by the exacerbated congestion costs. A much smaller increase in VMT of 3,826 million miles is seen in Panel C where the rebound effect is assumed to be near zero during peak periods. This simulation leads to larger pollution benefits of \$601 million/year and a significantly smaller \$63 million/year increase in congestion because the rebound effect occurs during off-peak periods. Assuming an inelastic peak erroneously leads the pollution benefits of increased fuel economy to exceed the congestion costs.

These conclusions can be seen clearly in Figure 4, which plots the changes in the external pollution and congestion costs as well as the net change in external costs by the hour of day under both elasticity regimes. Using the elasticities I estimate in this paper in the top panel, congestion costs increase significantly during morning and evening peaks, while there are modest decreases in pollution costs during the daytime hours. Erroneously assuming an inelastic peak in the bottom panel leads to a complete reversal of these findings. Large pollution benefits are accrued during peak periods because these hours have high VMT and relatively little rebound effect. Further, the assumed inelastic effect during peak periods leads there to be only minor increases in congestion costs.

Figure 4: Change in External Costs Due to 1.5% Increase in Fuel Economy



Notes: Figure depicts the hourly change in external pollution and congestion costs as well as the net difference from the policy analyses in Panels B and C of Table 6. The top panel uses elasticities estimated in this paper, while the bottom panel incorrectly assumes that drivers are inelastic during peak periods.

These estimates do not account for the benefits drivers accrue due to the additional VMT or fuel savings. Nor do they include changes in the external costs of accidents or noise or changes

in producer costs. As such, they should not be considered to represent a complete picture of the benefits and cost of fuel efficiency standards. They do however illustrate that the relative elasticities between peak and off-peak periods play an important role in determining the welfare effects of fuel economy standards and likely many other policies that uniformly shift the costs of driving throughout the day. While per-capita VMT increases only slightly when fuel economy improves, the bulk of this increase occurs during already congested periods. Though fuel economy standards reduce vehicle emissions, these benefits appear to be more than offset by an increase in congestion costs. In contrast, applying these elasticities to an analysis of a policy which increases costs like a gasoline tax would find much larger benefits than previous studies because of the relatively large reduction in driving during congested peak periods.

VII Conclusion

The congestion created by peaks within daily travel demand is a market failure that imposes enormous costs on society. While demand patterns are easily observed, how and why drivers respond to prices during these peak periods is less clear. Heterogeneity in elasticities between peak and off-peak periods is particularly important when considering transportation policies — like fuel economy standards — which uniformly affect the costs of driving but have the potential to disproportionately affect the demand for travel during congested periods. In the context of fuel economy standards, the rebound effect has been estimated widely, but studies have focused on the magnitude of the effect with little consideration for *when* the effect occurs.

I examine how drivers differentially respond to the costs of driving across the hours of the day. I find that, in contrast to past assumptions, drivers are more responsive to fuel costs — as measured by fuel economy — during peak periods. Instrumenting for fuel economy using exogenous shocks to ambient air temperature that affect fuel efficiency, I find that a 10% increase in fuel economy elicits a 4.3% increase in traffic counts during peak demand periods but only a 2.2% increase during off-peak periods.

This fuel economy elasticity — a novel measure of the rebound effect that loosens many of the assumptions made in prior studies — is critically important for the evaluation of fuel efficiency standards. A policy simulation that accounts for the near doubling of the rebound effect during

peak periods relative to off-peak periods leads congestion costs from fuel economy improvements to be exacerbated to the extent that they more than offset the pollution benefits. In contrast, erroneously assuming that response to fuel economy during peak periods is more inelastic than during off-peak periods leads pollution benefits to exceed the increase in congestion costs.

These results highlight the importance of timing when considering energy efficiency programs. This conclusion is similar to that of Boomhower and Davis (2020), which illustrates that much of the energy savings from air conditioner energy efficiency improvements occur when electricity demand is peaking. However, while energy efficiency improvements for air conditioners achieved the desirable outcome of smoothing electricity demand in Boomhower and Davis (2020), fuel economy improvements for vehicles appear to sharpen these demand peaks.²³ More broadly, the results suggest a more careful consideration of within-day elasticities when demand peaks are associated with high costs, as in the transportation and energy sectors, especially when considering policies that uniformly shift costs.

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²³The difference in outcomes here is because reducing peak electricity consumption is beneficial due to high electricity prices. In contrast, reducing peak vehicle miles traveled is beneficial due to high congestion costs. Fuel economy standards also reduce gasoline consumption during peak periods, but the cost of driving during peak periods is high due to congestion externalities, not fuel costs.

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Appendix

Table A1 provides summary statistics (mean, standard deviation, and observations) for each variable used in the analysis.

