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Timing Matters: Estimating within-day variation in the rebound effect

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KEYWORDS: Travel demand, energy efficiency, rebound effect, fuel economy standards, congestion

JEL CODES: R41, Q41, Q58, D62

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Abstract

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1 Introduction

Peak demand periods are often accompanied by high marginal costs due to capacity constraints. Time-varying prices could align incentives in these situations, but this solution is not always possible in practice (Vickrey, 1963, 1969). Instead, policies that uniformly affect prices across peak and off-peak periods are often levied when time-varying prices would be technologically difficult or politically infeasible. In these cases, the relative demand elasticities across periods can ultimately determine whether a policy helps or harms society.

The transportation sector provides a prominent example.[1] US drivers logged 3.2 *trillion* miles in 2017 (FHWA, 2018a). Such astronomic levels of demand on roads with finite capacity led to an immense loss of 8.8 billion hours to traffic congestion (Schrank et al., 2019). Yet, despite travel demand and congestion being highly temporal with known patterns, most policies affecting travel demand — like fuel economy standards which uniformly decrease per-mile driving costs by reducing fuel consumption — do not vary across the hour of day. Given the lack of congestion tolling, variation in travel demand elasticities between peak and off-peak periods should be 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 (commuting) and fuel costs are a smaller share of total costs (due to congestion), scant 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).[2]

In this article, I examine how drivers respond to fuel costs differentially across the hours of the day. I then illustrate the policy importance of heterogeneity in this elasticity 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 fuel costs of driving and therefore lead to more driving.

In practice, I accomplish this task by separately estimating how travel demand responds to fuel

[1] Other examples include congestible goods like popular attractions at national parks or the electricity sector, which experiences peak demand during the afternoon associated with high generation and pollution costs.

[2] Bento et al. (2013) is a notable exception which estimates how fuel prices impact highway travel in Southern California.

cost shocks during peak and off-peak periods. The empirical strategy uses high frequency travel demand data — 1 billion+ hourly vehicle counts from the network of traffic sensors in the US — and exogenous variation in fuel economy caused by fluctuations in ambient air temperature in an instrumental variables strategy. In addition, I find the effects are robust to estimation using ordinary least squares (OLS) and multiple instrumental variables strategies, and they can be replicated using an alternative data source and measure of fuel costs.

Ambient air temperature, particularly cold weather, plays a large role in real-world fuel economy as engines take longer to reach optimal operating temperatures, engine and transmission friction increases, and numerous other physical and mechanical issues 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 trips (EPA, 2019; Lohse-Busch et al., 2013; Ostrouchov, 1978). Because weather affects both fuel economy and driving patterns, I utilize only deviations from historic average temperatures for identification and simultaneously control for contemporaneous changes in weather (temperature, precipitation, snowfall, and snow depth) to satisfy the exclusion restriction. In other words, deviations from a state's historic cold-weather induced fuel economy penalty are used for identification while also controlling for changes in trip composition caused by contemporaneous weather.

This empirical strategy highlights the importance of the peak load and provides several other contributions. First, 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.[3] 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 as the instrument impacts all vehicles simultaneously. Finally, previous research has examined how fuel economy standards affect pollution and automobile collision externalities, but I provide a better understanding of the relationship between the standards and congestion by examining the rebound effect's temporal variation.

[3]See Gillingham (2020) and Linn (2016) for an overview of the rebound effect literature and common estimating assumptions.

I find drivers to be *more elastic* during peak travel periods.[4] A 1% increase in fuel economy leads to a 0.36% increase in vehicle counts during peak periods, but only a 0.16% increase during off-peak hours. Driver response to fuel efficiency more than doubles during peak periods. I then explore the mechanisms driving this differential response during peak periods. The results provide suggestive evidence that shorter (nonhighway), weekday commuting trips, in areas where higher shares of workers commute by modes other than passenger vehicles 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.[5]

Finally, because the elasticity I estimate is a measure of the rebound effect, I evaluate the change in external pollution and congestion costs induced by a fuel economy improvement while 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 like the Corporate Average Fuel Economy Standards in the US have the potential to exacerbate the congestion externality. I find that exogenously increasing the average fuel economy of every vehicle on the road today by 1.5%, the annual increase in stringency required for model years 2021 through 2026 by the Safer Affordable Fuel-Efficient (SAFE) Vehicles Rule, produces pollution benefits that are only modestly bigger than the induced congestion costs. Under some assumptions, the standards can even lead to a net increase in these external costs.[6] Though the magnitude of these costs and benefits depend on parameter assumptions, accounting for heterogeneity in the rebound effect has a substantial impact on the net change in externalities across scenarios.

[4] Peak 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.

[5] For 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, a friend's house, or restaurant via alternative modes likely has higher average mental costs per trip.

[6] This exercise only compares congestion and pollution externalities, and it does not provide a complete analysis of the benefits and costs of fuel efficiency standards.

2 Background

2.1 Travel Demand and Congestion

Though they vary in size and shape across regions, travel demand peaks are strongly correlated 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. As the number of vehicles increases though, 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 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. Individuals factor these private congestion costs into their decision to drive. 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 vehicles do not have a differential peak period effect, and Southern California travel is anecdotally known for car dependency and sprawl. 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.

2.2 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 for mechanical and physical reasons that are largely out of the control of drivers (EPA, 2019; Lohse-Busch et al., 2013; Ostrouchov, 1978). Low temperatures cause engines to take longer to reach optimal operating temperatures. Air becomes denser as temperatures fall, increasing aerodynamic drag on vehicles. 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. These effects have relatively similar impacts on fuel economy for all vehicles (Bielaczyc et al., 2011). The effects are also 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 uses these fluctuations in fuel economy caused by cold weather, but weather plays a significant role in when and where individuals drive. As will be described further in section 4, 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. Standard heating degree days are measured as the deviation in temperature below a base of 65 degrees. For example, a day with an average temperature of 40 degrees would be equal to 25 HDD while any day above 65 degrees would be equal to 0 HDD. HDDs are a measure of if and how much heating might be required for a residence on a cold day. *Anomalous* HDD are deviations from the historical average HDD for that state and month of year from a baseline period of 1901-2000. 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. Anomalous is not synonymous with extreme — identifying variation comes from small deviations from historic averages that persist over weeks, short periods that experience large deviations, and instances between.

The effects of cold weather on driving costs are potentially less salient than those caused by gas prices. However, the relationship between temperature and fuel economy is widely advertised by public agencies like the EPA, local and national media outlets, popular magazines like Scientific American, blogs, and other outlets.[7] Advances in vehicle technology have also made displays illustrating a vehicle's contemporaneous and recent fuel economy while driving ubiquitous. This allows drivers to easily understand their fuel usage — information that they do respond to (Boriboonsomsin et al., 2010; Sanguinetti et al., 2020). However, I do not have information on driver awareness of the relationship between temperature on fuel economy. If the relationship is not salient to many drivers, the effects estimated using this instrument will likely be a lower bound to the true effect. Regardless of these potential limitations, it is interesting that drivers respond to *any* shock differentially during the peak periods as I find.

There are also other weather-related concerns that drivers may be able to control to an extent. Cold temperatures reduce tire pressure which increases rolling resistance and driving at slower speeds, loss of traction from icy or snow-covered roads, and the use of heated seats may further decrease fuel economy. Some of these factors, like tire pressure and traction, could be mitigated by technologies like tire-pressure monitoring systems or traction control. Other technologies could have a countervailing effect — like heated seats which directly increase fuel usage — though these effects may be smaller. The availability of these features likely skews toward newer vehicles owned by high-income drivers, which have been shown to be more responsive to fuel costs (Gillingham, 2014; Gillingham et al., 2015; Spiller et al., 2017). To the extent that cold weather differentially affects vehicle MPG through these and similar channels, it seems plausible that older (more inelastic) vehicles could be impacted more. The elasticity estimates may therefore be a lower bound on

[7] See https://www.fueleconomy.gov/feg/coldweather.shtml, https://www.boston.com/cars/news-and-reviews/2016/01/22/how-cold-weather-kills-your-gas-mileage-and-what-to-c https://www.cnbc.com/2014/02/14/cold-weather-reduces-a-cars-mileage.html, or https://www.scientificamerican.com/article/why-is-the-fuel-economy-o/.

the true effect size.

While excessively hot weather may also impact fuel economy, I rely on HDD for identification. The primary pathway that warm weather reduces fuel economy is through the use of air conditioning. Not all individuals uniformly use their air conditioners during warm weather though and driving with windows open can have other efficiency impacts due to aerodynamics. In contrast, it is impossible for individuals to avoid many of the deleterious effects of cold weather on fuel economy. Though they may wish to avoid the additional drag cold air causes on their vehicle, drivers cannot alter air density, making a stronger case for the use of a cold weather IV.

While I focus on internal combustion engine vehicles and the rebound effect, the effect of cold weather on electric vehicles is also significant — decreasing both efficiency and battery range. Electric vehicle adoption in the US during the sample (2013–2018) was quite small though, and these vehicles are driven far less than the average internal combustion engine vehicle (Nehiba, 2024). It is therefore unlikely that these vehicles play a substantial enough role in aggregate traffic counts to bias the results.

2.3 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 by improving the efficiency of our automobiles, major appliances, and buildings. Improving a good's energy efficiency also lowers its usage costs which in turn leads owners 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). 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.[8]

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

[8] 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.

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.[9] Recent literature in this areas 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, 2022; Spiller et al., 2017).

I make several contributions to the rebound effect literature. First, I propose an 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 anomalous HDD 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, conditional on the included weather controls. In other words, the instrument creates limited incentives to switch to a more fuel efficient vehicle in the household because all vehicles receive a fuel economy penalty. While it is true that freezing temperatures, snow, and ice may lead to the use of larger more fuel-inefficient vehicles, the included weather controls and fixed effects capture this effect. This new strategy also provides one of the few direct estimates of the effect of fuel economy on driving demand. The strategy assumes that drivers respond similarly to real-world fuel economy changes and rated fuel economy of a vehicle at the time of purchase as opposed to the more often employed assumption 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.

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

3 Data Sources and Summary Statistics

3.1 Traffic Sensor Data

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 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. For each week in the sample, every traffic sensor has 24 observations — one for each hour of the day.[10] 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 99.5 million observations covering 24,734 individual traffic sensors in 1,879 counties between 2013 and 2018 in the US.

A majority of these traffic sensors are located on routes designated as "Interstates" or "Principal Arterial - Other Freeways and Expressways," but many sensors are located on smaller routes designated as "Minor Collector," "Major Collector," "Minor Arterial," and "Principal Arterial - Other." To the extent that the sample skews towards major roadways, the results may be more applicable to travel on these routes.

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.[11]

[10] In addition, I aggregate the data for weekdays and weekends separately for the analysis in Table 4.

