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ISSN: 2365-9793

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ABSTRACT

Slow Traffic, Fast Food: The Effects of Time Lost on Food Store Choice*

Time scarcity is one of the strongest correlates of fast food consumption. To estimate the causal effect of time lost on food choice, we match daily store-specific foot traffic data traced via smartphones to plausibly exogenous shocks in highway traffic data in Los Angeles. We find that on days when highways are more congested, individuals are more likely to dine out and less likely to grocery shop. The effects are particularly pronounced for afternoon rush hour traffic. Our results imply a net reduction in healthy food store choice due to time lost.

JEL Classification: I12, I30, J22, R41

Keywords: traffic congestion, time constraints, store choice, nutrition, fast food

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* We thank Markus Tran and Shannon Tran for their excellent research assistance. We thank Fiona Burlig, Sabrina Eisenbarth, Jamie Hansen-Lewis, Rhiannon Jerch, Paula Lorgelly, and Barton Willage for exceedingly helpful comments. Further, we thank seminar participants at Paris-Saclay University and conference participants at the American Economic Association, the American Society of Health Economists and the Agricultural and Applied Economics Association for their invaluable feedback.

Households combine time and market goods to produce commodities for consumption in the household, subject to income and time constraints. Since Becker's (1965) theory of the allocation of time, the economic literature has recognized the importance of time costs for understanding household behavior. Time constraints have been identified as particularly important regarding household food production, where time has been shown to be more constraining than money (Davis & You, 2011; Davis, 2014; Mancino & Newman, 2012; Yaktine & Caswell, 2013). When shopping for food, household decisions are more influenced by store convenience, and travel time to a store in particular, than by marginal changes in consumer surplus through price and variety (Marshall & Pires, 2018). Food store choice also correlates with the amount of time spent in other non-market activities. For instance, Americans purchase fast food as a means of saving time in sleeping, housework, and eating meals (Hamrick & Okrent, 2014).[1] Moreover, time constraints in food production are likely to be endogenous to local retail food environments - Business owners are likely to open stores focusing on time savings in areas where they expect strong demand, and consumers who value time savings are likely to frequent convenient store options.

In this study, we isolate the causal effect of time lost on food store choice by utilizing variation in weekday hourly traffic congestion with data on daily store visitations. Focusing on weekday traffic congestion is advantageous for several reasons. First, traffic likely plays a central role in determining food store choice due to its heavy influence on individual time constraints. Pre-pandemic, drivers were spending more time on the road than any time before, averaging nearly an hour per day (Gross, 2019). Directly linking food consumption to driving, the third most common location for Americans to

[1] In a survey with frequent fast food consumers, Rydell *et al.* (2008) find that fast food's quickness (92%) and location convenience (80%) were the biggest reasons for choosing fast food. The cost of fast food (64%) sits as the fourth biggest reason behind taste (69%).

do their "secondary" eating is in their car.[2] As an extreme example highlighting how fast food is tied to traffic, in 2019 Burger King launched a program delivering meals to drivers stuck in traffic (Holley, 2019).

Secondly, analyzing narrow fluctuations in traffic congestion allows us to utilize plausibly exogenous variation in traffic levels to isolate a causal effect of time on food store choice. To do so, we link SafeGraph daily visitation data from the census of Los Angeles stores to high-frequency highway traffic monitor data for the years of 2017 to 2019. Identification comes from exploiting natural hourly variation in traffic flows.[3] Due to the precision of the data, our most robust models are able to simultaneously estimate month-year, day of week, calendar day, and store fixed effects. This traffic variation data from Los Angeles are similarly utilized in studies from Anderson (2014) and Beland & Brent (2018), who investigate public transportation usage and domestic violence, respectively.[4] Similar to Beland & Brent (2018), our identification strategy utilizes deviations from "normal" traffic in order to isolate the effect of time lost via excess traffic on food store choice. Further robustness checks estimate the effects of past and future traffic on food store choice, as well as an instrumental variables approach where traffic deviations are instrumented with accident data.

We precisely estimate an increase in visitations to fast food restaurants in response to daily and hourly traffic congestion. On average, a one standard deviation increase

[2] Secondary eating is defined as eating while doing something else such as watching television (the first most common activity for secondary eating) and working (the second most common activity) (U.S. Department of Agriculture, 2019).

[3] According to transport engineers, "traffic flow is a complex amalgamation of heterogenous traffic fleet" (Akhtar & Moridpour, 2021), which makes traffic congestion notoriously hard to model and predict. For instance, a single car randomly driving much slower than the flow of traffic, or braking suddenly, due to inattention or distraction can create a random traffic jam. Given the complex nature of traffic flow, even well performing prediction models often only explain 87-92 percent of traffic flow, leaving 8–13 percent unexplained (Liu & Wu, 2017; Zafar & Ul Haq, 2020).

[4] Numerous studies also utilize the SafeGraph data, with recent examples including Farboodi *et al.* (2020), Cook *et al.* (2020), Gurun *et al.* (2020), Painter (2020), and Allcott *et al.* (2020).

in weekday traffic delay is associated with a 1.0% increase in fast food visits. Dining at full service restaurants increases by 0.9%. Meanwhile, visits to supermarkets slightly decrease with higher traffic congestion. Our back-of-the-envelope calculations show a 1% increase in daily visits would translate to roughly 1.7 million more fast food visits and 3.9 million more full-service restaurant visits in Los Angeles County per year.

We then estimate the effect of traffic congestion at each hour of the day and find the effects are largely driven by afternoon rush hours, further suggesting that our effects are operating through time constraints at mealtimes. We additionally find that traffic delay has no impact on lagged and future store visits, suggesting people are not simply changing the day they eat out in response to (or in anticipation of future day) traffic. These results are robust to various other considerations such as traffic direction (inbound vs. outbound), store proximity from the the highway, and to estimating results with a Poisson Model.

The relationship between time lost from traffic congestion and fast food visits is important to understand because more Americans are eating fast food than ever before. With an annual growth rate of over 2%, the fast food industry now serves meals to over one in three Americans daily (Fryar & Ahluwalia, 2018). This is concerning from a public health standpoint because food-away-from-home (FAFH)—and fast food in particular—tends to be higher in fat, sodium, and energy density, and lower in whole grains, fruits, vegetables, and nutrients than food-at-home (FAH)) (Lachat *et al.*, 2012; Kant *et al.*, 2015; Saksena *et al.*, 2018). Moreover, FAFH and fast food consumption patterns have been linked to the exponential rise in health conditions such as heart failure and diabetes and to the ongoing obesity epidemic (Currie *et al.*, 2010; Bezerra *et al.*, 2012; Fortin & Yazbeck, 2015; Mandal, 2019). On average, US adults consume 836 calories at each fast food visit, making up 42% of their recommended daily calorie intake (Block *et al.*, 2013). Todd *et al.* (2010) estimate an increase of 134 calories for meals eaten away from home (relative to eating at home), and find that for the average adult, one additional meal eaten away from home per week translates to an extra two pounds gained every year. For our estimates, a standard deviation increase in daily traffic delay is equal to 0.60 minutes (36 seconds) lost per mile driven. Thus, using the estimates from Todd *et al.* (2010), every 0.60 minutes lost corresponds to an increase of 1.9% (1.0%+0.9%) times 134 calories per meal, or 2.55 calories gained. Moreover, if a standard deviation increase in daily traffic delay occurred all five weekdays, we would expect drivers to gain an additional 0.19 lbs per year. To put this in perspective, the average adult is estimated to gain 1-2 lbs per year (Hutfless *et al.*, 2013). These back-of-the-envelope calculations show the caloric implications of time lost from traffic congestion on food store choice could be substantial.

In addition to the direct time costs of traffic congestion, there are emotional costs of traffic-induced stress.[5] A long literature from nutrition has found that individuals are more likely to consume high sugar and fatty foods in response to stress (Wardle *et al.*, 2000; Torres & Nowson, 2007; Barrington *et al.*, 2014). While we measure the marginal costs of time lost from traffic congestion on food store choice, we acknowledge that our estimates also include any responses in food choice due to traffic-induced stress or loss of will-power and energy, or potential cognitive strain. We predict that the amount of stress and strain from traffic congestion is likely related to the amount of time lost. Additionally, it is possible that the same amount of time lost can occur in less or more

[5]For instance, Gottholmseder *et al.* (2009) find that stress increases with commute time and decreases with commute predictability. With respect to traffic congestion externalities, Bento *et al.* (2020) distinguishes between the value of time, the value of reliability, the value of urgency due to schedule constraints, all of which could relate to stress. While not a direct measure of stress, Bento *et al.* (2020) calculate that the value of urgency accounts for 87 percent of total willingness-to-pay for time savings.

stressful situations than the average, which would lead to our results being attenuated or especially pronounced in these situations, respectively. Still, given transportation markets are inherently ones in which consumers express their value of time (Buchholz *et al.*, 2020) and the prevalence of people commuting directly before evening mealtimes, it is crucial to study the effects of time lost on food store choice in this setting.