Table A2 presents results from regressions with varying definitions of peak period to ensure that this modeling choice does not drive the results. The broadest definition of the peak period (05:00 and 09:59 and 15:00 and 19:59 for morning and evening peaks, respectively) is used in column (1). I progressively narrow this window across columns until only the hours 08:00–08:59 and 17:00–17:59 are defined as peak hours in column (4).

The results are qualitatively similar across the regressions and consistent with those estimated in the preferred specification in column (2) of Table 2. $\ln(\text{MPG})$ and $\ln(\text{MPG}) \times \text{Peak}$ are positive and statistically significant in each regression. As the definition of peak narrows (i.e., hours are moved from being defined as peak to being defined as off-peak hours), $\ln(\text{MPG})$ becomes larger in magnitude and $\ln(\text{MPG}) \times \text{Peak}$ becomes smaller in magnitude (with the exception of column (3)). This pattern is to be expected if the hours redefined as off-peak hours exhibit stronger responses to fuel efficiency. These results reinforce that traffic counts are more responsive to fuel efficiency changes during peak periods.

Table A3 examines the robustness of the results to the removal of months of the year that may be more likely to violate the instrumental variables exclusion restriction. It may be that abnormally cold weather affects driving patterns and activities to a greater extent during warmer months than already cold winter months. For example, a day that is 10 degrees colder than historical averages in July may dissuade an individual from going to the beach or bicycling to work. In contrast, a 10 degree drop in temperature from the historic average in December is likely to have a smaller impact on the probability that an individual engages in either of these activities because that probability was already small.

Column (1) includes only winter months (December–February) and the number of months included increases across the columns until only summer months (June–August) are excluded in column (4). The results are qualitatively similar across specifications and are consistent with the main results in Table 2. Interestingly, the magnitude of the $\ln(\text{MPG}) \times \text{Peak}$ effect becomes larger

when restricting the sample to only colder months (columns (1) and (2)). This result suggests that including all months of the year in the analysis may be producing a conservative estimate of the effects.

Table A4 provides OLS estimates of the effects of $\ln(\text{MPG})$ and $\ln(\text{MPG}) \times \text{Peak}$ on traffic counts. As expected, the magnitudes of the effects of both variables are smaller relative to the preferred IV estimation strategy; however, both variables are positive and statistically significant at conventional levels in every regression. I find that drivers respond to fuel economy shocks to a greater extent during peak periods, suggesting that the rebound effect is most pronounced during these hours of the day. While the evidence provided here supports the IV strategy used in the main text, it is reassuring that the main result of the analysis can be replicated using OLS.

Table A5 provides reduced form estimates of the effects of Anom. HDD and $\text{Anom. HDD} \times \text{Peak}$ on traffic counts. The reduced form estimates show that drivers respond to cold weather shocks to a greater extent during the peak period. Ultimately, drivers illustrating a larger response to any cost shifter, fuel or otherwise, during the peak period is of interest.

Table A6 provides estimates using coarser weather controls and instrumenting for fuel economy using raw HDD as opposed to anomalous HDD. Columns (1) and (2) control for state-level precipitation and average temperatures as opposed to the county-level weather controls used in the main analysis. The effect of $\ln(\text{MPG})$ becomes substantially larger in columns (1) and (2); however, the size of the $\ln(\text{MPG}) \times \text{Peak}$ effect remains relatively constant at 0.2 and statistically significant. This suggests that weather may be affecting estimates of the average rebound effect, but not the differential effect during the peak period. Columns (3) and (4) instrument for fuel economy using HDD, but control for county-level weather. The estimates for both $\ln(\text{MPG})$ and $\ln(\text{MPG}) \times \text{Peak}$ are nearly identical to those reported in the main analysis.

Table A7 separates the effect of fuel economy on traffic counts between morning and evening peak periods. I accomplish this by interacting $\ln(\text{MPG})$ with separate indicators for the morning and evening peak periods, which necessitates an additional first-stage regression with a similarly interacted IV. The results indicate that the differential effect of fuel economy is larger during the evening peak, but still exists at relevant and statistically significant levels during the morning peak period. These results alleviate concerns that the hourly elasticities shown in Figure 3 skew towards larger effects during evening hours — potentially suggesting that the morning peak is inconse-

quential.

Table A8 further decomposes the public transit mode share regressions from Table 5 to regressions for rail transit and bus transit. The results for both are qualitatively similar to the transit regressions in Table 5, confirming that areas with high levels of bus or rail transit are not driving the results.