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

3.2 Weather Data

I obtain weather data from two data sets provided by the National Oceanic and Atmospheric Administration (NOAA). Weather controls including contemporaneous measures of 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 the imputation of missing weather data 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.[12] The data are then averaged to the county-by-week level and the precipitation, snowfall, and snow depth variables are censored at zero.[13]

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.

3.3 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.

First, the VMT data capture total mileage from all vehicles (both passenger and commercial vehicles), including those not powered by gasoline. As diesel, electric, and alternative fuel vehicle miles are included, 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.

[12] The results are robust to the use of non-imputed weather controls (see Appendix Table A6).

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

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 is differenced out by location fixed effects, and time fixed effects mitigate concerns that this measurement error changes over the sample.

3.4 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.

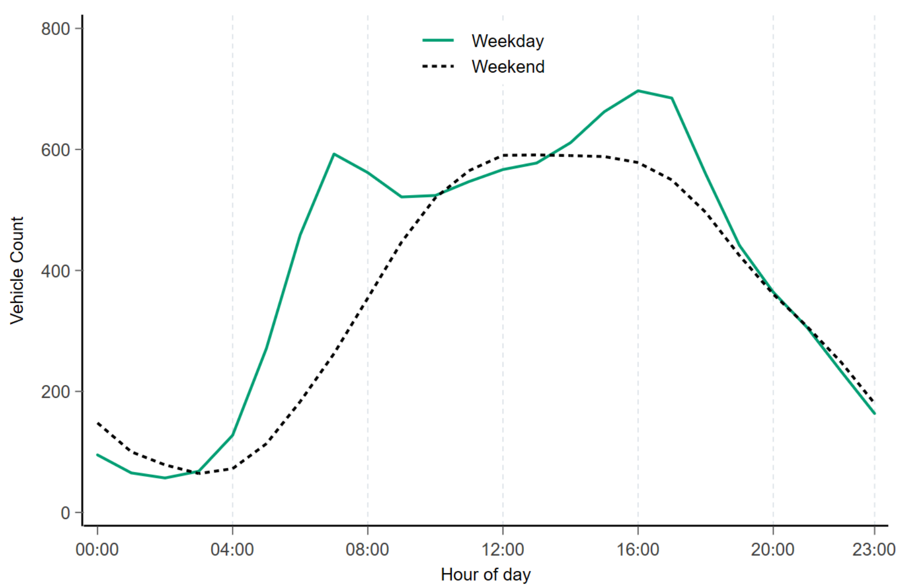
Finally, I obtain commuting mode shares for each county from the Census Transportation Planning Products (CTPP). These commute mode share values are five-year estimates covering 2012-2016, so only a single value is available for each mode and county.[14] In some cases, I aggregate commuting modes into 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 create an active transportation (bicycling plus walking), non-passenger vehicle (all modes besides passenger vehicle), and transit (all bus and rail modes) bins.

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

3.5 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).

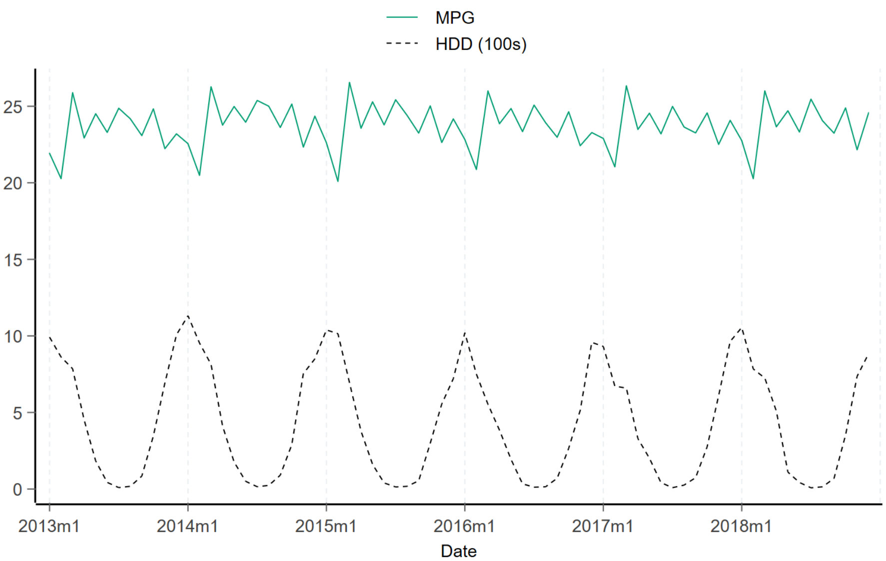
Figure 1: Hourly Vehicle Counts Throughout the Day



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).

Weekends exhibit a 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. 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,

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.

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 high levels during the summer. MPG also experiences sharp drops in February and increases in March, which may raise concerns regarding seasonal measurement error. While geography-specific month of year fixed effects capture this seasonal variation, I also find the results are robust to dropping these months entirely (as well as several other seasonal data restrictions) in Appendix Table A3. 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.

4 Empirical Setting

4.1 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 is

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

where h denotes the hour of the day, t denotes the week, and m denotes the month of the sample. X is a matrix of control variables, μ contains sensor fixed effects, and ρ contains time fixed effects. The coefficient of interest, η, measures the short-run fuel economy elasticity of traffic flows. Standard errors are clustered at the county level throughout the analysis.[15] X controls for factors that influence both fuel economy and driving behavior. In the preferred specification, I include county-by-week controls for contemporaneous temperature, precipitation, snowfall, and snow depth as well as controlling for county-by-month unemployment rate, county-by-year population, and state-by-week gas prices and taxes.[16]

To begin, I estimate equation 1 using OLS. However, fuel economy is a choice made by drivers, making a region's MPG endogenous. For example, a driver with a long commute may sort into a more fuel-efficient vehicle. While a single atomistic driver would have a minuscule effect on the estimates, this behavior leads to a correlation between fuel economy and unobservable local characteristics if a region on average has long commutes and therefore more fuel-efficient vehicles. Sensor fixed effects control for the average fleet fuel economy in an area, but unobservables that affect fuel economy like the fleet composition, vehicle usage intensity, policies, and preferences vary over time across regions. These issues would lead to biased estimates that understate the responsiveness of drivers to fuel economy, suggesting that OLS estimates could be interpreted as a conservative lower bound of the true effect.

To overcome this endogeneity issue, I leverage exogenous variation in fleet fuel economy

[15] Robustness to alternative error clustering is examined in Appendix Table A10.

[16] The results are robust to including additional control variables (e.g., GDP, income). See Appendix Table A11.

caused by fluctuations in ambient air temperature. As outlined in the section 2, cold temperature shocks affect automobile performance for various reasons outside the control of drivers — a change in temperature from 77 to 20 degrees Fahrenheit can reduce MPG by 15%. While cold temperatures can reduce a vehicle's fuel efficiency, they are 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 variables including contemporaneous temperature, precipitation, snowfall, and snow depth on driving behavior to be controlled for in all specifications. Further, because the effects of temperature on fuel economy are relatively similar across vehicles, these shocks provide little incentive for households with multiple vehicles to change vehicle utilization patterns.

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

$$\ln(MPG_{sm}) = \tau + \delta \cdot (\text{Anom. HDD}_{sm}) + \phi \cdot X_{ijsht} + \mu_i + \rho_t + \nu_{ijsht} \tag{2}$$

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

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. In a sense, the empirical strategy can be thought of as examining behavioral changes arising due to deviations from the state's climate while controlling for contemporaneous weather events.

Importantly, anomalous does not directly equate to extreme here. Identifying variation can come from prolonged periods of temperatures a few degrees below the average, single days far below the average, and situations between. Consider a state that in a given month of the year had an average HDD of 0 between 1901–2000. Anomalous HDD may measure 60 if the mean temperature is 63 for thirty days or if the mean temperature is 65 for twenty-eight days of the month and 35 for two days. In other words, the identifying variation does not solely come from a handful of extreme outlier events, but rather a wide array of instances where HDD deviates from historical averages by small and large amounts.

These deviations do however contribute first-stage identifying variation proportionally to their size. Larger deviations provide greater sources of identifying variation, and these larger shocks likely provide more salient changes in fuel economy for drivers.[17] Similarly, small daily fluctuations in gasoline prices may go unnoticed by many drivers, while larger price shocks elicit changes in driving behavior from broader groups. Having the most salient fuel economy shocks comprising much of the identification would suggest that the estimates here represent the average effect. I also find a relatively similar fuel economy response across months with more or less extreme weather fluctuations in Appendix Table A14, though the analysis has important limitations.

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

This set of fixed effects in conjunction with controlling for contemporaneous weather eliminates any exclusion restriction concerns regarding the anomalous HDD instrument, but they also eliminate much of the available identifying variation. As such, the empirical strategy relies on the large number of observations provided by the traffic sensor data to precisely estimate effects.

Another potential concern in this setting would be drivers putting off some types of trips due to weather shocks. For example, Ge and Ho (2019) provide evidence of such hysteresis or delayed

[17] Smaller fuel economy penalties induced by smaller temperature fluctuations could be missed by less observant drivers.

effect in thermostat settings. However, the aggregated nature of the data captures short-term hysteresis or delayed effects, and I fail to find evidence that drivers respond in a meaningful way to weather shocks in previous weeks in Appendix Table A13. The estimates are also robust to the exclusion of various months of the year that may be more susceptible to changes in driving behavior due to weather.[18]

4.2 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

$$\ln(V_{ijsht}) = \omega + \eta \cdot \ln(MPG_{sm}) + \lambda \cdot (\ln(MPG_{sm}) \times \mathrm{P}_h) + \alpha \cdot \mathrm{P}_h + \psi \cdot X_{ijsht} + \mu_i + \rho_t + \varepsilon_{ijsht} \quad (3)$$

where P is equal to one if the hour is between 05:00 and 09:59 or 16:00 and 18:59, though the results are robust to varying definitions of the peak period (see Appendix Table A2). The variable of interest is now $(\ln(MPG_{sm}) \times \mathrm{P}_h)$, which estimates how fleet fuel economy differentially affects vehicle counts during 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

$$\ln(MPG_{sm}) = \tau + \pi \cdot (\text{Anom. HDD}_{sm}) + \delta \cdot (\text{Anom. HDD}_{sm} \times \mathrm{P}_h) + \iota \cdot \mathrm{P}_h + \phi \cdot X_{ijsht} + \mu_i + \rho_t + \nu_{ijsht} \quad (4)$$

$$\ln(MPG_{st}) \times \mathrm{P}_h = \beta + \zeta \cdot (\text{Anom. HDD}_{st}) + \theta \cdot (\text{Anom. HDD}_{st} \times \mathrm{P}_h) + \upsilon \cdot \mathrm{P}_h + \kappa \cdot X_{ijsht} + \mu_i + \rho_t + \nu_{ijsht} \quad (5)$$

[18] See Appendix Table A3.