This paper improves upon the literature in multiple ways. To our knowledge, the only evidence potentially suggesting a causal link between time and food store choice comes from a literature using variation in the proximity of one's home to a (nearby) store (Currie *et al.*, 2010; Dunn, 2010; Anderson & Matsa, 2011; Courtemanche & Carden, 2011; Lhila, 2011). The majority of these studies utilize space-time variation in the introduction of stores, and have reported mixed results. Moreover, while distance to a store likely serves as a proxy for time cost, the "introduction" of a (nearby) store represents both a change in time cost as well as a change in choice set (what food is available), including food price and quality.[6] By using a different source of variation for time costs (i.e., variations in traffic congestion), our paper complements and advances the studies using store location variation.

Our results have several other important implications as well. Our results suggest that policies aimed at loosening time constraints would help battle unhealthy eating habits. For example, improvements in infrastructure to mitigate congestion or expanding public transport could reduce fast food dependency. Increasing work-from-home opportunities and reducing the number of days workers go in to work could also significantly reduce fast food consumption. Our results also contribute to a broad literature highlighting the negative economic and health externalities of traffic congestion, in-

[6] An additional identification concern highlighted in these studies comes from potential migration, where individuals moving decisions may be influenced by the introduction of a store.

cluding losses in time and fuel (Schrank *et al.*, 2012), increased air pollution (Gibson & Carnovale, 2015), increases in prematurity and low birth weight outcomes (Currie & Walker, 2011), increases in elderly mortality (Anderson, 2020), decreases in student learning (Heissel *et al.*, 2020), and increases in domestic violence (Beland & Brent, 2018).

Finally, our results complement the literature examining associations between traffic-related environmental factors (e.g., traffic flows near one's home) and weight-related behaviors and outcomes (e.g. physical activity and obesity). Wang *et al.* (2021) conduct a recent meta-analysis of this literature. With respect to weight-related behaviors, 9 out of 12 studies found that increased traffic flow is significantly associated with less physical activity. With respect to weight-related outcomes, 8 out of 14 studies found no relationship between traffic flows and obesity, 5 studies found a positive relationship, and one study found a negative relationship. Thus, while there is consistent evidence that living in a high-traffic area is associated with worse weight-related behaviors, the relationship between traffic flows and weight-related outcomes is less conclusive, though skews towards worse outcomes. Similarly, we find that more time spent in traffic leads to worse weight-related behaviors (i.e., increased visits to FAFH stores). While our back-of-the-envelope calculations suggest a standard deviation increase in weekday traffic delay would cause drivers to gain an additional 0.19 lbs per year, precisely measuring how time spent in traffic impacts weight-related outcomes is an area for future research and would benefit from individual-level data.

1 Data

This project draws upon two datasets, one to estimate visitations to stores (SafeGraph), and the other to estimate traffic congestion (Caltrans Performance Measurement System, or PeMS).

1.1 Store visits

We access information on the number of individuals who visit a store on a given day using data from SafeGraph (SafeGraph, 2020a). The dataset, covering the period of January 2017 to December 2019, is derived from cell phones' GPS data, enabling us to have a sample of the population of visitors to each store on each date. The dataset contains all stores for the county of Los Angeles across four store types: fast food restaurants, full-service restaurants, convenience stores, and supermarkets.[7] These four store types together cover the majority of ways in which food acquisition takes place.[8]

The dataset's daily visit count is generated as follows. Each store has its name, brand association (if it is part of a chain), address, and category (at 6 digit NAICS code) associated with the polygon of its location. Then, cell phone data using GPS coordinates is matched to the list of stores, generating a daily visitor count (SafeGraph, 2020b,c). The cell phone data panel includes approximately 10% of all US mobile devices, or over 45 million mobile devices (Fox Squire, 2019).

This sample represents the US population well. SafeGraph, using the mobile devices'

[7]These four categorizations are made by SafeGraph. Some stores flagged as one category may arguably be a better fit in another category (e.g. Mr. Pickle and Wienerschnitzel are categorized as full-service restaurants), generating plausible measurement error in our outcome variable. In additional robustness, we consider our own alternative categorizations of fast food vs. full service restaurants.

[8]Taylor & Villas-Boas (2016) find that over 55% of food expenditures take place at supermarkets and grocery stores, convenience stores, fast food restaurants, and full-service restaurants. Remaining food purchases are dominated by purchases in superstores, which sell a variety of products.

nighttime location, determined that the sample count of those residing in a county is proportional to the census population count for most counties; the sampling bias for Los Angeles County is below 0.1% (Fox Squire, 2019). While SafeGraph's data doesn't contain device-level owner demographics information,[9] SafeGraph shows that the sample likely has very minimal bias in race, age, and income, among others, as evidenced by the sample distribution within census block groups, and those block groups' demographic characteristics.

To create a balanced sample, we exclude all stores missing visitation data for any month.[10] Furthermore, because the SafeGraph sample size increases over time, we opt to effectively de-trend the sample by applying year-month fixed effects in all estimations (Painter, 2020). We also only focus on visitations made on weekdays because traffic trends are quite different between weekdays and weekends (Roh *et al.*, 2014; Morawska *et al.*, 2002) and because time constraints are likely more binding on weekdays when the average American commutes and works. Across the three years, we observe 20,865 stores.

1.2 Traffic congestion

Traffic experiences location-specific, natural fluctuations (Akhtar & Moridpour, 2021). We exploit these stochastic (from the driver's perspective) fluctuations using infor-

[9]The unit of observation for this data is at the store level—we do not observe the store visit trajectories of unique individuals.

[10]Missingness is present in the visitation data in two ways. First, 10% of stores never have visitation data (their daily visit count is always missing). This is due to the fact that SafeGraph, for data protection reasons, only publishes data if it records at least five visits to a store in a given month. Stores that always fall below five visits could be very rarely visited and/or may be located in areas with poor GPS functioning. Secondly, visitation data can also be missing for just certain months—i.e., months where visitor count was too low to display results. We find that an additional 9% of the stores have at least one such month (and that the distribution of the number of missing months is relatively evenly distributed). We exclude these stores from the analysis.

mation on travel speeds. The traffic data come from the California Department of Transportation through the Caltrans Performance Measurement System (PeMS). Observations for these data are unique at the highway station-hour level. To match to the timing and spread of the SafeGraph data, we compile files from the years 2017 to 2019 for PeMS district 7, covering the entire Los Angeles County area. These data closely reflect the datasets used in Anderson (2014) and Beland & Brent (2018), where Anderson (2014) utilizes the data to measure traffic as an outcome, while similar to our study, Beland & Brent (2018) utilize natural deviations from baseline traffic for causal identification. We find that a handful of monitors were installed (or uninstalled) during our observation period, and that some others had intermittent missing data. We exclude these, resulting in a balanced panel of stations, where stations have available data for every observation-month.[11] In total, we have 2,546 unique highway stations.

A visual representation of monitoring stations and stores within Los Angeles County can be seen in Figure 1. We match each store in the SafeGraph data to its nearest highway station based on latitude and longitude coordinates (see Figure 2 for examples of these matches). Then, we restrict our sample to stores that are located within five miles of a station.[12] We are left with 1,419 unique stations and 20,475 unique stores, and a total sample of 15,990,975 store-day observations. For each station-hour, we observe the average speed of passing cars measured in miles per hour. To later interpret our results as the impacts of "traffic," we borrow from Anderson (2014) and Bento *et al.* (2020) and calculate the average delay (in minutes per mile) relative to a speed of 60 miles per hour.[13] More specifically, for each day-hour we calculate minutes

[11]The PeMS dataset provides a range of variables. We opt to consider an observation missing if the variable for miles per hour is missing.

[12]Only 2% of stores in our initial sample are farther than 5 miles from a highway station. Later robustness checks consider the sensitivity of this sample restriction to stores located with 4, 3, 2, and 1 mile from a highway measurement station.

[13]Anderson (2014) found robust results across alternative values of free-flow speed, such as 55 and

per mile lost for speeds slower than 60 miles per hour; then, we average these losses across the hours of 6am to 9pm for each weekday to estimate how daily visitations are impacted by daily average delays. We focus on these hours since this is when traffic congestion occurs, as shown in appendix Figure A2. Assessing traffic flow as a delay measure is not only in line with prior economic literature, but also the Federal Highway Administration's definition of the "anatomy of congestion" that considers a base delay as its foundational feature (see for example Figure 2.3 in U.S. Department of Transportation Federal Highway Administration (2005)).

1.3 Descriptive Statistics

Table 1 presents the descriptive statistics for our sample, split by the four store types. The sample includes over 3 million fast food restaurant-day visits, with an average daily number of visits to fast food restaurants of around 12. Recall that the SafeGraph data only reflect a subsample of all visitations, covering approximately 10% of all US cellphones (Fox Squire, 2019). The average daily visitation numbers for supermarkets, convenience stores, and restaurants are 12, 7, and 8, respectively. Meanwhile, the average travel delay across all store types is 0.38 minutes per mile with a standard deviation of 0.60 minutes per mile. We also see that average delay measures are roughly equivalent across all four store types, showing that different store types on average are not any more or less likely to be located in high traffic areas. Our full sample includes nearly 16 million store-day visit observations.