Table A9 examines if the paper's main result, a differential response to fuel costs during peak periods, can be replicated using another data source. I examine if reported trip lengths in the 2017 National Household Travel Survey data respond differentially to fuel prices during peak periods. The dependent variable is the natural log of trip length in miles. Each regression is estimated using OLS with county and month fixed effects and standard errors clustered at the county level. I control for peak periods, the log of fuel prices, and the variable of interest, $\text{Peak} \times \ln(\text{Gas Price})$, which indicates if gasoline price elasticities vary between peak and off-peak periods.

Column (1) estimates the model using only data for trips where the household (HH) vehicle was used. Column (2) uses only data where the HH vehicle was not used. In other words, column (2) examines trips taken by modes other than HH vehicles (walking, public transit, etc.). Column (3) uses data from all trips.

A differential peak period effect is estimated in column (1) for HH vehicle trips. When fuel prices increase by 1%, peak period trips decrease in length by 0.132%. I fail to find a statistically significant effect of gasoline prices during off-peak periods. I also fail to find a statistically significant effect of fuel prices during peak or off-peak periods for trips not taken using the HH vehicle. Not surprisingly, column (3), which combines the data from columns (1) and (2), finds a somewhat smaller effect for $\text{Peak} \times \ln(\text{Gas Price})$ than column (1). These results confirm that fuel costs disproportionately affect driver behavior during peak demand periods.

Drivers appear to be more responsive to both fuel economy and gasoline prices during these peaks. Replicating the main result using survey data and a different measure of fuel costs is reassuring that the results are not driven by the data source or identification strategy used in the main text.

Table A10 examines if a peak period differential gasoline price elasticity exists in the traffic sensor data. I accomplish this by restricting the sample to the 380 counties for which county-level gasoline price data are available and instrumenting for gasoline prices using gasoline content

regulations — an identification strategy similar to Nehiba (2019). Gasoline content regulations are seasonal pollution controls, often mandated at the county level, that cause fuel prices to increase due to higher refining costs and market segmentation. They are shown to be plausibly exogenous to travel demand in Nehiba (2019) as the regulation stringency is due to a region’s weather and past travel demand, which can be readily controlled for using location fixed effects. Importantly, the content regulations are independent from contemporaneous changes in travel demand.

I examine how RVP 9, RVP 7.8, RVP 7, and RFG gasoline content regulations affect gasoline prices and the ensuing effect of these exogenous changes in prices on vehicle counts. Columns (1) and (2) examine the aggregate effect of these regulations. Each regulation is found to have a positive and statistically significant effect on gasoline prices. The gasoline price elasticity of traffic counts is found to be between -0.191 and -0.278, similar in magnitude to Nehiba (2019) and the results estimated in this paper for the fuel economy elasticity of traffic counts.

Columns (3) and (4) estimate how gasoline prices may differentially affect traffic counts during peak periods. Again, drivers are found to be more elastic during peak periods; however, drivers are estimated to have a positive baseline elasticity and a very large negative elasticity differential during peak periods. The total peak period elasticity is estimated to be approximately -1 in both specifications. Though this elasticity and the differential estimated are quite large in magnitude, the results again support the conclusion that drivers are more elastic during peak periods.

Table A11 varies the level of standard error clustering in the preferred specification. Column (1) clusters at the traffic sensor level. Column (2) clusters at the week level. Column (3) two-way clusters the errors at the county and week levels. The results remain statistically significant at conventional levels regardless of the level of clustering chosen.

Table A12 tests the robustness of the results to the inclusion of additional controls for economic conditions. Both specifications include controls for quarterly county-level GDP and annual county-level median income. The results are qualitatively similar to those in Table 2.

Table A1: Summary Statistics

| Variable | Mean | Std. Dev. | Obs. |
|-------------------------------|---------|-----------|-------------|
| Traffic Count | 398.6 | 613.6 | 104,575,132 |
| Fuel Economy (MPG) | 24.1 | 3.8 | 104,575,132 |
| Anom. HDD | -37.3 | 91.4 | 104,575,132 |
| HDD | 391.6 | 411.5 | 104,575,132 |
| Avg. Temperature (Fahrenheit) | 47.4 | 10.0 | 104,575,132 |
| Precipitation (mm) | 18.2 | 18.1 | 104,575,132 |
| Snowfall (mm) | 2.0 | 5.8 | 104,575,132 |
| Snow Depth (mm) | 15.8 | 30.6 | 104,575,132 |
| Gasoline Price (\$/gal) | 2.94 | 0.66 | 104,575,132 |
| Gasoline Tax (\$/gal) | 0.27 | 0.08 | 104,575,132 |
| Unemployment Rate | 0.053 | 0.021 | 104,575,132 |
| County Population | 514,509 | 980,758 | 104,575,132 |

Notes: All dollar values are inflation adjusted to 2019 dollars.