The greatest threat to identification in this setting is the potential for factors to differentially bias the effects of fuel economy across peak and off-peak periods. The fixed effects are therefore allowed to vary across the hours of day. For example, Peak$\times$Sensor and Peak$\times$Week fixed effects are included to separately control for time invariant sensor characteristics and traffic patterns that may differ between peak and off-peak periods and macroeconomic shocks that may differentially affect peak and off-peak traffic, respectively. Importantly, the remaining identification concerns not fully addressed by the fixed effects and included control variables likely impact the peak and off-peak periods equally, or arguably have larger impacts during the off-peak periods. This would suggest the peak-period differential I estimate is conservative. For example, cold weather may lead to more dangerous driving conditions and black ice formation even in the absence of precipitation. However, this concern would likely be more prevalent at night (off peak) when temperatures are lower, thus inflating the off-peak elasticity to a greater extent than the peak elasticity.

5 Results

5.1 Aggregate Response to Fuel Economy Shocks

I present results from estimating the OLS and instrumental variables models described in equations (1) and (2) in Table 1. Columns (1) and (2) provide the OLS results, and columns (3) and (4) provide IV results with first-stage estimates of the effects of anomalous HDD on MPG in Panel A. Panel B provides the OLS or second-stage estimates of the effect of the predicted changes in MPG on traffic counts. Fixed effects included vary across columns. Each regression includes controls for contemporaneous temperature, precipitation, snowfall, snow depth, gasoline prices, gasoline taxes, unemployment rate, and population. Standard errors are clustered at the county level.

The OLS results in columns (1) and (2) are stable across the specifications which include either Peak$\times$State$\times$Month-of-Year (MOY) or Peak$\times$County$\times$MOY fixed effects. The OLS results suggest that traffic counts increase by 0.9% when fuel economy increases by 10%. As discussed in the previous section, these OLS results are likely to understate this rebound effect though and should be interpreted as a lower bound to the true effect.

In the IV models in columns (3) and (4), anomalous HDD are a statistically significant predictor of fleet fuel economy, and the Kleibergen-Paap F-statistic of the excluded instruments exceeds 290 in each regression. As expected, cold weather reduces fleet fuel economy. One thousand anomalous HDD in a month reduces fleet fuel economy by approximately 1%. This relatively small effect is likely a result of the empirical strategy's tight focus, which eliminates much of the potential variation and relies on the large data set to precisely identify small changes in behavior. It is important to reiterate that *anomalous is not synonymous with extreme* in this setting. The identifying variation can arise due to small deviations from historic averages that persist over weeks, short periods that experience large deviations, and instances between. 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 empirical strategy also controls for contemporaneous weather (e.g., snow), alleviating concerns of any remaining correlations between anomalous HDD and driving behavior or the types of vehicles being used that do not arise due to fuel economy shocks. Further, if any such correlations remain after conditioning on the controls and fixed effects, they would likely bias the results away from finding a significant effect. For example, if cold weather makes individuals less likely to commute via bus or bicycle, one would expect an increase in driving when fuel economy falls due to anomalous HDD (the opposite of the effect I find).

Unlike the OLS estimates, the effect of fleet fuel economy on traffic counts importantly depends on the fixed effects included in the model. When Peak$\times$State$\times$Month-of-Year fixed effects are included, the elasticity is approximately 0.03 and statistically insignificant at conventional levels. The elasticity increases in size and becomes statistically significant when Peak$\times$County$\times$MOY fixed effects are included. These more granular county-level fixed effects likely better satisfy the exclusion restriction by controlling for unobservable differences in seasonal driving patterns and vehicle utilization that may vary greatly across space. For example, the changes in driving and vehicles being used across months of the year in Incline Village, NV, which averages over 130 inches of snowfall annually, may be very different from those in Las Vegas, NV. In the preferred specification in column (4), a 10% increase in fuel economy is estimated to increase traffic counts by 2.3%. As predicted, this effect is larger in magnitude than that estimated using the OLS model, suggesting that the OLS results are biased downard.

The elasticity estimates from the preferred OLS and IV specifications in columns (2) and (4) suggest a rebound effect between 9% and 23%. These estimates are similar to previous measures 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 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 estimates a rebound effect between 20% and 40% while carefully examining how common empirical assumptions made in the previous literature can impact results.

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

Table 1: Aggregate Effect of Fuel Economy on Traffic Counts

	(1)	(2)	(3)	(4)
	OLS		IV	
*Panel A: **ln(MPG)** first stage*				
Anomalous HDD			-0.093***	-0.093***
			(0.005)	(0.005)
*Panel B: **ln(Traffic Count)** second stage*				
ln(MPG)	0.088**	0.088**	0.026	0.233***
	(0.038)	(0.035)	(0.099)	(0.081)
Observations	99,522,862	99,522,861	99,522,862	99,522,861
F-stat of Excluded Instruments	-	-	291.475	355.802
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. Every regression controls for contemporaneous 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.

5.2 Evidence of Differential Response During Peak Periods

Next, Table 2 examines if the rebound effect varies between peak and off-peak periods using the methods described in equations (3), (4), and (5). Again, columns (1) and (2) present OLS results, and columns (3) and (4) present IV results. For the IV models, Panel A presents the first-stage estimates of anomalous HDD and the interaction of anomalous HDD and a peak indicator on the log of MPG. Similarly, Panel B presents the first stage with the dependent variable being the interaction of the log of MPG and an indicator for peak hours. Panel C presents the OLS or second-stage estimates of the effects on traffic counts. Controls include contemporaneous temperature, precipitation, snowfall, snow depth, gas prices and taxes, unemployment rate, and population, and standard errors are clustered at the county level.

The OLS estimates in columns (1) and (2) are once again consistent across specifications. The OLS models estimate a fuel economy elasticity of traffic counts during off peak periods — the ln(MPG) effect — around 0.07. The differential peak effect is positive and statistically significant in both regressions — suggesting that the peak and off peak periods do experience different responses. A 10% increase in MPG increases traffic counts by 0.53% *more* during peak periods. To get the total peak period elasticity, the effects of ln(MPG) and ln(MPG)$\times$Peak must be added together. Column (2) estimates this cumulative peak elasticity to be around 0.122.

Turning to the IV models in columns (3) and (4), the instruments have the predicted sign and are statistically significant in each regression with the exception of the Anom. HDD$\times$Peak variable in Panel A. This lack of significance is not surprising as the interaction 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 exceed 90 in both regressions.

In Panel C, the second-stage estimates of the effect of ln(MPG) are smaller than those estimated in Table 1 and are again only significant when County$\times$MOY FE are included in the regression.[19]

[19] Again, the disparities in magnitude and significance between specifications may be explained by the more granular County$\times$MOY fixed effects better controlling for unobservable differences in seasonal driving patterns and vehicle utilization that vary greatly across space.

Table 2: Differential Effect of Fuel Economy during Peak Periods

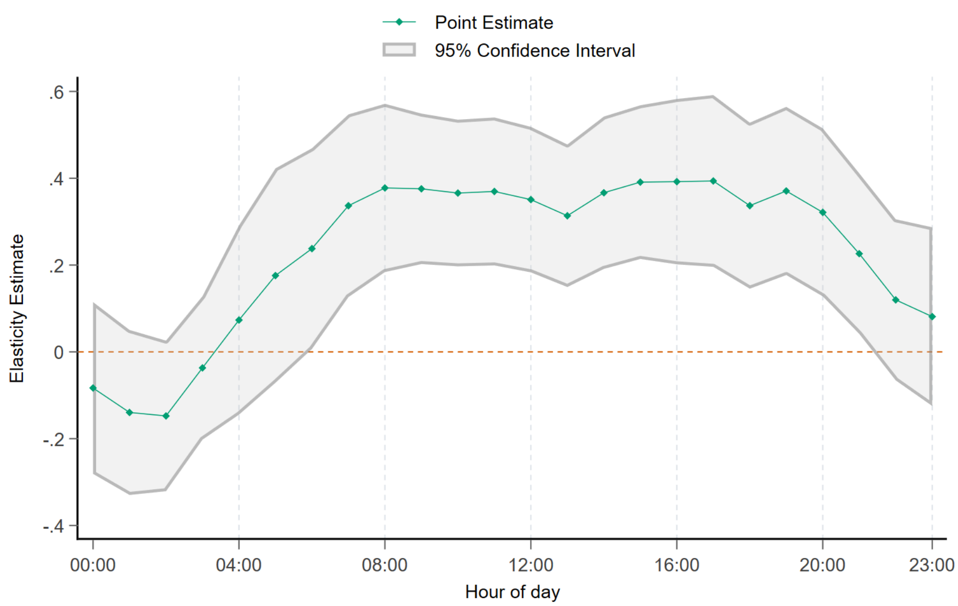
	(1)	(2)	(3)	(4)
	OLS		IV	
Panel A: ***ln(MPG)*** *first stage*				
Anom. HDD			-0.093***	-0.093***
			(0.005)	(0.005)
Anom. HDD×Peak			-0.000	-0.000
			(0.000)	(0.000)
Panel B: ***ln(MPG)×Peak*** *first stage*				
Anom. HDD			-0.005***	-0.005***
			(0.001)	(0.001)
Anom. HDD×Peak			-0.081***	-0.080***
			(0.006)	(0.006)
Panel C: ***ln(Traffic Count)*** *second stage*				
ln(MPG)	0.068*	0.069**	-0.048	0.156*
	(0.036)	(0.035)	(0.101)	(0.082)
ln(MPG) × Peak	0.052***	0.053***	0.199***	0.204***
	(0.017)	(0.017)	(0.053)	(0.054)
Observations	99,522,862	99,522,861	99,522,862	99,522,861
F-stat of Excluded Instruments	-	-	95.074	91.430
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. Every regression controls for contemporaneous 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.

In contrast, the variable of interest, ln(MPG)×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. The preferred specification in column (2) suggests that the effect of fuel economy on traffic counts more than doubles from 0.16 to 0.36 during peak periods with an average effect — from column (4) of Table 1 — of 0.233. Though the OLS results are again somewhat muted relative to these IV estimates, the magnitude of the differential peak period (nearly twice that of the off peak elasticity) is similar across the models.

Figure 3 illustrates the heterogeneity in the rebound effect by estimating a separate model for each hour of the day and plotting 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 slightly decrease in the middle of the day before rising to another peak in the evening before tapering off. I also 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.

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(MPG) is instrumented for using Anomalous HDD. Every regression controls for contemporaneous temperature, precipitation, snow, snow depth, gasoline prices, gasoline taxes, unemployment rate, and population. Every regression includes sensor, week, and County×MOY fixed effects. Standard errors are clustered at the county level.