65 miles per hour.

2 Econometric Specifications

Our primary specification estimates the following equation:

$$\text{Visits}_{sdmy} = \alpha + \beta \text{Delay}_{sdmy} + \lambda_s + \lambda_d + \lambda_{my} + X_{dmy} + \epsilon_{sdmy} \tag{1}$$

where each observation belongs to a balanced panel at the store s and day-of-month d, month m and year y level. The outcome variable Visits_{sdmy} measures the the number of visits made to store s on date dmy. The regressor of interest Delay_{sdmy} is the average delay in minutes per mile of vehicular traffic going through store s's nearest highway station on date dmy. Recall that delay for each day-hour is calculated as minutes per mile lost for speeds slower than 60 miles per hour (and zero otherwise), then we average these losses across the hours of 6am to 9pm for each date dmy. Larger values for this variable indicate greater traffic (more minutes passed per mile driven). Our primary specification estimates fixed effects λ_s, λ_d, and λ_{my} at the store, day-of-month, and month-year levels, respectively. The vector X_{dmy} includes controls at the date level, including indicators for the day of week (Monday through Friday), for holidays, and for the daily mean temperature (Celsius) in Los Angeles County.

Store fixed effects account for all unobserved factors at the store level that may correlate with visitations and traffic, such as the store's location. Consequently, this model utilizes variation within stores, across days in highway traffic. Month-year fixed effects account for any Los Angeles-wide traffic patterns that differ across month-years, which in turn account for any month-year trends in traffic that may also happen to correlate with month-year trends in visitations. Thus, with month-year fixed effects, our models are relying on both spatial variation in traffic within Los Angeles, and variation in traffic across weekdays within each month-year. Day-of-month fixed effects, day-of-week indicators, and a holiday indicator account for additional potential date-varying differences in traffic and store visits.

Given this two-way fixed effect specification utilizing variation in traffic across space and time, our primary identifying assumption is that there are no unobserved space-date specific shocks that drive both traffic and fast food consumption.[14] This plausibly exogenous variation is similarly utilized by Beland & Brent (2018), who look at the effects of space-date variation in Los Angeles traffic on domestic violence.

Congestion—when speeds are slower than the free-flow speed—arises due to reasons that fall into three broad categories: physical highway features, traffic demand, and traffic-influencing events (U.S. Department of Transportation Federal Highway Administration, 2005). Physical highway futures, such as traffic control signs, are largely consistent across time (and thus absorbed by store fixed effects). Traffic demand, especially those tied to special occasions (football games or holidays, as examples) could potentially influence traffic and food demand at once, but we address these through excluding weekends (when most entertainment events occur) and including a holiday-specific control variable.

Finally, the category of traffic-influencing events include ongoing accidents, debris from recent accidents, events that might occur along the highway that distract drivers, weather characteristics, and phantom traffic jams.[15] These are the events our methodology exploits, and therefore our identifying assumption is that these natural fluctuations

[14] There is an emerging literature that highlights the potential for bias in two-way fixed effects (TWFE) estimators and develops new estimators to address this bias. In particular, several estimators have been developed for difference-in-difference models with staggered treatment timing and/or with continuous treatment (de Chaisemartin & D'Haultfœuille, 2020; Borusyak *et al.*, 2021; Callaway & Sant'Anna, 2021; Goodman-Bacon, 2021; Sun & Abraham, 2021; de Chaisemartin *et al.*, 2022). However, to our knowledge, no new estimators have been developed for TWFE models such as ours, where the treatment variable varies continuously for all units across all time periods.

[15] Accidents are considered erratic in nature, both in whether they occur and how long they last and how disruptive they are (U.S. Department of Transportation Federal Highway Administration, 2005).

in traffic impact food demand only via their impact on the traffic flow. When thinking about congestion, some might associate it with large accidents or traffic jams; however it might help with intuition to consider smaller fluctuations, such as phantom traffic jams. Phantom traffic jams are where very minor disruptions to the flow of traffic (such as someone breaking slightly a few seconds later than ideal) impact cars behind the given driver, which in turn impacts drivers further back, resulting in a slowdown that has been shown to be stochastic from the driver's perspective, and naturally occurs even when everyone follows the recommended driving rules (Goldmann & Sieg, 2020; Sugiyama *et al.*, 2008). Equation (1) tests whether these instances, which constantly change traffic speed—and therefore delay—have an impact on food store choices. Described in further detail later, as an additional robustness check, we consider a specification where we instrument for traffic with highway accidents.

One type of traffic-influencing event to address directly with regards to identification is weather. Any seasonality is controlled for in our specification due to the year-month fixed effects, while any spatially specific weather characteristics (such as potential micro-climates) are controlled for with the store fixed effects. Regardless, daily weather fluctuations might matter. Perhaps hotter temperatures drive both demand for dining out and impacts traffic flow due to poorer driving performance.[16] To mitigate this concern we include a control variable for daily mean temperature (Celsius) for Los Angeles County in our vector X_{dmy}.[17]

A secondary assumption of this model is that store visitations do not drive highway traffic (i.e. no reverse causality). For example, a brand might run an advertisement campaign that encourages purchases for a limited time that entices people to add a

[16]Basagaña *et al.* (2015) find the estimated risk of motor vehicle crashes increase by 2.9% on heat wave days.

[17]Temperature data comes from PRISM Climate Group (https://prism.oregonstate.edu/).

driving trip or lengthen their drive to visit that brand. However, this is unlikely in our sample because even the 5 largest chains by number of locations (i.e., Subway, 7-Eleven, McDonald's, Jack in the Box, and Pizza Hut) together only take up 7% of all stores in the study and because such extremely enticing advertisements tend to run only on a very limited time frame. Though it is theoretically possible for store popularity to spill over into road traffic, we believe this is unlikely to matter for weekday highway traffic, particularly across the full sample of stores in Los Angeles. Moreover, as shown later in our results section, we estimate zero or negative effects across some store types; if store visitations were directly inducing traffic, one would not expect to estimate a differential effect by store type.

3 Results

3.1 Main effects

We begin with Table 2 which estimates specification (1) for each of the four different store types in the sample. Standard errors in parentheses are clustered at the highway station level. Starting with visits to fast food restaurants in the first column, we find that increases in traffic delays cause a statistically significant increase in visits (1% significance level). To get a sense of the magnitude of this effect, we can see from Table 1 that the standard deviation in our average delay measure for fast food restaurants is 0.52. Thus, a one standard deviation increase in traffic delay is associated with a 0.227*0.52=0.118 increase in fast food visits. With a sample mean number of visits to fast food restaurants of 11.70, this translates to roughly a 1% increase in fast food visits. Using the SafeGraph sample of fast food restaurants in Los Angeles County in a back-of-the-envelope calculation, a 1% increase in daily visits would translate to roughly 1.7 million more fast food visits in Los Angeles County per year.[18]

Visits to restaurants follow a similar, albeit smaller in magnitude, statistically significant increase in response to traffic delay. Visits to convenience stores appear to be unaffected by traffic. Increases in traffic delays are associated with fewer visits to supermarkets, though the point estimate is only statistically significant at the 10% level. Importantly, if store demand was instead causing traffic delay (i.e., a reverse causation effect), we would have expected a positive coefficient for all types of stores. Finally, the sum of the four coefficients is positive, suggesting that in general, when traffic increases, people are more likely to eat out - tested more carefully in the next subsection, this finding is consistent with a story of drivers commuting between home and work and choosing whether to dine out or not.

In the final column of Table 2, we estimate the net effect of traffic on visits by store type by combining all store types into one estimation. More specifically, we take the full sample of stores while interacting our delay measure with indicators for convenience stores, restaurants, and fast food stores (supermarkets are the omitted category). We first estimate significant drops in supermarket visits in response to average delay. Visits to restaurants and fast food stores experience a significant increase in response to delay, showing that visitors are substituting away from supermarkets and into restaurants and fast food stores in response to greater traffic congestion. Once again, convenience stores experience no change in visits due to traffic congestion.

[18] The average fast food restaurant receives 11.7 visits per day in the SafeGraph sample. Given SafeGraph covers 10% of cellphones, this would extrapolate to 117 visits per day in the population. Thus, the back-of-the-envelope increase in fast food visits from a one standard deviation increase in delay can be calculated as 117 visits per day times 365 days per year times a 1% increase in store visits, which is equal to 427 more visits per store per year. This is multiplied by the number of SafeGraph fast food restaurants in Los Angeles County (i.e., 4089) to get 1.7 million visits.