Table A2: Varying Peak Definitions

| | (1) | (2) | (3) | (4) |
|--|----------------------|----------------------|----------------------|----------------------|
| Peak=1 if hour of day= | 05:00–09:59 | 06:00–08:59 | 07:00–08:59 | 08:00–08:59 |
| | 15:00–19:59 | 16:00–18:59 | 17:00–18:59 | 17:00–17:59 |
| <i>Panel A: ln(MPG) first stage</i> | | | | |
| Anom. HDD | -0.089*** (0.005) | -0.089*** (0.005) | -0.089*** (0.005) | -0.089*** (0.005) |
| Anom. HDD×Peak | -0.000 (0.000) | -0.000 (0.000) | -0.000 (0.000) | 0.000 (0.000) |
| <i>Panel B: ln(MPG)×Peak first stage</i> | | | | |
| Anom. HDD | -0.004*** (0.001) | -0.002*** (0.001) | -0.002*** (0.000) | -0.001*** (0.000) |
| Anom. HDD×Peak | -0.079*** (0.006) | -0.079*** (0.006) | -0.079*** (0.006) | -0.079*** (0.006) |
| <i>Panel C: ln(Traffic Count) second stage</i> | | | | |
| ln(MPG) | 0.187** (0.093) | 0.237** (0.094) | 0.247*** (0.093) | 0.275*** (0.094) |
| ln(MPG)×Peak | 0.264*** (0.049) | 0.216*** (0.045) | 0.269*** (0.038) | 0.187*** (0.041) |
| Observations | 104,575,134 | 104,575,134 | 104,575,133 | 104,575,132 |
| F-stat of Excluded Instruments | 98.743 | 98.812 | 98.824 | 98.604 |
| Peak×Sensor FE | Yes | Yes | Yes | Yes |
| Peak×Week FE | Yes | Yes | Yes | Yes |
| Peak×County×MOY FE | Yes | Yes | Yes | Yes |

Notes: Standard errors are clustered at the county level. Every regression controls for average temperature, precipitation, snow, snow depth, gasoline prices, gasoline taxes, unemployment rate, and population. ln(MPG) is fleet average fuel economy in miles per gallon. Anomalous HDD are deviations in historic average HDD in a state-month-of-year from a baseline of 1901–2000 measured in 1000s. Peak is an indicator variable equal to one if the hour of the day is between those listed at the top of each column. *** Statistically significant at the 1% level; ** 5% level; * 10% level.

Table A3: Varying the Months Included

| MOY included: | (1) | (2) | (3) | (4) |
|--|----------------------|----------------------|----------------------|----------------------|
| | Dec.–Feb. | Nov.–Mar. | Oct.–Apr. | Sep.–May |
| <i>Panel A: ln(MPG) first stage</i> | | | | |
| Anom. HDD | -0.107*** (0.006) | -0.100*** (0.005) | -0.092*** (0.005) | -0.087*** (0.005) |
| Anom. HDD×Peak | -0.000 (0.000) | -0.000 (0.000) | -0.000 (0.000) | -0.000 (0.000) |
| <i>Panel B: ln(MPG)×Peak first stage</i> | | | | |
| Anom. HDD | -0.005*** (0.001) | -0.005*** (0.001) | -0.004*** (0.001) | -0.003*** (0.001) |
| Anom. HDD×Peak | -0.095*** (0.007) | -0.087*** (0.006) | -0.083*** (0.005) | -0.078*** (0.005) |
| <i>Panel C: ln(Traffic Count) second stage</i> | | | | |
| ln(MPG) | 0.187** (0.091) | 0.139* (0.081) | 0.253** (0.099) | 0.198** (0.098) |
| ln(MPG)×Peak | 0.332*** (0.057) | 0.345*** (0.053) | 0.194*** (0.059) | 0.214*** (0.053) |
| Observations | 25,282,586 | 42,679,452 | 60,631,172 | 78,170,675 |
| F-stat of Excluded Instruments | 160.569 | 108.591 | 185.516 | 180.157 |
| Peak×Sensor FE | Yes | Yes | Yes | Yes |
| Peak×Week FE | Yes | Yes | Yes | Yes |
| Peak×County×MOY FE | Yes | Yes | Yes | Yes |

Notes: Data are restricted to months of the year listed at the top of each column. Standard errors are clustered at the county level. Every regression controls for average temperature, precipitation, snow, snow depth, gasoline prices, gasoline taxes, unemployment rate, and population. ln(MPG) is fleet average fuel economy in miles per gallon. Anomalous HDD are deviations in historic average HDD in a state-month-of-year from a baseline of 1901–2000 measured in 1000s. Peak is an indicator variable equal to one if the hour of the day is between 05:00 and 09:59 or 16:00 and 18:59. *** Statistically significant at the 1% level; ** 5% level; * 10% level.