Alternative Estimation of the Differential Peak Response

As further evidence, Table 3 examines if a similar peak period differential can be found using an entirely different travel demand data set and measure of fuel costs. I estimate how reported individual trip lengths in miles and trip durations in minutes differentially respond to fuel costs during peak periods using survey data from the 2017 National Household Travel Survey. I control for peak periods, the log of fuel prices, and the variable of interest, Peak×ln(Gas Price), which indicates if gasoline price elasticities vary between peak and off-peak periods. Regressions are estimated using OLS with county and month fixed effects and standard errors clustered at the county level.[20]

Columns (1) and (2) show the effects of fuel prices on trip mileage while columns (3) and (4) show the effects on trip duration. Column (1) estimates the model using only data for trips where a 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.) that theoretically should not have their length (in mileage or duration) affected by fuel prices. Columns (3) and (4) vary in a similar fashion.

Table 3: Evidence of Differential Peak Elasticity Using NHTS Data

	(1) ln(Miles)- HH Vehicle Used	(2) ln(Miles)- HH Vehicle NOT Used	(3) ln(Trip Duration)- HH Vehicle Used	(4) ln(Trip Duration)- HH Vehicle NOT Used
ln(Gas Price)	0.019	0.010	0.090	0.159
	(0.119)	(0.386)	(0.083)	(0.210)
ln(Gas Price)×Peak	-0.132**	0.020	-0.087**	-0.053
	(0.052)	(0.151)	(0.037)	(0.086)
Peak	0.241***	0.096	0.143***	0.144*
	(0.045)	(0.136)	(0.033)	(0.077)
Observations	758,296	164,022	757,526	164,607
County FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes

Notes: Dependent variable is either the log of trip length in miles or trip duration in minutes. Data is separated between trips where a household vehicle was or was not used. 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.

[20]While gasoline prices may be endogenous here, the direction of the bias likely means the estimates are conservative. Further, using crude oil prices as an instrument for gasoline prices (a common strategy in previous literature) is not possible while also including month fixed effects because these global price series do not provide spatial variation. Including month fixed effects, as is done in these regressions, therefore controls for any endogeneity that a crude oil price IV might correct.

A differential peak period effect is estimated in columns (1) and (3) for HH vehicle trips. When fuel prices increase by 1%, peak period trips decrease in length by 0.132% and durations fall by 0.087%.[21] I fail to find a statistically significant effect of gasoline prices during off-peak periods, suggesting that the commonly estimated cumulative effect of gasoline prices on travel demand largely occurs during peak periods. Not surprisingly, I fail to find a statistically significant effect of fuel prices during peak or off-peak periods on trip lengths when the HH vehicle is not used. These trips are unlikely to be affected by fuel prices (except perhaps in total quantity) as gas prices are largely inconsequential to the costs of these modes. 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 primary data source or identification strategy. In addition to the intensive margin responses shown here, I examine how fuel costs affect the share of trips taken and share of miles driven during the peak period in Appendix Table A5 finding similar, though statistically insignificant, results.

I further examine the robustness of my results in Appendix Tables A4, A6, A9, and A12. Table A4 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. In Table A9, 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 done in Nehiba (2022). Finally, in Table A12, I include time-varying regional fixed effects. These fixed effects control for unobservable time-varying confounders that arise between regions like a particularly cold winter covering the entire Midwest. I find that controlling for these effects does not qualitatively change the peak-period differential response, but does increase the aggregate effect of fuel economy on traffic counts.

Beyond the importance of these results for the rebound effect, it is generally fascinating that *any* shift in driving costs would have a larger effect during peak hours. Whether the change be due to fuel policies like fuel economy standards or gasoline taxes, congestion tolls, or other factors, a

[21] The drop in trip durations does not appear to be due to increases in speed, as evidenced by Appendix Table A5.

differential peak-period response may have enormous implications.[22]

5.3 Mechanisms Driving Differential Response

In contrast to the estimates presented in Table 2, 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 4 provide IV 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 81 to 92; however, the second-stage results diverge between weekdays and weekends. The effect of ln(MPG) decreases for weekdays and increases for weekends. In contrast, the effect of ln(MPG)$\times$Peak becomes larger in magnitude during weekdays and much smaller for weekends, relative to the estimates in Table 2. Further, the effects of ln(MPG)$\times$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.

[22]Consider even the reduced form results presented in Appendix Table A4. The anticipated mechanism is that anomalous HDD impact MPG and therefore traffic counts. However, even if this were not true, it is interesting that the effect of anomalous HDD on traffic counts is larger during the peak period.

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 4: Weekday and Weekend Estimates of Fuel Economy Elasticities

	(1)	(2)	(3)	(4)
	Weekdays		Weekends	
Panel A: ***ln(MPG)*** *first stage*				
Anom. HDD	-0.092***	-0.091***	-0.089***	-0.089***
	(0.005)	(0.005)	(0.006)	(0.005)
Anom. HDD×Peak	-0.000	-0.000	-0.000***	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Panel B: ***ln(MPG)×Peak*** *first stage*				
Anom. HDD	-0.004***	-0.004***	-0.005***	-0.005***
	(0.001)	(0.001)	(0.000)	(0.001)
Anom. HDD×Peak	-0.080***	-0.080***	-0.077***	-0.077***
	(0.006)	(0.006)	(0.006)	(0.006)
Panel C: ***ln(Traffic Count)*** *second stage*				
ln(MPG)	-0.098	0.117	0.151	0.341***
	(0.104)	(0.087)	(0.124)	(0.109)
ln(MPG) × Peak	0.257***	0.271***	0.111*	0.118*
	(0.058)	(0.059)	(0.062)	(0.063)
Observations	98,746,716	98,746,716	96,023,855	96,023,855
F-stat of Excluded Instruments	91.929	89.923	80.905	77.589
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 contemporaneous 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 5 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 81.2 million highway observations relative to the 18.3 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 5 use 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(MPG) effect and somewhat diminished peak differential.

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; Nehiba and Tyndall, 2023).

Table 5: Variation in Fuel Economy Elasticities between Road Types

	(1)	(2)	(3)	(4)
	Nonhighways		Highways	
Panel A: ***ln(MPG)*** *first stage*				
Anom. HDD	-0.091***	-0.090***	-0.093***	-0.094***
	(0.005)	(0.005)	(0.006)	(0.005)
Anom. HDD×Peak	-0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Panel B: ***ln(MPG)×Peak*** *first stage*				
Anom. HDD	-0.003***	-0.003***	-0.005***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
Anom. HDD×Peak	-0.083***	-0.082***	-0.080***	-0.079***
	(0.005)	(0.005)	(0.007)	(0.007)
Panel C: ***ln(Traffic Count)*** *second stage*				
ln(MPG)	-0.208	-0.124	-0.025	0.201**
	(0.145)	(0.116)	(0.113)	(0.093)
ln(MPG) × Peak	0.316***	0.315***	0.178***	0.178***
	(0.085)	(0.086)	(0.059)	(0.059)
Observations	18,336,280	18,336,280	81,186,582	81,186,581
F-stat of Excluded Instruments	158.041	154.794	73.503	70.454
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: 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 contemporaneous 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.

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 highlights whether having a high share of a commuting mode is associated with higher peak period elasticities.

Table 6 presents the results from five separate commuting mode choices. Each mode has two regressions — one including counties above the US median share of commuters selecting that mode and a second containing counties 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 previously. 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(MPG) and ln(MPG)×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 anecdotally known for sprawl and car dependency.

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(MPG)×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 6: Results by Commuting Mode Share

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Commute mode:	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
*Panel A: **ln(MPG)** first stage*										
Anom. HDD	-0.089***	-0.105***	-0.090***	-0.107***	-0.102***	-0.077***	-0.083***	-0.111***	-0.094***	-0.100***
	(0.006)	(0.009)	(0.006)	(0.006)	(0.006)	(0.008)	(0.005)	(0.007)	(0.006)	(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)
*Panel B: **ln(MPG)×Peak** first stage*										
Anom. HDD	-0.005***	-0.000	-0.006***	-0.002**	-0.006***	-0.004***	-0.005***	-0.006***	-0.004***	-0.004**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Anom. HDD×Peak	-0.075***	-0.104***	-0.074***	-0.102***	-0.087***	-0.067***	-0.071***	-0.095***	-0.084***	-0.090***
	(0.008)	(0.011)	(0.007)	(0.006)	(0.008)	(0.009)	(0.006)	(0.009)	(0.006)	(0.010)
*Panel C: **ln(Traffic Count)** second stage*										
ln(MPG)	0.209**	-0.077	0.203*	0.038	0.158	0.194	0.430***	-0.077	0.138	0.099
	(0.106)	(0.121)	(0.104)	(0.088)	(0.099)	(0.144)	(0.121)	(0.091)	(0.112)	(0.103)
ln(MPG) × Peak	0.286***	0.020	0.176**	0.291***	0.234***	0.146	0.305***	0.200***	0.284***	0.124**
	(0.076)	(0.071)	(0.071)	(0.054)	(0.063)	(0.115)	(0.083)	(0.068)	(0.078)	(0.062)
Observations	68,801,755	30,721,106	76,312,659	23,210,202	55,079,376	44,443,485	42,936,226	56,586,635	57,817,923	41,704,938
F-stat of Excluded Instruments	43.323	62.142	48.888	170.232	52.887	26.547	81.638	59.242	129.246	69.714
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 contemporaneous 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.

6 Interaction Between the Rebound Effect and Externalities

I next apply the results to an analysis of fuel economy standards in the US. For simplicity, I omit many implementation issues surrounding the Corporate Average Fuel Economy Standards and focus solely on the effects of an exogenous shock to fuel economy on driving. I do not account for how CAFE standards 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.

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 Rule[23], would affect pollution and congestion if applied to the entire fleet. Given the

[23]The 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, and itself has since been replaced by a rule for 2024–2026 model year vehicles. See https://www.nhtsa.gov/laws-regulations/corporate-average-fuel-economy#light-duty-vehicles for more information on CAFE and

limitations, this is not a direct or complete analysis of fuel economy 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 recently updated social cost of greenhouse gas (SC-GHG) values from EPA (2023) 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.[24] Unfortunately, estimates of US average marginal external congestion costs per mile that vary by the time of day are not available. I therefore take a conservative approach using a range of costs. As a baseline for 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. This calculation estimates peak period congestion costs to be \$0.164 per mile while off-peak costs are \$0.012 per mile. These costs are 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). I then perform the analysis assuming peak congestion costs that are ± \$0.10/mile from the baseline of \$0.164/mile. Finally, I use values of light-duty vehicle VMT and average fuel economy in 2019 from the Bureau of Transportation Statistics.

Table 7 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 0.36, while the off-peak elasticity is significantly smaller at 0.156. In contrast, Panel C assumes that the peak elasticity is 0, while the off-peak elasticity is identical to Panel B at 0.156.

Panel B estimates a total increase in VMT of 8,687 million miles due to the rebound effect. This VMT increase equates to just over 26 miles per capita annually, or an individual changing their daily VMT by less than a tenth of a mile. The improved fuel efficiency leads to a reduction in pollution valued at \$1,101 million in that year due to reduced fuel consumption. However,

SAFE.