3.2 Rush hour effects

Next, we consider how delay by hour of day have differential effects on daily visits. First, in appendix Figure A1 using data from the American Time Use Survey (ATUS), we plot weekday hours that people are the most likely to dine out and to grocery shop. The distribution of weekday hours at supermarkets is roughly uniform with a small peak around 4 and 5pm, while dining out experiences the largest shocks from noon to 1pm and again at 6 and 7pm. In appendix Figure A2, we plot the average traffic delay by hour from the PeMS data to find that afternoon rush hours experience sharper delays, peaking at 5pm, than morning rush hours. Together, these two pieces of evidence suggest that afternoon traffic patterns are likely to impact store visitations more so than other hours. Meanwhile, traffic during off hours should have little to no impact on store visits.

To test for this, we estimate specification (1) but replace our delay measure with the average delay for each date-hour, estimated separately. Thus, each estimate comes from separate regressions of store-date level visits on highway station-date-hour traffic. All other aspects of the model are kept the same. The results from this exercise are plotted in Figure 3. In Panels A and B, we see that the increase in visitations to fast food stores and restaurants are driven by afternoon and early evening traffic, with the largest effects for fast food stores coming around 7 pm and for restaurants coming at noon. Morning traffic has no effect on visits to fast food stores and restaurants.[19] Convenience store visits in Panel C still display no response to highway traffic. Finally, in Panel D, we see that the negative visitation effect on supermarkets is largely driven by traffic in early morning and late afternoon hours, though estimates for each individual hour are

[19]These patterns are in line with descriptive evidence suggesting that the most common meal for fast food are lunch and dinner (Fryar & Ahluwalia, 2018).

mostly marginally insignificant. This evidence further reinforces the narrative of time loss impacting (healthy) food store choice—when drivers are commuting home in heavy traffic, they are significantly more likely to dine out and eat fast food.

3.3 Substitution across days?

First, we consider how daily traffic impacts past and future store visits using leads and lags. Absent serial correlation in traffic shocks, regressing past store visits on today's traffic largely serves as a placebo test—the only possibility of past visits being affected by today's traffic is if customers accurately forecast future traffic, and if this forecast impacts their store decisions today. Regressing future visits on today's traffic helps to identify a potential temporal substitution effect in store visits—for example, given increased traffic induces greater fast food consumption today, customers may decide to reduce their fast food consumption in subsequent days.

The results from this exercise are presented in Figure 4, where we separately regress up to 10 past and future store visits on today's delay measure. Starting in Panel A with fast food, we see that the same day effect is the largest of the 21 estimated coefficients. The coefficients on future visits are mostly negative, suggesting some intertemporal substitution effect, but the estimates are largely statistically insignificant. Coefficients for past visits are also small and statistically insignificant. Full-service restaurants in Panel B display a similar pattern as fast food stores, though some lag and lead coefficients are negative and significant, suggesting restaurant consumption may be influenced by intertemporal substitution effects and/or predicted traffic on future days. Convenience stores in Panel C again display no responses to present, past, or future traffic. With supermarket visits in Panel D, we see that the coefficients on past and future visits are of similar magnitudes to the same day effect, suggesting the overall impact of traffic on supermarket visits is zero. Overall, our evidence suggests traffic delay increases food-away-from-home consumption (especially fast food), and that the increased fast food consumption is not offset by reduced consumption on future days.

4 Robustness checks

In this section, we consider a series of robustness checks to our main results. First, our primary analysis is agnostic about the direction of the highway monitor (e.g. Northbound vs. Southbound), only considering the closest highway monitor to each store. Given our results are strongest for afternoon hours, it may also be the case that "outbound" traffic (relative to where people work) has a stronger influence than inbound traffic. For this consideration, we identify each highway monitor as inbound or outbound relative to downtown Los Angeles, then match each store to both its closest inbound monitor and outbound monitor. We then reproduce our main results from Table 2 in Table 3[20] to find that the pattern from our main results are almost entirely explained by variation in outbound traffic, though inbound traffic does still partially explain fast food consumption. In appendix Figure A4 and Figure A5, we reproduce Figure 3 but focus strictly on inbound and outbound monitors separately, respectively. Once again, the resulting pattern is completely unsurprising: outbound traffic disproportionately affects food store choice in afternoon hours, while inbound traffic has a lesser effect concentrated around noon hours.

Our data also include information on accidents along Los Angeles highways, giving us a plausible instrumental variable for traffic delay. In order to be a valid instrument, this model assumes that accidents only affect store visits through its effect on traffic

[20] See appendix Table A1 for differences in store visits across store subsamples.

delay. We match each highway station to the number of accidents along its highway-direction for each date, then instrument for our delay measure with the number of accidents. We also consider the reduced form model, regressing store visits directly on the number of accidents. The results from this exercise are presented in Table 4, which produce even stronger results compared to our primary OLS models. Once again, we see that delay is associated with more visits to fast food restaurants and regular restaurants relative to supermarket visits.

Next, in appendix Table A2, we replicate Table 2 but replace our average delay measure with indicators for quartiles of delay (omitting bottom quartile as the reference group). This model is to test for potential nonlinear responses in visitations to traffic, and more closely aligns with Beland & Brent (2018) whose primary specification considers the effects of "extreme" traffic on crime. The results from this exercise reveal a clear pattern of stronger store visits in response to higher quartiles of traffic delays, i.e. extreme traffic has the strongest influence on food store choice.

Another margin of variation we could utilize comes from the store's proximity to the highway. While our primary sample includes all stores within five miles of a highway station, we alter this restriction by considering samples of stores within 4, 3, 2, and 1 mile from a highway measurement station. These results are presented in appendix Table A3. Coefficients remain significant and similar in size for fast food and full service restaurants, suggesting that our estimates are not driven by stores that are located particularly close to a highway. Meanwhile, for supermarkets and convenience stores, those particularly close to a highway line (with highways being more densely located near downtown) are significant, while those further are not. Near-highway supermarkets are less visited on high traffic days, while near-highway convenience stores are more visited.[21]

Finally, because our delay measure can take values of zero (when it is possible to travel at a speed of 60 miles per hour or faster), we re-estimate Figure 3's results of visits on hourly traffic with a Poisson model. As can be seen in appendix Figure A3, the pattern of results remain largely consistent, though estimates for fast food and restaurant visits become less precise, while estimates for supermarkets become more precisely estimated.

5 Conclusion

Americans continue to eat fast food at an increasing rate. This pattern likely plays a central role in the exponential rise in obesity, heart failure and diabetes, given that fast food is typically less healthy than other options. Now, over 18 percent of deaths among Americans over the age of 40 can be attributed to overweight and obesity issues, one of the leading causes of preventable death (Masters *et al.*, 2013). Worldwide, obesity is a major risk factor for a range of diseases, such as heart disease, one of the leading causes of death (World Health Organization, 2020). Large economic losses are also associated with obesity due to medical care costs and productivity losses (CDC, 2020).

Prior studies have suggested that time constraints are one of the most important correlates of food consumption, more so than other factors including income. For example, a larger share of high income families eat fast food daily compared to lower income families (Fryar & Ahluwalia, 2018). Research from Currie *et al.* (2010) show how

[21] In other unreported results, we also investigate potential heterogeneities in the types of neighborhoods the stores service by income. Overall, we find no evidence of differential effects in visits to supermarkets, while FAFH visits in higher income neighborhoods appear to have a slightly stronger response to traffic relative to lower income neighborhoods. This may simply reflect how higher income neighborhoods are more likely to dine out, on average.

households gain more weight if there is a fast food restaurant near them. Despite an abundance of studies suggesting a central role for time, no study to date has explicitly identified a causal link between time and food store choice. Naturally, identifying such a link is challenging, given strong correlations between time scarcity and other food-determining variables such as income.

In this study, we identify the causal effect of time lost on food store choice by utilizing data on hourly traffic flows in Los Angeles County. Studying traffic flows is advantageous for several reasons. First, traffic itself likely plays a central role in determining food store choice due to its impact on individual time constraints. For example, time spent traveling is correlated with higher levels of individual fast food purchases (Hamrick & Okrent, 2014). Secondly, narrow fluctuations in traffic congestion generate plausibly exogenous variation in traffic levels, granting us the opportunity to isolate a causal link between time and food store choice. Already, these traffic data and plausibly exogenous variation have been utilized in studies by Anderson (2014) and Beland & Brent (2018), who investigate public transportation usage and domestic violence, respectively. To measure outcomes, we collect SafeGraph daily visitation data from the census of Los Angeles stores (fast food, restaurants, supermarkets, convenience stores) for the years of 2017 to 2019. Stores are then linked to their closest highway stations spatially. Due to the precision of the data, our most robust models are able to simultaneously estimate month-year, day-of-week, day-of-month, and store fixed effects.