Table A4: OLS Estimates

| | <i>Dependent Variable: ln(Traffic Count)</i> | | | |
|--------------------|--|--------------------|---------------------|---------------------|
| | (1) | (2) | (3) | (4) |
| ln(MPG) | 0.083** (0.037) | 0.081** (0.034) | 0.063* (0.035) | 0.061* (0.033) |
| ln(MPG)×Peak | | | 0.052*** (0.016) | 0.053*** (0.016) |
| Observations | 104,575,134 | 104,575,134 | 104,575,134 | 104,575,134 |
| R-squared | 0.666 | 0.667 | 0.666 | 0.667 |
| Peak×Sensor FE | Yes | Yes | Yes | Yes |
| Peak×Week FE | Yes | Yes | Yes | Yes |
| Peak×State×MOY FE | Yes | No | Yes | No |
| Peak×County×MOY FE | No | Yes | No | Yes |

Notes: All specifications estimated using Ordinary Least Squares. Standard errors are clustered at the county level. Every regression controls for average temperature, precipitation, snow, snow depth, gasoline prices, gasoline taxes, unemployment rate, and population. ln(MPG) is fleet average fuel economy in miles per gallon. Peak is an indicator variable equal to one if the hour of the day is between 05:00 and 09:59 or 16:00 and 18:59. *** Statistically significant at the 1% level; ** 5% level; * 10% level.

Table A5: Reduced Form

| | <i>Dependent Variable: ln(Traffic Count)</i> | | | |
|--------------------|--|----------------------|----------------------|----------------------|
| | (1) | (2) | (3) | (4) |
| Anom. HDD | -0.008 (0.010) | -0.026*** (0.008) | -0.002 (0.010) | -0.020** (0.008) |
| Anom. HDD×Peak | | | -0.016*** (0.004) | -0.017*** (0.004) |
| Observations | 104,575,134 | 104,575,134 | 104,575,134 | 104,575,134 |
| R-squared | 0.666 | 0.667 | 0.666 | 0.667 |
| Peak×Sensor FE | Yes | Yes | Yes | Yes |
| Peak×Week FE | Yes | Yes | Yes | Yes |
| Peak×State×MOY FE | Yes | No | Yes | No |
| Peak×County×MOY FE | No | Yes | No | Yes |

Notes: All specifications estimated using Ordinary Least Squares. Standard errors are clustered at the county level. Every regression controls for average temperature, precipitation, snow, snow depth, gasoline prices, gasoline taxes, unemployment rate, and population. ln(MPG) is fleet average fuel economy in miles per gallon. Peak is an indicator variable equal to one if the hour of the day is between 05:00 and 09:59 or 16:00 and 18:59. *** Statistically significant at the 1% level; ** 5% level; * 10% level.

Table A6: Alternative Weather Controls and HDD Instrument

| Specification: | (1) | (2) | (3) | (4) |
|--|-----------------------|----------------------|----------------------|----------------------|
| | Alt. Weather Controls | | Alt. HDD Instrument | |
| <i>Panel A: ln(MPG) first stage</i> | | | | |
| Anom. HDD | -0.160*** (0.013) | -0.161*** (0.013) | | |
| HDD | | | -0.089*** (0.005) | -0.089*** (0.005) |
| Anom. HDD×Peak | -0.000 (0.000) | -0.000 (0.000) | | |
| HDD×Peak | | | -0.000 (0.000) | -0.000 (0.000) |
| <i>Panel B: ln(MPG)×Peak first stage</i> | | | | |
| Anom. HDD | -0.030*** (0.004) | -0.030*** (0.004) | | |
| HDD | | | -0.003*** (0.001) | -0.004*** (0.001) |
| Anom. HDD×Peak | -0.080*** (0.006) | -0.079*** (0.006) | | |
| HDD×Peak | | | -0.080*** (0.006) | -0.079*** (0.006) |
| <i>Panel C: ln(Traffic Count) second stage</i> | | | | |
| ln(MPG) | 0.566*** (0.153) | 0.618*** (0.150) | 0.017 (0.115) | 0.218** (0.094) |
| ln(MPG)×Peak | 0.204*** (0.052) | 0.211*** (0.052) | 0.203*** (0.052) | 0.209*** (0.052) |
| Observations | 104,575,134 | 104,575,134 | 104,575,134 | 104,575,134 |
| F-stat of Excluded Instruments | 73.945 | 77.504 | 102.392 | 98.731 |
| Peak×Sensor FE | Yes | Yes | Yes | Yes |
| Peak×Week FE | Yes | Yes | Yes | Yes |
| Peak×State×MOY FE | Yes | No | Yes | No |
| Peak×County×MOY FE | No | Yes | No | Yes |