[24] For simplicity, the SC-GHG values use a 2.5% near-term Ramsey discount rate, an emission year of 2020, and values are adjusted to 2019 dollars.

because the increase in VMT occurs mostly during peak periods, the increase in fuel economy leads to large increases in congestion. Congestion damages range from $417–$1,621 million, with the baseline per-mile congestion cost ($0.164/mile) leading to an estimated $1,019 million increase in congestion damages. Under the lowest congestion cost scenario, net external damages are estimated to decrease. However, a net increase in external damages is found under the highest congestion cost scenario, and the changes in costs between pollution and congestion nearly cancel out under the baseline congestion cost scenario. In other words, the pollution benefits have the *potential* to be entirely offset by the exacerbated congestion costs under plausible assumptions when I account for the relatively elastic peak period. A much smaller increase in VMT of 2,666 million miles is seen in Panel C where the rebound effect is assumed to be zero during peak periods. This simulation leads to larger pollution benefits of $1,365 million/year and substantially smaller increases in congestion costs. These smaller congestion costs arise because the rebound effect occurs solely during the uncongested off-peak periods in this setting. Assuming an inelastic peak produces a vastly different conclusion of the net change in external damages.

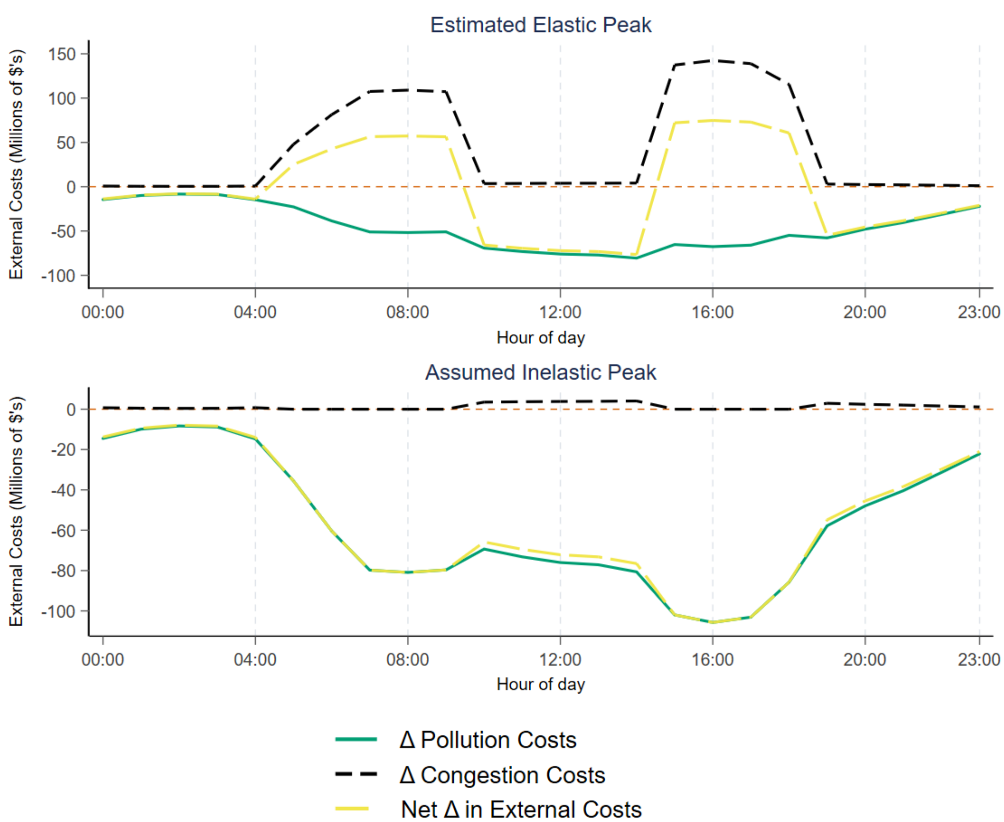
Table 7: Policy Analysis

Panel A: Baseline Simulation Parameters	
Peak congestion costs per mile[a]	[$0.064, $0.164, $0.264]
Off-peak congestion costs per mile[a]	$0.012
Pollution costs per gallon[b]	$1.076
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	0.156
Peak Elasticity	0.36
Δ VMT (millions)	8,687
Pollution Damages (millions)	-$1,101
Congestion Damages (millions)	[+$417, +$1,019, +$1,621]
Net Δ External Damages (millions)	**[-$684, -$82, +$521]**
Panel C: Effects of 1.5% Increase in MPG Assuming Inelastic Peak Period	
Off-Peak Elasticity	0.156
Peak Elasticity	0
Δ VMT (millions)	2,666
Pollution Damages (millions)	-$1,365
Congestion Damages (millions)	+$32
Net Δ External Damages (millions)	**-$1,333**

Notes:
[a] https://www.fhwa.dot.gov/policy/hcas/addendum.cfm;
[b] Muller and Mendelsohn (2012) and EPA (2023)
[c] https://www.bts.gov/content/us-vehicle-miles
[d] https://www.bts.gov/content/average-fuel-efficiency-us-light-duty-vehicles

These conclusions can be seen clearly in Figure 4. This figure 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 peak congestion costs of \$0.164 per mile. Using the elasticities I estimate in this paper in the top panel, congestion costs increase significantly during morning and evening peaks, while pollution costs decrease during the daytime hours. Erroneously assuming an inelastic peak in the bottom panel leads to a reversal of these findings. Large pollution benefits are accrued during peak periods because these hours have high VMT and no 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 in external costs from the policy analyses in Panels B and C of Table 7, assuming peak congestion costs of \$0.164/mile. The top panel uses elasticities estimated in this paper, while the bottom panel incorrectly assumes that drivers are inelastic during peak periods.

These calculations are intended for illustrative purposes only. They do not represent a complete picture of the benefits and costs of fuel efficiency standards nor do they amount to a complete accounting of net benefits of externalities associated with fuel economy standards. However, this exercise sheds light on the importance of accounting for differential behavioral responses to policy in a second-best setting. The relative behavioral responses, measured as elasticities, between peak and off-peak periods play an important role in determining the welfare effects of fuel economy standards and many other policies that uniformly shift the costs of driving throughout the day. Per-capita VMT increases only slightly when fuel economy improves, but the bulk of this increase occurs during already congested periods. Though fuel economy standards reduce vehicle emissions, these benefits have the potential to be almost entirely or more than offset by increases in congestion costs depending on parameter assumptions. 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.

7 Conclusion

The congestion created by peaks within daily travel demand is an enormously costly negative externality. 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 which uniformly affect the costs of driving but have the potential to disproportionately affect the demand for travel during congested periods. However, the rebound effect from fuel economy standards 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 drivers are more responsive to fuel costs, as measured by fuel economy, during peak periods. A 10% increase in fuel economy elicits a 3.6% increase in traffic counts during peak demand periods but only a 1.6% increase during off-peak periods. This estimate proves to be robust to various estimation methods, numerous tests of instrument validity, and replication using a different data source and measure of fuel costs. This estimated fuel economy elasticity — a 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 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 nearly cancel out or, in some cases, exceed the pollution benefits.

These results highlight the importance of timing when considering energy efficiency programs. However, the context of the specific durable good and market failures involved will play a role in the effectiveness of the programs. For example, Boomhower and Davis (2020) illustrate that much of the energy savings from air conditioner energy efficiency improvements occur during peak electricity demand hours — a desirable outcome because electricity costs are high during these peak hours. Fuel economy standards, while reducing peak period gasoline consumption and therefore emissions, have the undesirable effect of exacerbating congestion externalities. Likewise, substitution patterns may influence these conclusions. Automobiles, particularly for trips during peak commuting hours, appear to have relatively low-cost alternatives that individuals can switch to, driving some of the within-day variation in the rebound effect. Other goods covered by energy efficiency programs, say household appliances like a washing machine or oven, may or may not have high-quality substitutes available. Individuals may be more likely to shift the timing of use for these goods from high-cost peak periods as opposed to substituting to another product during that period, which could have substantial welfare implications.

References

Auffhammer, M., Hsiang, S. M., Schlenker, W., and Sobel, A. (2013). Using weather data and climate model output in economic analyses of climate change. *Review of Environmental Economics and Policy*, 7(2):181–198.

Barla, P., Herrmann, M., Criado, C. O., and Miranda-Moreno, L. F. (2015). Are gasoline demand elasticities different across cities? Working Paper 2015-4, Center for Research on the Economics of the Environment, Agri-food, Transports and Energy.

Bento, A., Gillingham, K., and Roth, K. (2017). The effect of fuel economy standards on vehicle weight dispersion and accident fatalities. Working Paper 23340, National Bureau of Economic Research.

Bento, A. M., Goulder, L. H., Jacobsen, M. R., and von Haefen, R. H. (2009). Distributional and efficiency impacts of increased US gasoline taxes. *American Economic Review*, 99(3):667–99.

Bento, A. M., Hughes, J. E., and Kaffine, D. (2013). Carpooling and driver responses to fuel price changes: Evidence from traffic flows in Los Angeles. *Journal of Urban Economics*, 77:41–56.

Bielaczyc, P., Szczotka, A., and Woodburn, J. (2011). The effect of a low ambient temperature on the cold-start emissions and fuel consumption of passenger cars. *Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering*, 225(9):1253–1264.

Boomhower, J. and Davis, L. (2020). Do energy efficiency investments deliver at the right time? *American Economic Journal: Applied Economics*, 12(1):115–39.

Boriboonsomsin, K., Vu, A., and Barth, M. J. (2010). Eco-driving: Pilot evaluation of driving behavior changes among U.S. drivers.

Davis, L. W. and Knittel, C. R. (2019). Are fuel economy standards regressive? *Journal of the Association of Environmental and Resource Economists*, 6(S1):S37–S63.

EPA (2019). Fuel economy in cold weather. Technical report.

EPA (2023). EPA report on the social cost of greenhouse gases: Estimates incorporating recent scientific advances. Supplementary material for the regulatory impact analysis for the final rulemaking, Standards of Performance for New, Reconstructed, and Modified Sources and Emissions Guidelines for Existing Sources: Oil and Natural Gas Sector Climate Review, Environmental Protection Agency.

FHWA (2000). Addendum to the 1997 federal highway cost allocation study. Final report, Federal Highway Administration.

FHWA (2014). Traffic montioring guide 2013: Chapter 1. Traffic monitoring theory, technology, and concepts. Technical report.

FHWA (2018a). Public road mileage, lane-miles, and VMT 1900 - 2017. Technical report.

FHWA (2018b). Traffic data computation method: Pocket guide. Technical report.

Ge, Q. and Ho, B. (2019). Energy use and temperature habituation: Evidence from high frequency thermostat usage data. *Economic Inquiry*, 57(2):1196–1214.

Gillingham, K. (2011). *The consumer response to gasoline prices: Empirical evidence and policy implications*. PhD thesis, Stanford University.