We first precisely estimate an increase in visitations to fast food restaurants in response to increased traffic congestion. On average, a standard deviation increase in daily traffic delay leads to a 1% increase in fast food visits. Dining in at full service restaurants also significantly increases. Meanwhile, visits to supermarkets slightly decrease with higher traffic congestion. Thus, consumers substitute into less healthy options, on average, in response to traffic. Additional results reveal that the effects are largely driven by afternoon rush hours and by traffic leaving downtown Los Angeles, further implying an effect on individual time constraints. Furthermore, we find that traffic delay has no impact on lagged and future store visits, suggesting that people are not simply changing the day they eat out in response to (or in anticipation of future day) traffic.

Our results suggest that policies aimed at loosening time constraints could substantially reduce unhealthy eating. For example, fast food dependency could be mitigated through improvements in roads and highways or by expanding public transport. Increasing work-form-home opportunities, reducing the number of days workers go in to work, and introducing more flexible worker schedules can also significantly reduce fast food consumption.

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6 Tables and figures

Table 1: Descriptive statistics

	Mean	Std Dev	Median	Min	Max	Obs
Fast Food						
Visits per day	11.70	13.12	8.00	0.00	1407.00	3,193,509
Delay, 6am to 9pm	0.33	0.52	0.12	0.00	12.53	3,193,509
Restaurant						
Visits per day	7.85	14.05	5.00	0.00	8208.00	10,556,777
Delay, 6am to 9pm	0.40	0.63	0.16	0.00	12.53	10,556,777
Convenience						
Visits per day	6.58	7.03	5.00	0.00	472.00	534,204
Delay, 6am to 9pm	0.32	0.53	0.13	0.00	9.03	534,204
Supermarket						
Visits per day	11.97	15.35	6.00	0.00	552.00	1,706,485
Delay, 6am to 9pm	0.35	0.54	0.13	0.00	8.24	1,706,485
Total						
Visits per day	9.02	13.96	6.00	0.00	8208.00	15,990,975
Delay, 6am to 9pm	0.38	0.60	0.15	0.00	12.53	15,990,975

Notes: Sample includes all stores less than 5 miles from a highway monitor.

Table 2: Effect of traffic delays on daily visits

	Fast Food	Restaurant	Convenience	Supermarket	Combined
	(1)	(2)	(3)	(4)	(5)
Avg. delay, 6am–9pm	0.227***	0.114***	0.019	-0.156*	-0.228***
	(0.082)	(0.040)	(0.074)	(0.092)	(0.081)
Convenience × Avg. delay, 6am–9pm					0.111
					(0.117)
Restaurant × Avg. delay, 6am–9pm					0.290***
					(0.087)
Fast Food × Avg. delay, 6am–9pm					0.719***
					(0.102)
Observations	3,193,509	10,556,777	534,204	1,706,485	15,990,975
Store FE	X	X	X	X	X
Day FE	X	X	X	X	X
Month-Year FE	X	X	X	X	X
Day of week FE	X	X	X	X	X
Controls	X	X	X	X	X

Notes: Weekdays only. Stores within 5 miles of a highway monitor. Standard errors in parentheses clustered at the highway monitor ID. Controls include an indicator for public holidays and daily mean temperature (Celsius) for Los Angeles County. OLS model.

Table 3: Effect of traffic delays on daily visits - Substitution away from supermarkets - Inbound vs outbound traffic

	Inbound	Outbound
	(1)	(2)
Average delay, 6am to 9pm	0.029	-0.276**
	(0.101)	(0.107)
Convenience $\times$ Average delay, 6am to 9pm	0.043	0.132
	(0.146)	(0.166)
Restaurant $\times$ Average delay, 6am to 9pm	-0.041	0.395***
	(0.114)	(0.139)
Fast Food $\times$ Average delay, 6am to 9pm	0.350***	0.727***
	(0.115)	(0.117)
Observations	13,474,129	13,419,142
Store FE	X	X
Day FE	X	X
Month-Year FE	X	X
Day of week FE	X	X
Controls	X	X

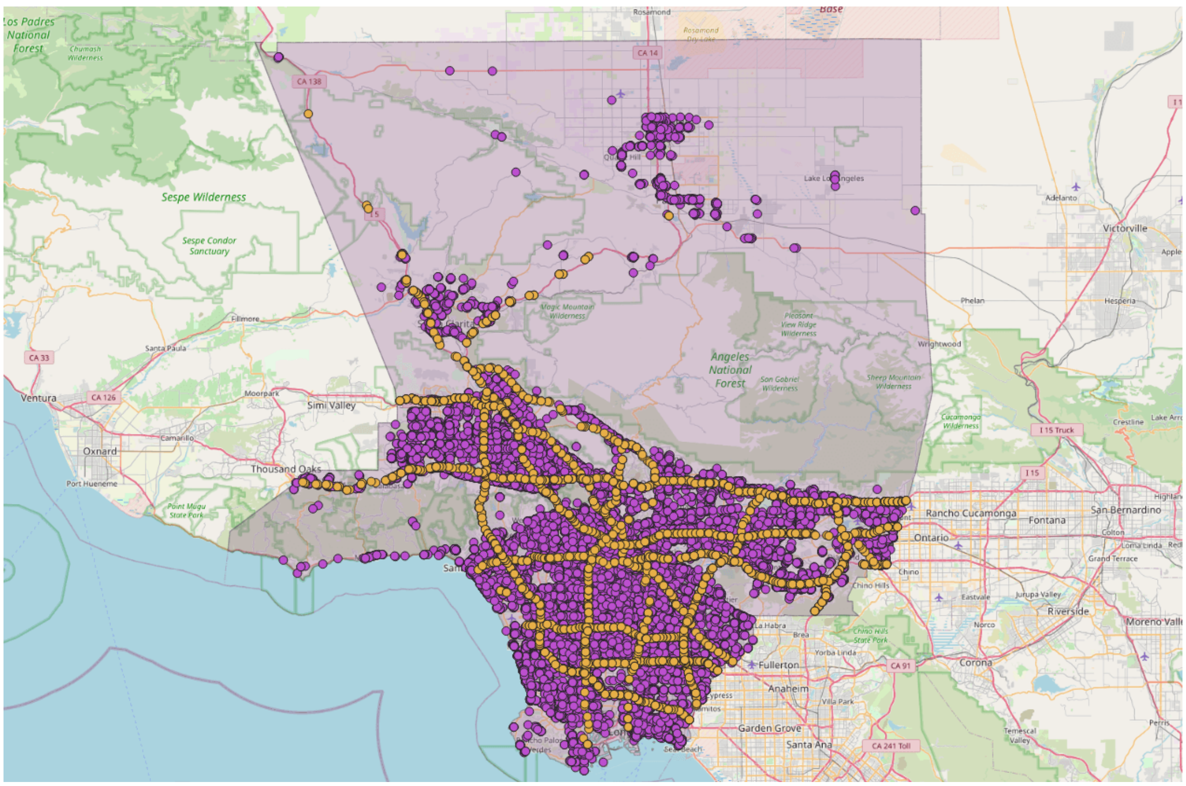
Notes: Weekdays only. Stores within 5 miles of highway monitors. Standard errors in parentheses clustered at the highway monitor ID. Controls include an indicator for public holidays and daily mean temperature (Celsius) for Los Angeles County. OLS model.

Table 4: Effect of traffic delays on daily visits - IV with number of accidents

	# of accidents IV	Reduced form
	(1)	(2)
Average delay, 6am to 9pm	-2.697***	
	(0.483)	
Convenience X Average delay, 6am to 9pm	3.921***	
	(0.518)	
Restaurant X Average delay, 6am to 9pm	4.250***	
	(0.470)	
Fast Food X Average delay, 6am to 9pm	4.894***	
	(0.471)	
Number of accidents		-0.014***
		(0.002)
Convenience X Number of accidents		0.017***
		(0.002)
Restaurant X Number of accidents		0.019***
		(0.002)
Fast Food X Number of accidents		0.022***
		(0.002)
Observations	15,990,975	15,990,975
Store FE	X	X
Day FE	X	X
Month-Year FE	X	X
Day of week FE	X	X
Controls	X	X

Notes: Weekdays only. Stores within 5 miles of a highway monitor. Standard errors in parentheses clustered at the highway monitor ID. Controls include an indicator for public holidays and daily mean temperature (Celsius) for Los Angeles County. Traffic instrumented for with number of accidents that day along highway-direction of highway monitor. First stage F-statistic is 69.09.