Notes: Standard errors are clustered at the county level. Columns (1) and (2) control for state-level average temperature and precipitation while columns (3) and (4) control for county-level average temperature, precipitation, snow, snow depth. Every regression controls for gasoline prices, gasoline taxes, unemployment rate, and population. ln(MPG) is fleet average fuel economy in miles per gallon. Anomalous HDD are deviations in historic average HDD in a state-month-of-year from a baseline of 1901–2000 measured in 1000s. HDD are simple contemporaneous HDD for a state and month. Peak is an indicator variable equal to one if the hour of the day is between 05:00 and 09:59 or 16:00 and 18:59. *** Statistically significant at the 1% level; ** 5% level; * 10% level.

Table A7: AM and PM Peak Differences

| | (1) | (2) |
|--|----------------------|----------------------|
| <i>Panel A: ln(MPG) first stage</i> | | |
| Anom. HDD | -0.089*** (0.005) | -0.089*** (0.005) |
| Anom. HDD×Morning Peak | 0.000 (0.000) | 0.000 (0.000) |
| Anom. HDD×Evening Peak | -0.000 (0.000) | -0.000 (0.000) |
| <i>Panel B: ln(MPG)×Morning Peak first stage</i> | | |
| Anom. HDD | -0.001*** (0.001) | -0.001** (0.001) |
| Anom. HDD×Morning Peak | -5.387*** (0.147) | -5.387*** (0.147) |
| Anom. HDD×Evening Peak | 6.656*** (0.189) | 6.657*** (0.189) |
| <i>Panel C: ln(MPG)×Evening Peak first stage</i> | | |
| Anom. HDD | -0.002*** (0.000) | -0.002*** (0.000) |
| Anom. HDD×Morning Peak | 5.307*** (0.148) | 5.308*** (0.148) |
| Anom. HDD×Evening Peak | -6.736*** (0.187) | -6.736*** (0.187) |
| <i>Panel D: ln(Traffic Count) second stage</i> | | |
| ln(MPG) | 0.015 (0.115) | 0.216** (0.094) |
| ln(MPG)×Morning Peak | 0.112** (0.052) | 0.119** (0.052) |
| ln(MPG)×Evening Peak | 0.331*** (0.051) | 0.338*** (0.052) |
| Observations | 104,575,134 | 104,575,134 |
| F-stat of Excluded Instruments | 68.257 | 65.821 |
| Peak×Sensor FE | Yes | Yes |
| Peak×Week FE | Yes | Yes |
| Peak×State×MOY FE | Yes | No |
| Peak×County×MOY FE | No | Yes |

Notes: This table separately estimates the effects of ln(MPG) during morning and evening peaks. Morning peak is an indicator variable equal to one if the hour of the day is between 05:00 and 09:59, and evening peak is an indicator equal to one if the hour of the day is between 16:00–18:59. Standard errors are clustered at the county level. Every regression controls for average temperature, precipitation, snow, snow depth, gasoline prices, gasoline taxes, unemployment rate, and population. ln(MPG) is fleet average fuel economy in miles per gallon. Anomalous HDD are deviations in historic average HDD in a state-month-of-year from a baseline of 1901–2000 measured in 1000s. *** Statistically significant at the 1% level; ** 5% level; * 10% level.

Table A8: Bus and Rail Commute Shares

| Sample: | (1) | (2) | (3) | (4) |
|--|----------------------|----------------------|----------------------|----------------------|
| | Bus transit | | Rail transit | |
| | Above Median | Below Median | Above Median | Below Median |
| <i>Panel A: ln(MPG) first stage</i> | | | | |
| Anom. HDD | -0.085*** (0.006) | -0.101*** (0.005) | -0.083*** (0.007) | -0.098*** (0.005) |
| Anom. HDD×Peak | -0.000 (0.000) | 0.000 (0.000) | -0.000 (0.000) | 0.000 (0.000) |
| <i>Panel B: ln(MPG)×Peak first stage</i> | | | | |
| Anom. HDD | -0.005*** (0.001) | -0.001 (0.001) | -0.004*** (0.001) | -0.002*** (0.001) |
| Anom. HDD×Peak | -0.073*** (0.007) | -0.099*** (0.006) | -0.071*** (0.008) | -0.093*** (0.005) |
| <i>Panel C: ln(Traffic Count) second stage</i> | | | | |
| ln(MPG) | 0.198* (0.105) | 0.264* (0.151) | 0.168 (0.119) | 0.341*** (0.117) |
| ln(MPG)×Peak | 0.165** (0.068) | 0.339*** (0.055) | 0.149* (0.079) | 0.305*** (0.056) |
| Observations | 79,779,204 | 24,795,930 | 68,349,634 | 36,225,500 |
| F-stat of Excluded Instruments | 53.766 | 172.334 | 37.91 | 216.519 |
| Peak×Sensor FE | Yes | Yes | Yes | Yes |
| Peak×Week FE | Yes | Yes | Yes | Yes |
| Peak×State×MOY FE | No | No | No | No |
| Peak×County×MOY FE | Yes | Yes | Yes | Yes |