Gillingham, K. (2014). Identifying the elasticity of driving: Evidence from a gasoline price shock in California. *Regional Science and Urban Economics*, 47:13 – 24. SI: Tribute to John Quigley.

Gillingham, K., Jenn, A., and Azevedo, I. M. (2015). Heterogeneity in the response to gasoline prices: Evidence from Pennsylvania and implications for the rebound effect. *Energy Economics*, 52:S41 – S52. Frontiers in the Economics of Energy Efficiency.

Gillingham, K. and Munk-Nielsen, A. (2019). A tale of two tails: Commuting and the fuel price response in driving. *Journal of Urban Economics*, 109:27 – 40.

Gillingham, K., Rapson, D., and Wagner, G. (2016). The rebound effect and energy efficiency policy. *Review of Environmental Economics and Policy*, 10(1):68–88.

Gillingham, K. T. (2020). The rebound effect and the proposed rollback of U.S. fuel economy standards. *Review of Environmental Economics and Policy*, 14(1):136–142.

Greene, D. L. (2012). Rebound 2007: Analysis of U.S. light-duty vehicle travel statistics. *Energy Policy*, 41:14–28. Modeling Transport (Energy) Demand and Policies.

Hymel, K. M. and Small, K. A. (2015). The rebound effect for automobile travel: Asymmetric response to price changes and novel features of the 2000s. *Energy Economics*, 49:93–103.

Hymel, K. M., Small, K. A., and Dender, K. V. (2010). Induced demand and rebound effects in road transport. *Transportation Research Part B: Methodological*, 44(10):1220–1241.

Jacobsen, M. R. and van Benthem, A. A. (2015). Vehicle scrappage and gasoline policy. *American Economic Review*, 105(3):1312–38.

Jevons, W. S. (1865). *The coal question; an enquiry concerning the progress of the Nation, and the probable exhaustion of our coal-mines*. Macmillan, 2 edition.

Knittel, C. R. and Sandler, R. (2018). The welfare impact of second-best uniform-pigouvian taxation: Evidence from transportation. *American Economic Journal: Economic Policy*, 10(4):211–42.

Langer, A., Maheshri, V., and Winston, C. (2017). From gallons to miles: A disaggregate analysis of automobile travel and externality taxes. *Journal of Public Economics*, 152:34–46.

Leung, W. C. C. (2015). *Three Essays in Energy Economics*. PhD thesis, University of California, San Diego.

Liao, B., E. W. van den Berg, P., van Wesemael, P. J. V., and A. Arentze, T. (2020). How does walkability change behavior? A comparison between different age groups in the Netherlands. *International Journal of Environmental Research and Public Health*, 17(2).

Linn, J. (2016). The rebound effect for passenger vehicles. *The Energy Journal*, 37(Number 2).

Liu, Y., Tremblay, J.-M., and Cirillo, C. (2014). An integrated model for discrete and continuous decisions with application to vehicle ownership, type and usage choices. *Transportation Research Part A: Policy and Practice*, 69(C):315–328.

Lohse-Busch, H., Duoba, M., Rask, E., Stutenberg, K., Gowri, V., Slezak, L., and Anderson, D. (2013). Ambient temperature (20f, 72f and 95f) impact on fuel and energy consumption for several conventional vehicles, hybrid and plug-in hybrid electric vehicles and battery electric vehicle. In *SAE Technical Paper*. SAE International.

Muller, N. Z. and Mendelsohn, R. (2012). Efficient pollution regulation: Getting the prices right: Corrigendum (mortality rate update). *The American Economic Review*, 102(1):613–616.

Nehiba, C. (2022). Correcting heterogeneous externalities: Evidence from local fuel taxes. *Journal of the Association of Environmental and Resource Economists*, 9(3):495–529.

Nehiba, C. (2024). Electric vehicle usage, pollution damages, and the electricity price elasticity of driving. *Journal of Environmental Economics and Management*, 124:102915.

Nehiba, C. and Tyndall, J. (2023). Highways and pedestrian deaths in US neighborhoods. *Regional Science and Urban Economics*, 102:103938.

Ostrouchov, N. (1978). Effect of cold weather on motor vehicle emissions and fuel economy. In *SAE Technical Paper*. SAE International.

Parry, I., Fischer, C., and Harrington, W. (2005). Should Corporate Average Fuel Economy (CAFE) standards be tightened?

Parry, I. W. H. (2005). Is pay-as-you-drive insurance a better way to reduce gasoline than gasoline taxes? *American Economic Review*, 95(2):288–293.

Parry, I. W. H. and Small, K. A. (2005). Does Britain or the United States have the right gasoline tax? *American Economic Review*, 95(4):1276–1289.

Parry, I. W. H. and Small, K. A. (2009). Should urban transit subsidies be reduced? *American Economic Review*, 99(3):700–724.

Portney, P. R., Parry, I. W., Gruenspecht, H. K., and Harrington, W. (2003). Policy watch: The economics of fuel economy standards. *Journal of Economic Perspectives*, 17(4):203–217.

Sanguinetti, A., Queen, E., Yee, C., and Akanesuvan, K. (2020). Average impact and important features of onboard eco-driving feedback: A meta-analysis. *Transportation Research Part F: Traffic Psychology and Behaviour*, 70:1–14.

Schrank, D., Eisele, B., and Lomax, T. (2019). Urban mobility report. Technical report, Texas A & M Transportation Institute.

Small, K. and Van Dender, K. (2007). Fuel efficiency and motor vehicle travel: The declining rebound effect. *The Energy Journal*, 28:25–52.

Spiller, E., Stephens, H. M., and Chen, Y. (2017). Understanding the heterogeneous effects of gasoline taxes across income and location. *Resource and Energy Economics*, 50:74 – 90.

Vickrey, W. S. (1963). Pricing in urban and suburban transport. *The American Economic Review*, 53(2):452–465.

Vickrey, W. S. (1969). Congestion theory and transport investment. *The American Economic Review*, 59(2):251–260.

West, J., Hoekstra, M., Meer, J., and Puller, S. L. (2017). Vehicle miles (not) traveled: Fuel economy requirements, vehicle characteristics, and household driving. *Journal of Public Economics*, 145:65–81.

Yang, J., Purevjav, A.-O., and Li, S. (2020). The marginal cost of traffic congestion and road pricing: Evidence from a natural experiment in Beijing. *American Economic Journal: Economic Policy*, 12(1):418–53.

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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. A broad definition of the peak periods (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). In column 5, I denote a single period from 05:00 to 19:59 as the peak period.

The results are qualitatively similar across the regressions and consistent with those estimated in the preferred specification in column (4) of Table 2. ln(MPG) and ln(MPG)$\times$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(MPG) becomes larger in magnitude and ln(MPG)$\times$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 varying months of the year. In columns (1)–(4), warmer months that may be more likely to violate the instrumental variables exclusion restriction are removed. 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 (5) removes February and March to examine if the results are robust to seasonal patterns in the MPG measure that arise due to changes in the VMT and fuel sales estimates used to construct MPG.

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(MPG)×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. However, ln(MPG) is negative and statistically significant in column (2), so these results should be interpreted with caution. Excluding February and March in column (5) also does not qualitatively impact the results.

Table A4 provides reduced form estimates of the effects of Anom. HDD and Anom. HDD×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 A5 presents additional results using the NHTS travel data. In columns (1) and (2), I test whether the differential decrease in trip durations during the peak period seen in Table 3 is due to increases in speed. This MPH variable is constructed using the trip miles and duration, and I fail to find a statistically significant effect regardless of whether a household vehicle was used for the trip. This result suggests that the change in peak trip durations is due to reductions in distance. In columns (3) and (4), I collapse the data to the household by month level to examine how the share of a household's mileage and total number of trips during the peak period varies with gasoline prices. While I fail to estimate a statistically significant result in either column, I estimate that higher gasoline prices have a negative effect on the share of mileage and quantity of trips occurring during the peak period. This lack of precision may be due to smaller number of observations caused by the data aggregation, but the results are broadly consistent with those presented in the main text.

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 contemporaneous state-level precipitation and temperatures as opposed to the county-level weather controls used in the main analysis. The effect of ln(MPG) becomes substantially larger in columns (1) and (2); however, the size of the ln(MPG)×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(MPG) and ln(MPG)$\times$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(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.

Table A8 further decomposes the public transit mode share regressions from Table 6 to regressions for rail transit and bus transit. The results for both are qualitatively similar to the transit regressions in Table 6, confirming that areas with high levels of bus or rail transit are not driving the results.

Table A9 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 (2022). 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 (2022) 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 -0.254 and -0.259, similar in magnitude to Nehiba (2022) 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 A10 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 A11 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 A12 includes regional fixed effects that vary over time. I group states using the EIA's Petroleum Administration for Defense Districts (PADDs) definitions.[25] I then include PADD$\times$Month and PADD$\times$Week fixed effects and their counterparts interacted with the Peak period indicator as well. The inclusion of these fixed effects controls for unobservable time-varying confounders across regions. The fixed effects further isolate the identifying variation to changes within the PADD region and time. The results remain qualitatively similar — the fuel economy elasticity is around 0.14–0.29 larger during peak periods — though the aggregate effect of fuel economy on traffic counts increases in magnitude across all specifications.

Following (Ge and Ho, 2019), Table A13 includes lags of the weather variables to examine potential hysteresis in driver decisions — do individuals adjust their travel patterns this week due to weather shocks that happened in previous weeks. In column 1, I include 1-week lag term for each of the weather variables. Column 2 includes lag terms for 2-weeks, and column 3 in includes a third week so that the specification (including the contemporaneous week) covers approximately a month of weather shocks. Column 4 includes 3-weeks of lag terms for only temperature.

The results are highly robust to these (and other) lag specifications. Focusing on column 3, higher contemporaneous temperatures lead to a statistically and economically significant increase

[25]These groupings and more information about PADDs can be found at https://www.eia.gov/todayinenergy/detail.php?id=4890. Following the EIA, I break the East Coast PADD 1 into PADD 1A, PADD 1B, and PADD 1C.

in driving during the week. The effect of temperature in previous weeks remains positive, but it is far smaller. Though the first and third lags are statistically significant, all estimates are small enough to be considered economically insignificant. Similarly, precipitation and snow in a week greatly reduces driving, but small effects are found for the lagged variables. Based on these results, it appears that there is either little hysteresis or delayed effects in driver response to weather, or it is already largely captured by using week-level data.

It is possible that drivers respond differently to fluctuations in MPG that are caused by small and persistent changes in anomalous HDD versus fluctuations from extreme deviations. Small, persistent anomalous HDD variation may have a less salient impact on MPG, leading only ultra-price sensitive individuals to respond to these shocks. Likewise, larger shocks may have a more salient impact, and a broader set of individuals could respond. Similar differences may arise when considering driver response to typically small daily gasoline price fluctuations versus large salient fluctuations in prices (e.g., changes from Russia invading Ukraine or gasoline taxes).