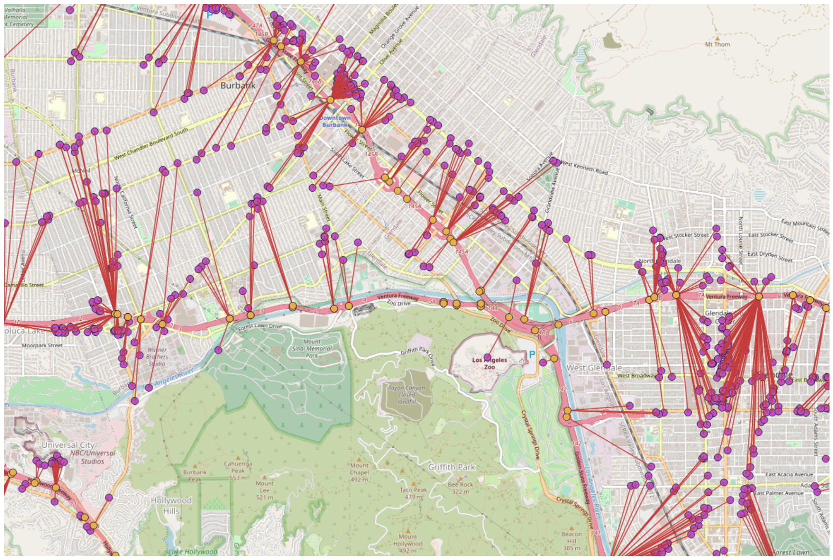
Figure 1: Map of Los Angeles County with PeMS stations and stores



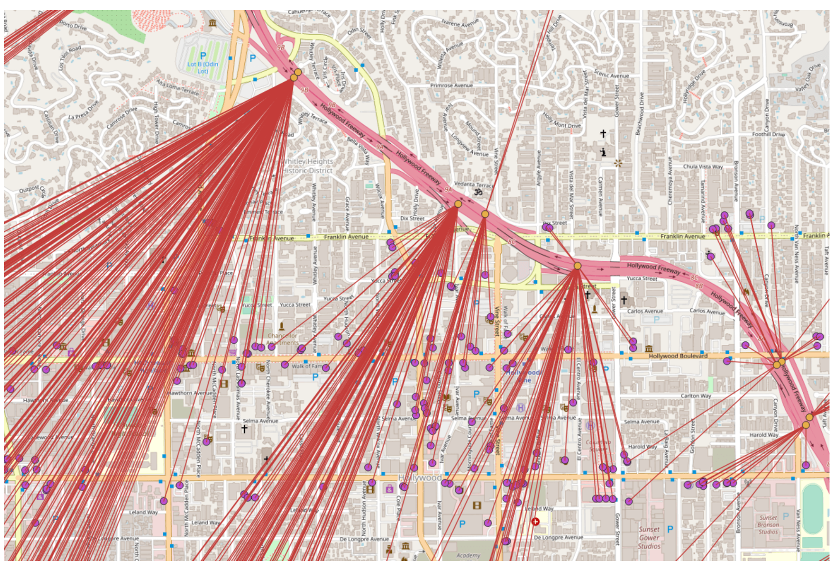
Note: Official county boundary is highlighted. PeMS stations are denoted with yellow circles, while stores are denoted with purple circles. The map displays all stations with valid speed observations for every observation-month and stores that have GPS coordinates falling within the county boundary.

Figure 2: Location of stores and the nearest highway monitor station

Panel A: The area around Griffith Park

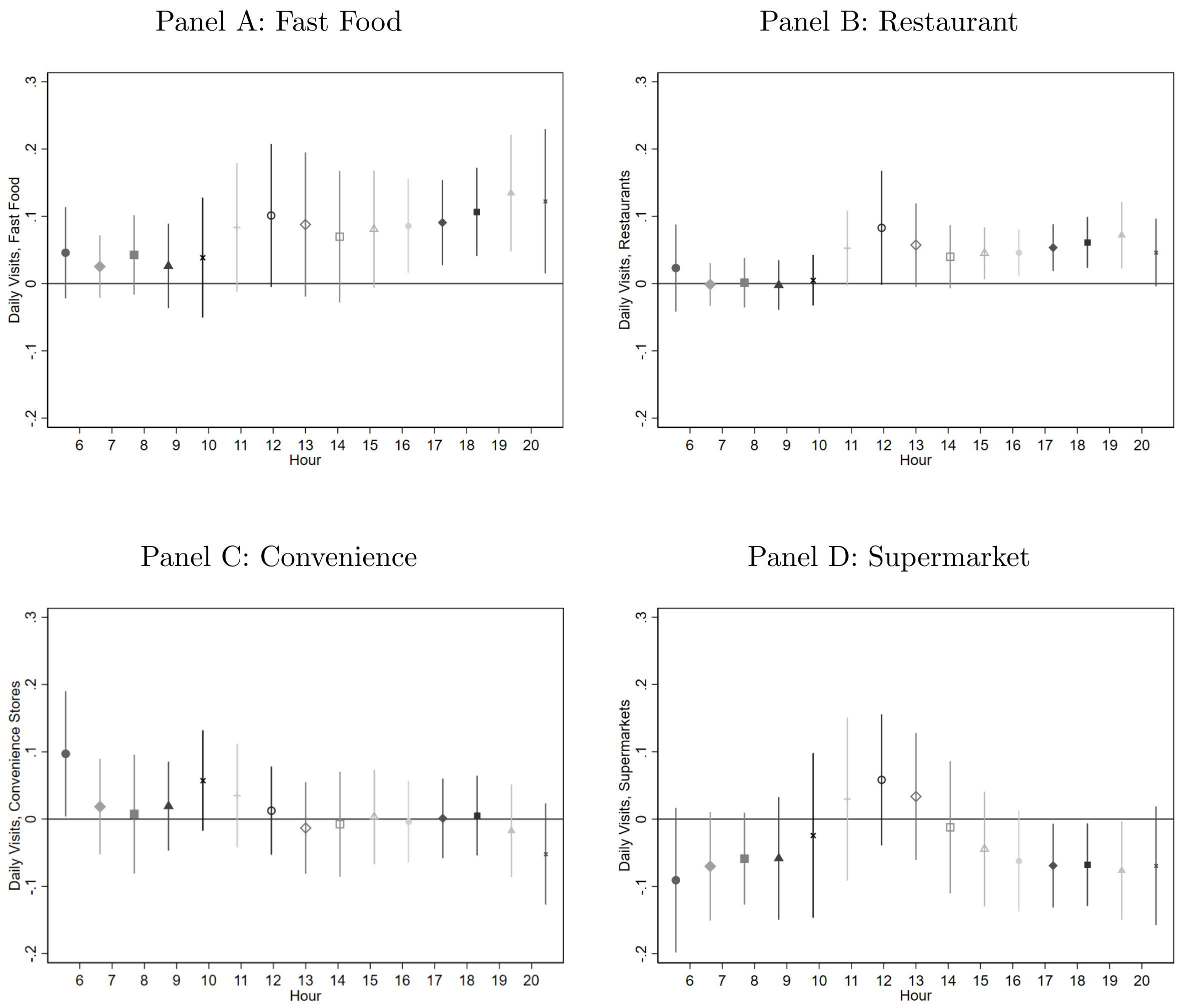


Panel B: Streets around Hollywood Boulevard



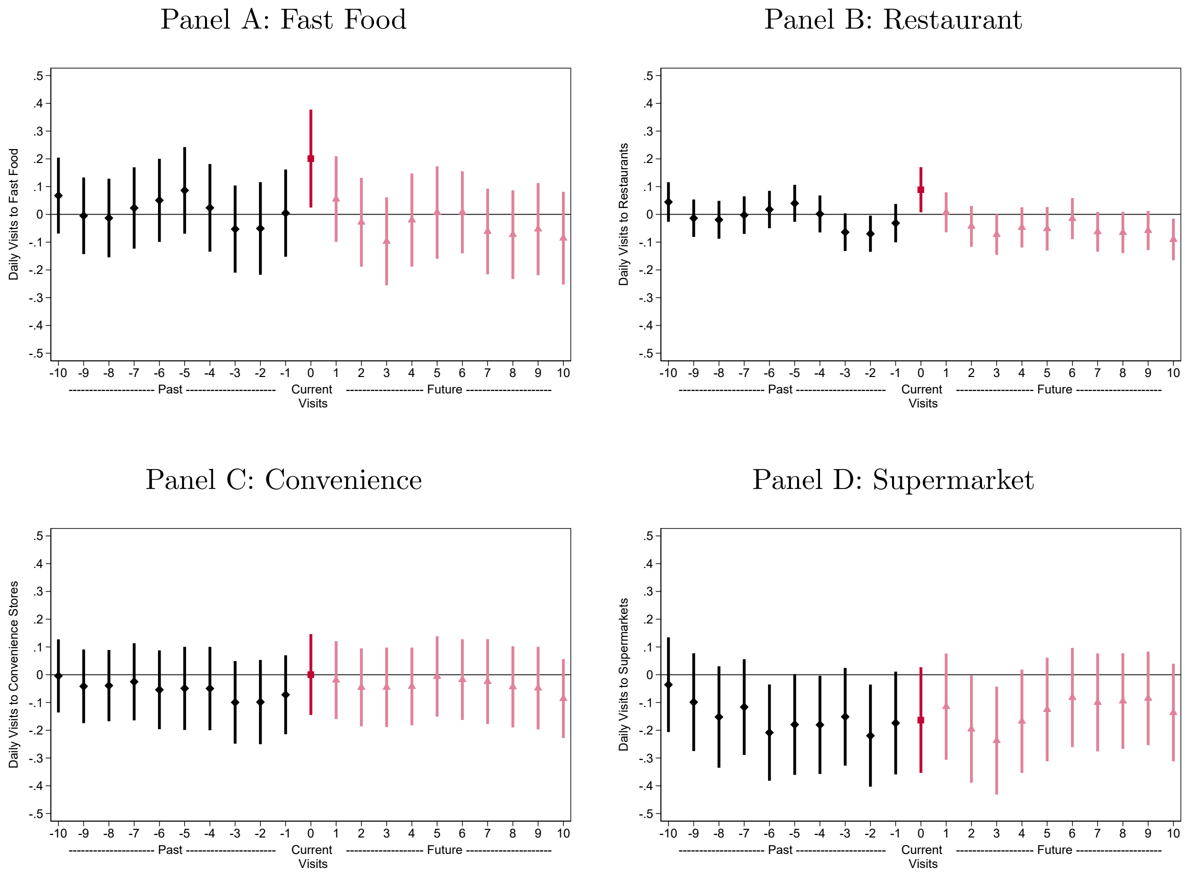
Note: The above two maps—zoomed in at different scales—represent how each store is joined to its nearest highway station.