Notes: Bus transit covers all bus modes and rail transit covers all rail modes. Standard errors are clustered at the county level. Every regression controls for average temperature, precipitation, snow, snow depth, gasoline prices, gasoline taxes, unemployment rate, and population. ln(MPG) is fleet average fuel economy in miles per gallon. Anomalous HDD are deviations in historic average HDD in a state-month-of-year from a baseline of 1901–2000 measured in 1000s. Peak is an indicator variable equal to one if the hour of the day is between 05:00 and 09:59 or 16:00 and 18:59. *** Statistically significant at the 1% level; ** 5% level; * 10% level.

Table A9: Evidence of Differential Peak Elasticity Using NHTS Data

| | (1) ln(Miles)- HH Vehicle Used | (2) ln(Miles)- HH Vehicle NOT Used | (3) ln(Miles)- All Trips |
|--------------------|--------------------------------------|--|--------------------------------|
| ln(Gas Price) | 0.019 (0.119) | 0.010 (0.386) | -0.007 (0.129) |
| ln(Gas Price)×Peak | -0.132** (0.052) | 0.020 (0.151) | -0.083* (0.048) |
| Peak | 0.241*** (0.045) | 0.096 (0.136) | 0.195*** (0.042) |
| Observations | 758,296 | 164,022 | 922,422 |
| County FE | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes |

Notes: Dependent variable is the log of trip length in miles. Standard errors are clustered at the county level. Peak is an indicator variable equal to one if the hour of the day is between 05:00 and 09:59 or 16:00 and 18:59. *** Statistically significant at the 1% level; ** 5% level; * 10% level.

Table A10: Evidence of Differential Peak Elasticity Using Gasoline Content Instruments

| | (1) | (2) | (3) | (4) |
|--|----------------------|----------------------|----------------------|----------------------|
| | Aggregate Effect | | Differential Peak | |
| <i>Panel A: ln(Gas Price) first stage</i> | | | | |
| RVP 9 | 0.046*** (0.002) | 0.051*** (0.002) | 0.046*** (0.002) | 0.051*** (0.002) |
| RVP 7.8 | 0.055*** (0.011) | 0.092*** (0.021) | 0.056*** (0.011) | 0.092*** (0.021) |
| RVP 7 | 0.080*** (0.009) | 0.058*** (0.004) | 0.080*** (0.009) | 0.058*** (0.004) |
| RFG | 0.053*** (0.006) | 0.056*** (0.004) | 0.053*** (0.006) | 0.056*** (0.004) |
| RVP 9×Peak | | | -0.000 (0.000) | 0.000 (0.000) |
| RVP 7.8×Peak | | | -0.000 (0.000) | 0.000 (0.001) |
| RVP 7×Peak | | | -0.000 (0.000) | -0.001 (0.002) |
| RFG×Peak | | | -0.000 (0.000) | -0.000 (0.001) |
| <i>Panel B: ln(Gas Price)×Peak first stage</i> | | | | |
| RVP 9 | 0.006*** (0.002) | 0.006*** (0.002) | 0.006*** (0.001) | 0.006*** (0.000) |
| RVP 7.8 | 0.010 (0.010) | 0.010 (0.010) | 0.007** (0.003) | 0.013*** (0.003) |
| RVP 7 | 0.010* (0.005) | 0.010* (0.005) | 0.009*** (0.001) | 0.006*** (0.001) |
| RFG | 0.013*** (0.005) | 0.013*** (0.005) | 0.003** (0.002) | 0.010*** (0.001) |
| RVP 9×Peak | | | 0.029*** (0.002) | 0.036*** (0.001) |
| RVP 7.8×Peak | | | 0.037*** (0.006) | 0.057** (0.028) |
| RVP 7×Peak | | | 0.055*** (0.008) | 0.042*** (0.007) |
| RFG×Peak | | | 0.044*** (0.007) | 0.030*** (0.002) |
| <i>Panel C: ln(Traffic Count) second stage</i> | | | | |
| ln(Gas Price) | -0.278*** (0.080) | -0.191*** (0.040) | 0.184* (0.099) | 0.349*** (0.056) |
| ln(Gas Price)×Peak | | | -1.236*** (0.109) | -1.442*** (0.087) |
| Observations | 32,376,493 | 32,376,493 | 32,376,493 | 32,376,493 |
| F-stat of Excluded Instruments | 146.688 | 300.124 | 33.354 | 129.981 |
| Peak×Sensor FE | Yes | Yes | Yes | Yes |
| Peak×State×MOY FE | Yes | No | Yes | No |
| Peak×County×MOY FE | No | Yes | No | Yes |