To investigate if drivers do have different responses to MPG due to the underlying first-stage variation, Table A14 splits the sample based on how many days in a month have "extreme" levels of anomalous HDD. I define an extreme day as follows. First, I calculate a state-level daily anomalous HDD variable using the disaggregated weather station data and historic HDD values based on the more aggregated NOAA Climate at a Glance data. Monthly measures of anomalous HDD based on the weather station data do not perfectly align with the Climate at a Glance data due to differences in imputation and aggregation, but the two measures are very strongly correlated. I then define an extreme day as one that has an anomalous HDD value that is plus-or-minus two standard deviations from the average anomalous HDD in the sample.

Table A14 splits the sample along these extreme weather days. Column 1 includes only months with at least 6 extreme days while column 2 includes only months with fewer than 6 extreme days. Columns 3 and 4 set the threshold at 10 extreme days. The first-stages for each regression are strong, but the F-statistics and coefficients for and first-stage effects are smaller for columns 2 and 4 which include less extreme weather days as extreme weather provides a stronger source of identifying variation. In the second stage, the effect of ln(MPG) varies substantially in magnitude and significance. However, the effect of ln(MPG) is statistically significant, quite stable in magnitude, and similar to the main result across each specification.

These results provide some suggestive evidence that drivers respond in a similar fashion to MPG shocks during peak periods caused by large and small weather events. There are several limitations in splitting the sample as I do in Table A14 though. First, the aggregated nature of the data creates some temporal mismatch when looking for this type of differential behavior. Second, there is a mechanical relationship between extreme days and the strength of the first stage. More extreme weather leads to more fluctuation in anomalous HDD and therefore more identifying variation. Table A14 purposefully splits the sample such that the first stage is strong (as defined by usual measures of statistical significance and F-statistics). Drivers appear to respond similarly to peak-period MPG fluctuations induced during months with fewer than 6 and more than 6 extreme weather days. It is difficult to say if this similarity holds as the number of extreme days decreases though.

Table A1: Summary Statistics

Variable	Mean	Std. Dev.	Obs.
Traffic Count	399.8	616.3	99,522,862
Fuel Economy (MPG)	24.1	3.8	99,522,862
Anom. HDD	-37.8	91.3	99,522,862
Contemporaneous HDD	394.4	412.9	99,522,862
Contemporaneous Temperature (Fahrenheit)	55.3	18.4	99,522,862
Contemporaneous Precipitation (mm)	29.2	30.1	99,522,862
Contemporaneous Snowfall (mm)	2.4	6.5	99,522,862
Contemporaneous Snow Depth (mm)	42.4	129.3	99,522,862
Gasoline Price ($/gal)	2.94	0.66	99,522,862
Gasoline Tax ($/gal)	0.27	0.08	99,522,862
Unemployment Rate	0.053	0.021	99,522,862
County Population	528,281	998,972	99,522,862

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

Table A2: Varying Peak Definitions

Peak=1 if hour of day=	(1) 05:00–09:59 15:00–19:59	(2) 06:00-08:59 16:00–18:59	(3) 07:00–08:59 17:00–18:59	(4) 08:00–08:59 17:00–17:59	(5) 05:00–18:59
Panel A: ***ln(MPG)*** *first stage*					
Anom. HDD	-0.093***	-0.093***	-0.093***	-0.093***	-0.093***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Anom. HDD×Peak	-0.000	-0.000	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel B: ***ln(MPG)×Peak*** *first stage*					
Anom. HDD	-0.005***	-0.003***	-0.002***	-0.001***	-0.008***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)
Anom. HDD×Peak	-0.080***	-0.080***	-0.080***	-0.080***	-0.080***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Panel C: ***ln(Traffic Count)*** *second stage*					
ln(MPG)	0.127	0.176**	0.185**	0.212***	0.059
	(0.081)	(0.081)	(0.080)	(0.081)	(0.089)
ln(MPG)×Peak	0.258***	0.210***	0.261***	0.178***	0.302***
	(0.050)	(0.046)	(0.039)	(0.042)	(0.067)
Observations	99,522,861	99,522,861	99,522,861	99,522,860	99,522,860
F-stat of Excluded Instruments	91.453	91.5	91.489	91.239	91.529
Peak×Sensor FE	Yes	Yes	Yes	Yes	Yes
Peak×Week FE	Yes	Yes	Yes	Yes	Yes
Peak×County×MOY FE	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors are clustered at the county level. Every regression controls for contemporaneous 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) Dec.–Feb.	(2) Nov.–Mar.	(3) Oct.–Apr.	(4) Sep.–May	(5) Apr.–Jan.
Panel A: ***ln(MPG)*** *first stage*					
Anom. HDD	-0.104***	-0.101***	-0.094***	-0.090***	-0.087***
	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)
Anom. HDD×Peak	-0.000	-0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel B: ***ln(MPG)×Peak*** *first stage*					
Anom. HDD	-0.003***	-0.005***	-0.004***	-0.004***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Anom. HDD×Peak	-0.096***	-0.089***	-0.084***	-0.080***	-0.079***
	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)
Panel C: ***ln(Traffic Count)*** *second stage*					
ln(MPG)	-0.090	-0.138**	0.031	0.070	0.289**
	(0.078)	(0.069)	(0.087)	(0.083)	(0.118)
ln(MPG) × Peak	0.323***	0.334***	0.185***	0.208***	0.237***
	(0.058)	(0.054)	(0.060)	(0.054)	(0.065)
Observations	24,090,951	40,655,621	57,731,222	74,420,332	83,202,509
F-stat of Excluded Instruments	149.19	183.651	178.809	168.716	98.429
Peak×Sensor FE	Yes	Yes	Yes	Yes	Yes
Peak×Week FE	Yes	Yes	Yes	Yes	Yes
Peak×County×MOY FE	Yes	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 contemporaneous 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: Reduced Form

	*Dependent Variable:**ln(Traffic Count)***			
	(1)	(2)	(3)	(4)
Anom. HDD	-0.002	-0.022***	0.004	-0.016**
	(0.009)	(0.007)	(0.009)	(0.007)
Anom. HDD×Peak			-0.016***	-0.016***
			(0.004)	(0.004)
Observations	99,522,862	99,522,861	99,522,862	99,522,861
R-squared	0.667	0.668	0.667	0.668
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 contemporaneous 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: Additional Results Using NHTS Data

	(1) ln(Avg. MPH)- HH Vehicle Used	(2) ln(Avg. MPH)- HH Vehicle NOT Used	(3) HH Share of Mileage During Peak	(4) HH Share of Trips During Peak
ln(Gas Price)	-0.079	-0.120	-0.010	-0.010
	(0.072)	(0.273)	(0.079)	(0.079)
ln(Gas Price)×Peak	-0.042	0.066		
	(0.050)	(0.106)		
Peak	0.095**	-0.044		
	(0.043)	(0.096)		
Observations	757,352	163,646	94,814	94,810
County FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes

Notes: Dependent variable is either the log of trip average speed, the share of a household's mileage occurring during peak periods, or the share of a household's trips that took place during the peak period. Data is separated between trips where a household vehicle was or was not used in columns (1) and (2). 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 A6: Alternative Weather Controls and HDD Instrument

	(1)	(2)	(3)	(4)
Specification:	Alt. Weather Controls		Alt. HDD Instrument	
Panel A: ***ln(MPG)*** *first stage*				
Anom. HDD	-0.160***	-0.161***		
	(0.013)	(0.013)		
Contemporaneous HDD			-0.093***	-0.093***
			(0.005)	(0.005)
Anom. HDD×Peak	-0.000	-0.000		
	(0.000)	(0.000)		
Contemporaneous HDD×Peak			-0.000	-0.000
			(0.000)	(0.000)
Panel B: ***ln(MPG)×Peak*** *first stage*				
Anom. HDD	-0.030***	-0.030***		
	(0.004)	(0.004)		
Contemporaneous HDD			-0.005***	-0.005***
			(0.001)	(0.001)
Anom. HDD×Peak	-0.080***	-0.079***		
	(0.006)	(0.006)		
Contemporaneous HDD×Peak			-0.081***	-0.080***
			(0.006)	(0.006)
Panel C: ***ln(Traffic Count)*** *second stage*				
ln(MPG)	0.566***	0.618***	-0.048	0.156*
	(0.153)	(0.150)	(0.101)	(0.082)
ln(MPG) × Peak	0.204***	0.211***	0.199***	0.204***
	(0.052)	(0.052)	(0.053)	(0.054)
Observations	104,575,134	104,575,134	99,522,862	99,522,861
F-stat of Excluded Instruments	73.945	77.504	95.08	91.434
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 contemporaneous state-level temperature and precipitation while columns (3) and (4) control for county-level 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)
Panel A: ***ln(MPG)*** *first stage*		
Anom. HDD	-0.093***	-0.093***
	(0.005)	(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)
Panel B: ***ln(MPG)×Morning Peak*** *first stage*		
Anom. HDD	-0.003***	-0.002***
	(0.001)	(0.000)
Anom. HDD×Morning Peak	-5.452***	-5.453***
	(0.153)	(0.153)
Anom. HDD×Evening Peak	6.737***	6.738***
	(0.197)	(0.197)
Panel C: ***ln(MPG)×Evening Peak*** *first stage*		
Anom. HDD	-0.002***	-0.003***
	(0.000)	(0.000)
Anom. HDD×Morning Peak	5.372***	5.373***
	(0.155)	(0.155)
Anom. HDD×Evening Peak	-6.818***	-6.818***
	(0.195)	(0.195)
Panel D: ***ln(Traffic Count)*** *second stage*		
ln(MPG)	-0.049	0.155*
	(0.101)	(0.082)
ln(MPG)×Morning Peak	0.106**	0.112**
	(0.053)	(0.054)
ln(MPG)×Evening Peak	0.326***	0.332***
	(0.052)	(0.053)
Observations	99,522,862	99,522,861
F-stat of Excluded Instruments	63.383	60.953
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 contemporaneous 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

	(1)	(2)	(3)	(4)
Sample:	Bus transit		Rail transit	
	Above Median	Below Median	Above Median	Below Median
Panel A: ***ln(MPG)*** *first stage*				
Anom. HDD	-0.090***	-0.105***	-0.088***	-0.103***
	(0.006)	(0.006)	(0.007)	(0.005)
Anom. HDD×Peak	-0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Panel B: ***ln(MPG)***×***Peak*** *first stage*				
Anom. HDD	-0.006***	-0.002*	-0.006***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Anom. HDD×Peak	-0.074***	-0.101***	-0.072***	-0.096***
	(0.007)	(0.006)	(0.009)	(0.006)
Panel C: ***ln(Traffic Count)*** *second stage*				
ln(MPG)	0.203**	0.034	0.209*	0.122
	(0.102)	(0.091)	(0.118)	(0.079)
ln(MPG) × Peak	0.164**	0.328***	0.158*	0.280***
	(0.069)	(0.057)	(0.081)	(0.056)
Observations	76,920,852	22,602,009	65,956,372	33,566,489
F-stat of Excluded Instruments	49.882	164.422	35.408	240.171
Peak×Sensor FE	Yes	Yes	Yes	Yes
Peak×Week FE	Yes	Yes	Yes	Yes
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 contemporaneous 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 Gasoline Content Instruments