Figure 3: Effect of traffic delay, by each hour of day, on daily store visits



Note: Store, day, month-year, and day-of-the-week fixed effects. Controls for holidays and daily mean temperature. Weekdays only. Stores within 5 miles of highway monitors. 95% confidence errors using standard errors clustered at the highway monitor ID. OLS model.

Figure 4: Effect of traffic delay on past and future daily store visits



Note: Store, day, month-year, and day-of-the-week fixed effects. Controls for holidays and daily mean temperature. Weekdays only. Stores within 5 miles of highway monitors. 95% confidence errors using standard errors clustered at the highway monitor ID. OLS model.

Appendix: Additional Tables and Figures

Table A1: Effect of traffic delays on daily visits - Inbound vs Outbound

	Fast Food	Restaurant	Convenience	Supermarket
Inbound Traffic	(1)	(2)	(3)	(4)
Average delay, 6am to 9pm	0.138	0.071	0.113	0.063
	(0.090)	(0.051)	(0.093)	(0.098)
Observations	2,848,928	8,675,857	476,394	1,472,950
Store FE	X	X	X	X
Day FE	X	X	X	X
Month-Year FE	X	X	X	X
Day of week FE	X	X	X	X
Controls	X	X	X	X
Outbound Traffic	(5)	(6)	(7)	(8)
Average delay, 6am to 9pm	0.190**	0.169**	0.041	-0.172
	(0.085)	(0.073)	(0.074)	(0.114)
Observations	2,828,782	8,652,699	477,972	1,459,689
Store FE	X	X	X	X
Day FE	X	X	X	X
Month-Year FE	X	X	X	X
Day of week FE	X	X	X	X
Controls	X	X	X	X

Notes: Weekdays only. Stores within 5 miles of a highway monitor. Standard errors in parentheses clustered at the highway monitor ID. Controls include an indicator for public holidays and daily mean temperature (Celsius) for Los Angeles County. OLS model.

Table A2: Effect of traffic delays on daily visits - Using indicators for delay severity

	Fast Food	Restaurant	Convenience	Supermarket
	(1)	(2)	(3)	(4)
$>$ 75 percentile delay	0.261***	0.146***	0.042	-0.125
	(0.069)	(0.050)	(0.076)	(0.082)
50–75 percentile delay	0.074	0.011	-0.024	-0.081
	(0.059)	(0.041)	(0.064)	(0.064)
25–50 percentile delay	0.092**	-0.014	-0.024	-0.046
	(0.045)	(0.033)	(0.061)	(0.053)
Observations	3,193,509	10,556,777	534,204	1,706,485
Store FE	X	X	X	X
Day FE	X	X	X	X
Month-Year FE	X	X	X	X
Day of week FE	X	X	X	X
Controls	X	X	X	X

Notes: Weekdays only. Stores within 5 miles of highway monitors. Standard errors in parentheses clustered at the highway monitor ID. Controls include an indicator for public holidays and daily mean temperature (Celsius) for Los Angeles County. OLS model.

Table A3: Robustness by store proximity to highway monitors

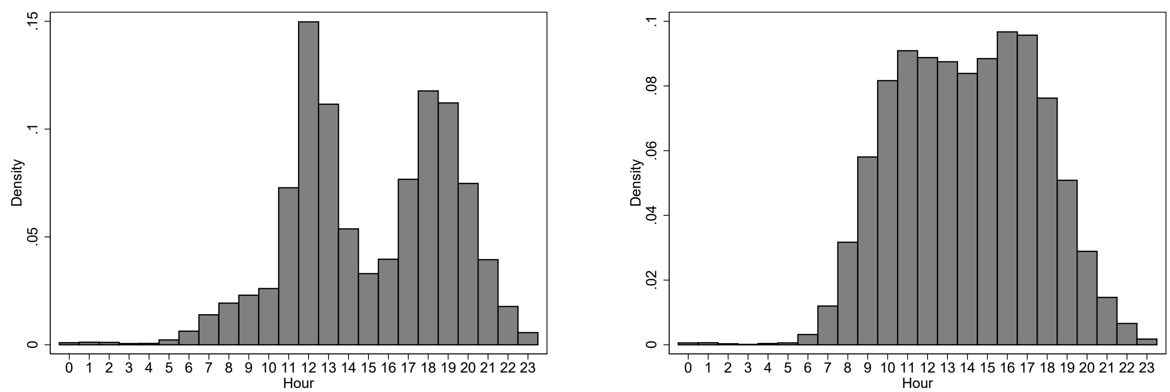
	Fast Food	Restaurant	Convenience	Supermarket
Stores within 4 miles of highway	(1)	(2)	(3)	(4)
Average delay, 6am to 9pm	0.246***	0.122***	0.020	-0.150
	(0.077)	(0.041)	(0.074)	(0.092)
Observations	3,156,021	10,447,437	531,861	1,695,551
Store FE	X	X	X	X
Day FE	X	X	X	X
Month-Year FE	X	X	X	X
Day of week FE	X	X	X	X
Controls	X	X	X	X
Stores within 3 miles of highway	(5)	(6)	(7)	(8)
Average delay, 6am to 9pm	0.257***	0.129***	0.038	-0.129
	(0.074)	(0.043)	(0.071)	(0.088)
Observations	3,077,140	10,134,256	515,460	1,661,968
Store FE	X	X	X	X
Day FE	X	X	X	X
Month-Year FE	X	X	X	X
Day of week FE	X	X	X	X
Controls	X	X	X	X
Stores within 2 miles of highway	(9)	(10)	(11)	(12)
Average delay, 6am to 9pm	0.270***	0.128***	0.069	-0.155*
	(0.075)	(0.044)	(0.073)	(0.086)
Observations	2,788,951	9,065,848	466,257	1,520,607
Store FE	X	X	X	X
Day FE	X	X	X	X
Month-Year FE	X	X	X	X
Day of week FE	X	X	X	X
Controls	X	X	X	X
Stores within 1 mile of highway	(13)	(14)	(15)	(16)
Average delay, 6am to 9pm	0.212***	0.103*	0.155*	-0.187*
	(0.075)	(0.058)	(0.084)	(0.103)
Observations	1,984,521	6,417,477	313,181	1,057,474
Store FE	X	X	X	X
Day FE	X	X	X	X
Month-Year FE	X	X	X	X
Day of week FE	X	X	X	X
Controls	X	X	X	X

Notes: Weekdays only. Standard errors in parentheses clustered at the highway monitor ID. Controls include an indicator for public holidays and daily mean temperature (Celsius) for Los Angeles County. OLS model.