Notes: Standard errors are clustered at the county level. Every regression controls for average temperature, precipitation, snow, and snow depth. RVP 9, RVP 7.8, RVP 7, and RFG are indicator variables equal to one when the gasoline content regulation is active. Regressions contain only data from the 380 counties for which county-level gasoline price data are available. Peak is an indicator variable equal to one if the hour of the day is between 05:00 and 09:59 or 16:00 and 18:59. *** Statistically significant at the 1% level; ** 5% level; * 10% level.

Table A11: Alternative Error Clustering

| Cluster level: | (1) Traffic Sensor | (2) Week | (3) County and Week |
|--|-----------------------|----------------------|------------------------|
| <i>Panel A: ln(MPG) first stage</i> | | | |
| Anom. HDD | -0.089*** (0.001) | -0.089*** (0.006) | -0.089*** (0.008) |
| Anom. HDD×Peak | -0.000 (0.000) | -0.000 (0.000) | -0.000 (0.000) |
| <i>Panel B: ln(MPG)×Peak first stage</i> | | | |
| Anom. HDD | -0.004*** (0.000) | -0.004*** (0.001) | -0.004** (0.001) |
| Anom. HDD×Peak | -0.079*** (0.001) | -0.079*** (0.006) | -0.079*** (0.008) |
| <i>Panel C: ln(Traffic Count) second stage</i> | | | |
| ln(MPG) | 0.217*** (0.042) | 0.217 (0.150) | 0.217 (0.171) |
| ln(MPG)×Peak | 0.210*** (0.025) | 0.210** (0.104) | 0.210* (0.110) |
| Observations | 104,575,134 | 104,575,134 | 104,575,134 |
| F-stat of Excluded Instruments | 3413.526 | 95.508 | 51.637 |
| Peak×Sensor FE | Yes | Yes | Yes |
| Peak×Week FE | Yes | Yes | Yes |
| Peak×County×MOY FE | Yes | Yes | Yes |

Notes: Standard error clustering varies across regressions with two-way clustering used in column (3). Every regression controls for average temperature, precipitation, snow, snow depth, gasoline prices, gasoline taxes, unemployment rate, and population. ln(MPG) is fleet average fuel economy in miles per gallon. Anomalous HDD are deviations in historic average HDD in a state-month-of-year from a baseline of 1901–2000 measured in 1000s. Peak is an indicator variable equal to one if the hour of the day is between 05:00 and 09:59 or 16:00 and 18:59. *** Statistically significant at the 1% level; ** 5% level; * 10% level.

Table A12: Additional Controls

| | (1) | (2) |
|--|----------------------|----------------------|
| <i>Panel A: ln(MPG) first stage</i> | | |
| Anom. HDD | -0.089*** (0.005) | -0.089*** (0.005) |
| Anom. HDD×Peak | -0.000 (0.000) | -0.000 (0.000) |
| <i>Panel B: ln(MPG)×Peak first stage</i> | | |
| Anom. HDD | -0.003*** (0.001) | -0.004*** (0.001) |
| Anom. HDD×Peak | -0.080*** (0.006) | -0.079*** (0.006) |
| <i>Panel C: ln(Traffic Count) second stage</i> | | |
| ln(MPG) | 0.018 (0.114) | 0.220** (0.094) |
| ln(MPG)×Peak | 0.203*** (0.052) | 0.210*** (0.052) |
| Observations | 104,575,134 | 104,575,134 |
| F-stat of Excluded Instruments | 102.385 | 98.729 |
| Peak×Sensor FE | Yes | Yes |
| Peak×Week FE | Yes | Yes |
| Peak×State×MOY FE | Yes | No |
| Peak×County×MOY FE | No | Yes |

Notes: Standard error are clustered at the county level. Every regression controls for average temperature, precipitation, snow, snow depth, gasoline prices, gasoline taxes, unemployment rate, population, GDP, and income. ln(MPG) is fleet average fuel economy in miles per gallon. Anomalous HDD are deviations in historic average HDD in a state-month-of-year from a baseline of 1901–2000 measured in 1000s. Peak is an indicator variable equal to one if the hour of the day is between 05:00 and 09:59 or 16:00 and 18:59. *** Statistically significant at the 1% level; ** 5% level; * 10% level.