	(1)	(2)	(3)	(4)
	Aggregate Effect		Differential Peak	
Panel A: ***ln(Gas Price)*** *first stage*				
RVP 9	0.072***	0.078***	0.072***	0.078***
	(0.003)	(0.003)	(0.003)	(0.003)
RVP 7.8	0.066***	0.108***	0.066***	0.108***
	(0.010)	(0.022)	(0.010)	(0.022)
RVP 7	0.100***	0.097***	0.100***	0.098***
	(0.010)	(0.009)	(0.010)	(0.009)
RFG	0.085***	0.097***	0.085***	0.097***
	(0.007)	(0.005)	(0.007)	(0.005)
RVP 9×Peak			-0.000	-0.000
			(0.000)	(0.000)
RVP 7.8×Peak			-0.001**	0.000
			(0.000)	(0.001)
RVP 7×Peak			-0.000	-0.000
			(0.000)	(0.001)
RFG×Peak			-0.000	-0.000
			(0.000)	(0.001)
Panel B: ***ln(Gas Price)×Peak*** *first stage*				
RVP 9			0.016***	0.016***
			(0.001)	(0.001)
RVP 7.8			0.011***	0.019***
			(0.002)	(0.003)
RVP 7			0.017***	0.021***
			(0.001)	(0.002)
RFG			0.015***	0.025***
			(0.002)	(0.002)
RVP 9×Peak			0.029***	0.036***
			(0.002)	(0.001)
RVP 7.8×Peak			0.037***	0.057**
			(0.006)	(0.028)
RVP 7×Peak			0.055***	0.042***
			(0.008)	(0.007)
RFG×Peak			0.044***	0.030***
			(0.007)	(0.002)
Panel C: ***ln(Traffic Count)*** *second stage*				
ln(Gas Price)	-0.259***	-0.254***	0.203***	0.286***
	(0.049)	(0.027)	(0.073)	(0.046)
ln(Gas Price)×Peak			-1.235***	-1.441***
			(0.109)	(0.088)
Observations	32,376,493	32,376,493	32,376,493	32,376,493
F-stat of Excluded Instruments	130.427	220.447	34.425	129.867
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 contemporaneous 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 A10: Alternative Error Clustering

Cluster level:	(1) Traffic Sensor	(2) Week	(3) County and Week
Panel A: ***ln(MPG)*** *first stage*			
Anom. HDD	-0.093***	-0.093***	-0.093***
	(0.001)	(0.007)	(0.008)
Anom. HDD×Peak	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
Panel B: ***ln(MPG)×Peak*** *first stage*			
Anom. HDD	-0.005***	-0.005***	-0.005***
	(0.000)	(0.001)	(0.002)
Anom. HDD×Peak	-0.080***	-0.080***	-0.080***
	(0.001)	(0.006)	(0.008)
Panel C: ***ln(Traffic Count)*** *second stage*			
ln(MPG)	0.156***	0.156	0.156
	(0.038)	(0.143)	(0.158)
ln(MPG) × Peak	0.204***	0.204**	0.204*
	(0.025)	(0.103)	(0.110)
Observations	99,522,861	99,522,861	99,522,861
F-stat of Excluded Instruments	3316.243	97.689	50.339
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 contemporaneous 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 A11: Additional Controls

	(1)	(2)
Panel A: ***ln(MPG)*** *first stage*		
Anom. HDD	-0.093***	-0.093***
	(0.005)	(0.005)
Anom. HDD×Peak	-0.000	-0.000
	(0.000)	(0.000)
Panel B: ***ln(MPG)×Peak*** *first stage*		
Anom. HDD	-0.005***	-0.005***
	(0.001)	(0.001)
Anom. HDD×Peak	-0.081***	-0.080***
	(0.006)	(0.006)
Panel C: ***ln(Traffic Count)*** *second stage*		
ln(MPG)	-0.044	0.166**
	(0.101)	(0.082)
ln(MPG) × Peak	0.199***	0.204***
	(0.053)	(0.054)
Observations	99,522,862	99,522,861
F-stat of Excluded Instruments	95.074	91.430
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 contemporaneous 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.

Table A12: Including Regional Time Fixed Effects

	(1)	(2)	(3)	(4)
Panel A: ***ln(MPG)*** *first stage*				
Anom. HDD	-0.104***	-0.104***	-0.111***	-0.111***
	(0.009)	(0.009)	(0.006)	(0.006)
Anom. HDD×Peak	-0.000	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Panel B: ***ln(MPG)×Peak*** *first stage*				
Anom. HDD	-0.009***	-0.008***	-0.012***	-0.007***
	(0.003)	(0.001)	(0.002)	(0.001)
Anom. HDD×Peak	-0.080***	-0.084***	-0.080***	-0.091***
	(0.006)	(0.010)	(0.006)	(0.008)
Panel C: ***ln(Traffic Count)*** *second stage*				
ln(MPG)	0.488**	0.512**	0.363***	0.331**
	(0.193)	(0.199)	(0.123)	(0.129)
ln(MPG) × Peak	0.204***	0.140	0.204***	0.291***
	(0.053)	(0.092)	(0.053)	(0.077)
Observations	99,522,861	99,522,861	99,522,861	99,522,861
F-stat of Excluded Instruments	72.479	32.519	175.704	73.918
Peak×Sensor FE	Yes	Yes	Yes	Yes
Peak×Week FE	Yes	Yes	Yes	No
Peak×County×MOY FE	No	Yes	No	Yes
PADD×Month FE	Yes	No	No	No
PADD×Month×Peak FE	No	Yes	No	No
PADD×Week FE	No	No	Yes	No
PADD×Week×Peak FE	No	No	No	Yes

Notes: PADD refers to Petroleum Administration for Defense Districts. Standard errors are clustered at the county level. Every regression controls for contemporaneous 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 A13: Hysteresis in Weather Effects

	(1)	(2)	(3)	(4)
Panel A: ***ln(MPG)*** *first stage*				
Anom. HDD	-0.096***	-0.097***	-0.097***	-0.097***
	(0.005)	(0.005)	(0.005)	(0.005)
Anom. HDD×Peak	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Panel B: ***ln(MPG)×Peak*** *first stage*				
Anom. HDD	-0.006***	-0.007***	-0.007***	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
Anom. HDD×Peak	-0.080***	-0.079***	-0.077***	-0.077***
	(0.006)	(0.006)	(0.006)	(0.006)
Panel C: ***ln(Traffic Count)*** *second stage*				
ln(MPG)	0.137*	0.108	0.081	0.073
	(0.080)	(0.081)	(0.080)	(0.079)
ln(MPG) × Peak	0.203***	0.220***	0.231***	0.231***
	(0.054)	(0.055)	(0.057)	(0.057)
Contemporaneous Temperature	0.021***	0.021***	0.021***	0.021***
	(0.001)	(0.001)	(0.001)	(0.001)
Contemporaneous Temperature 1-Week Lag	0.000**	0.000**	0.000**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Contemporaneous Temperature 2-Week Lag		0.000*	0.000	0.000
		(0.000)	(0.000)	(0.000)
Contemporaneous Temperature 3-Week Lag			0.000***	0.000***
			(0.000)	(0.000)
Contemporaneous Precip.	-0.035***	-0.035***	-0.035***	-0.035***
	(0.001)	(0.001)	(0.001)	(0.001)
Contemporaneous Precip. 1-Week Lag	0.000***	0.000***	0.000***	
	(0.000)	(0.000)	(0.000)	
Contemporaneous Precip. 2-Week Lag		0.000	0.000	
		(0.000)	(0.000)	
Contemporaneous Precip. 3-Week Lag			0.000	
			(0.000)	
Contemporaneous Snow	-0.260***	-0.261***	-0.262***	-0.263***
	(0.029)	(0.029)	(0.029)	(0.027)
Contemporaneous Snow 1-Week Lag	0.000***	0.000**	0.000***	
	(0.000)	(0.000)	(0.000)	
Contemporaneous Snow 2-Week Lag		0.000***	0.000***	
		(0.000)	(0.000)	
Contemporaneous Snow 3-Week Lag			0.000***	
			(0.000)	
Contemporaneous Snow Depth	-0.005***	-0.004***	-0.004***	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)
Contemporaneous Snow Depth 1-Week Lag	0.000	0.000	0.000	
	(0.000)	(0.000)	(0.000)	
Contemporaneous Snow Depth 2-Week Lag		-0.000	-0.000	
		(0.000)	(0.000)	
Contemporaneous Snow Depth 3-Week Lag			-0.000	
			(0.000)	
Observations	99,456,638	99,096,770	98,734,285	98,734,285
F-stat of Excluded Instruments	177.508	171.077	166.766	170.288
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 contemporaneous 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 A14: Extreme Weather Months

	(1) $\geq$ 6 Extreme Days	(2) $<$ 6 Extreme Days	(3) $\geq$ 10 Extreme Days	(4) $<$ 10 Extreme Days
Panel A: ***ln(MPG)*** *first stage*				
Anom. HDD	-0.160***	-0.073***	-0.225***	-0.094***
	(0.011)	(0.009)	(0.023)	(0.006)
Anom. HDD×Peak	0.000	-0.000	0.001	-0.000
	(0.000)	(0.000)	(0.001)	(0.000)
Panel B: ***ln(MPG)***×***Peak*** *first stage*				
Anom. HDD	-0.008***	-0.005***	-0.002	-0.005***
	(0.002)	(0.001)	(0.004)	(0.001)
Anom. HDD×Peak	-0.137***	-0.059***	-0.220***	-0.082***
	(0.012)	(0.010)	(0.020)	(0.007)
Panel C: ***ln(Traffic Count)*** *second stage*				
ln(MPG)	0.037	0.369**	0.042	0.127
	(0.075)	(0.151)	(0.133)	(0.091)
ln(MPG) × Peak	0.253***	0.247***	0.224**	0.250***
	(0.065)	(0.082)	(0.113)	(0.055)
Observations	11,795,226	87,727,509	5,019,396	94,503,389
F-stat of Excluded Instruments	67.127	16.798	50.73	65.891
Peak×Sensor FE	Yes	Yes	Yes	Yes
Peak×Week FE	Yes	Yes	Yes	Yes
Peak×County×MOY FE	Yes	Yes	Yes	Yes

Notes: Extreme days are defined as a day plus-or-minus 2 standard deviations from average anomalous HDD. The sample is split between months with more or less extreme days as noted at the top of each column. Standard errors are clustered at the county level. Every regression controls for contemporaneous 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.