Figure A1: Relative frequency of when people dine out and grocery shop on weekdays - American Time Use Survey

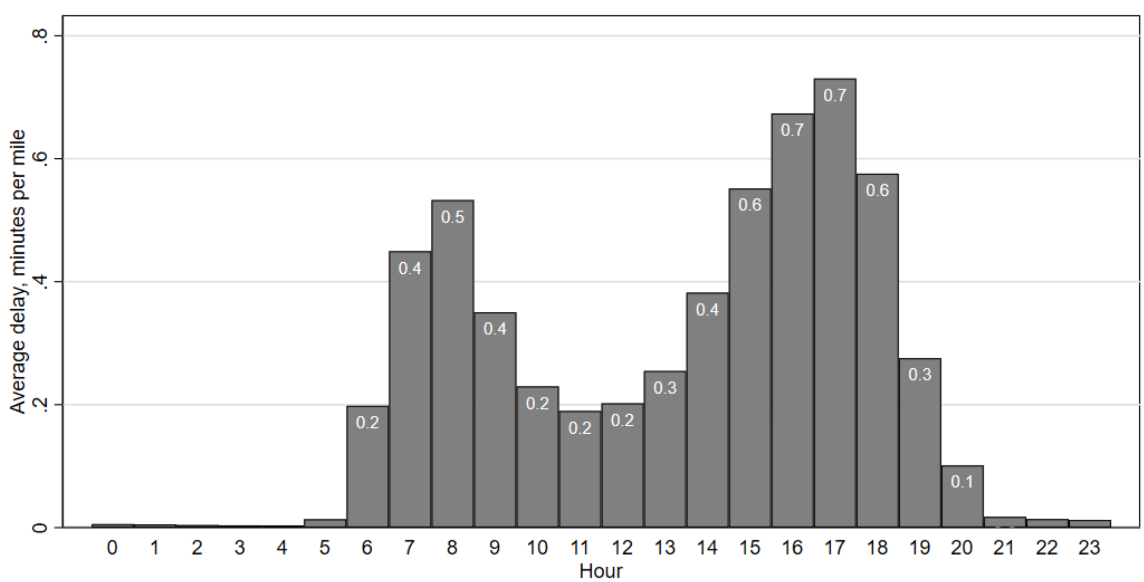
Panel A: When people dine out

Panel B: When people grocery shop



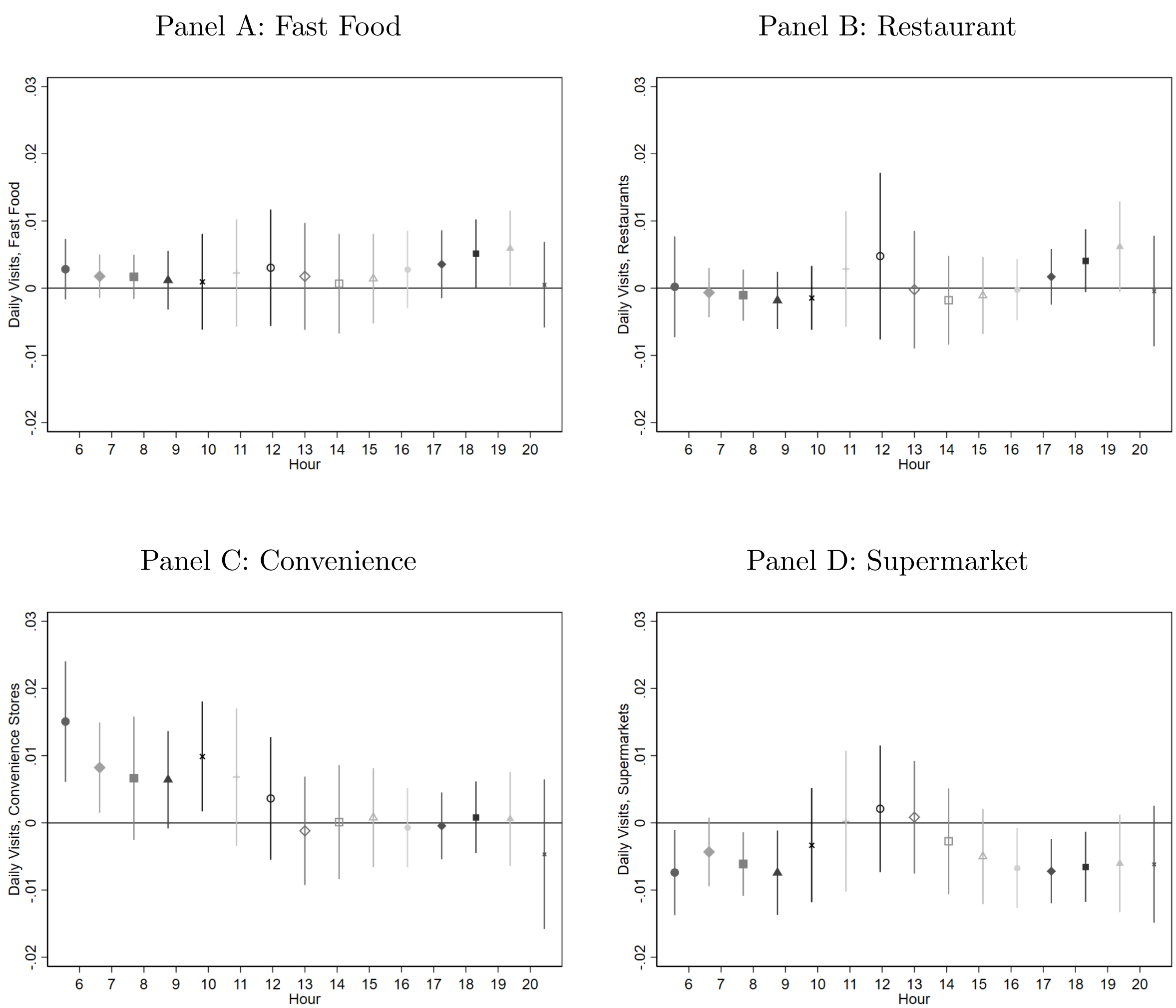
Note: Sample spans years of 2003 to 2019 across the entire US.

Figure A2: Average traffic delay by hour of the weekday



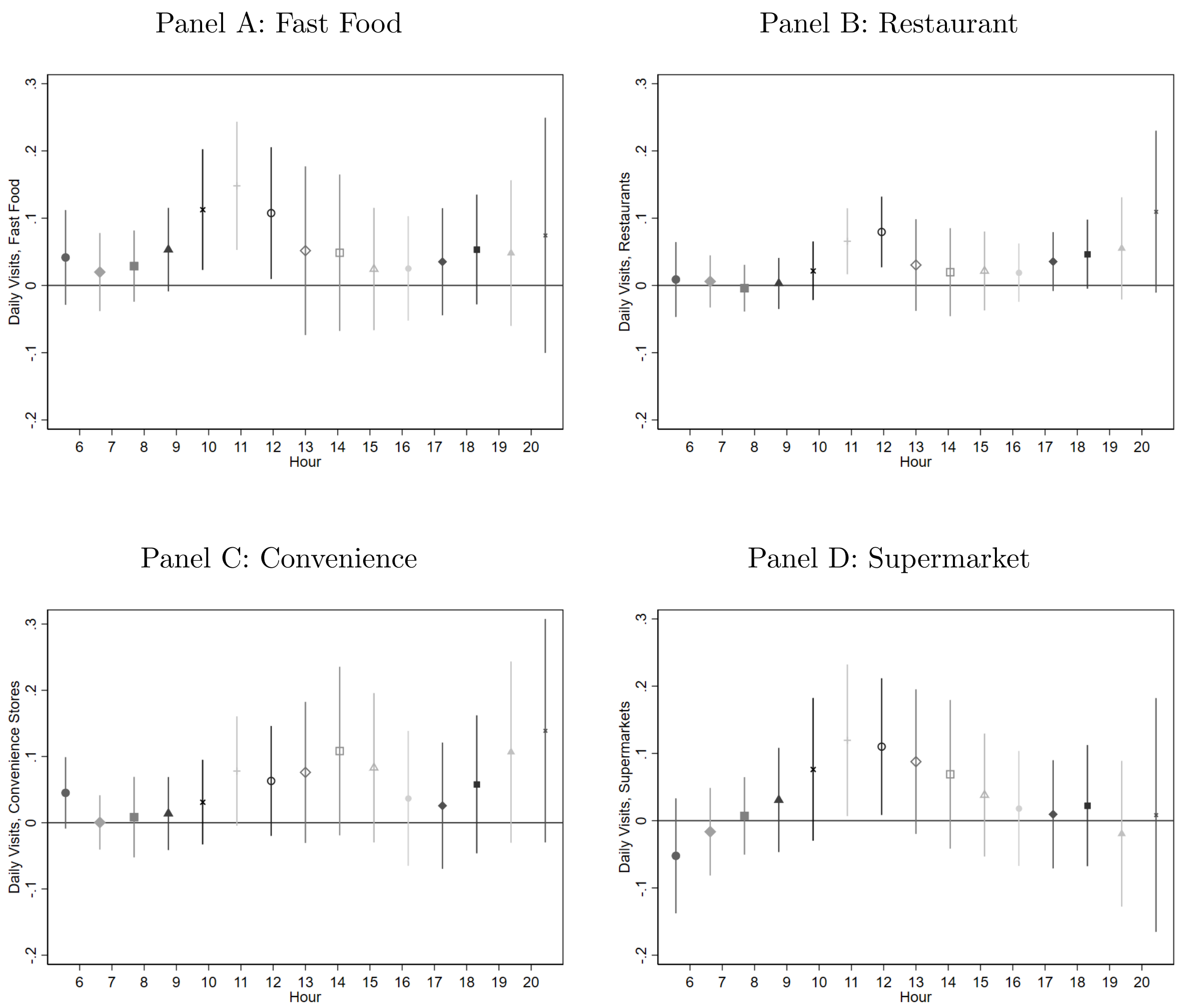
Note: Hourly averages for all stores within 5 miles of a highway monitor.

Figure A3: Effect of traffic delay, by each hour of day, on daily store visits - Poisson Model



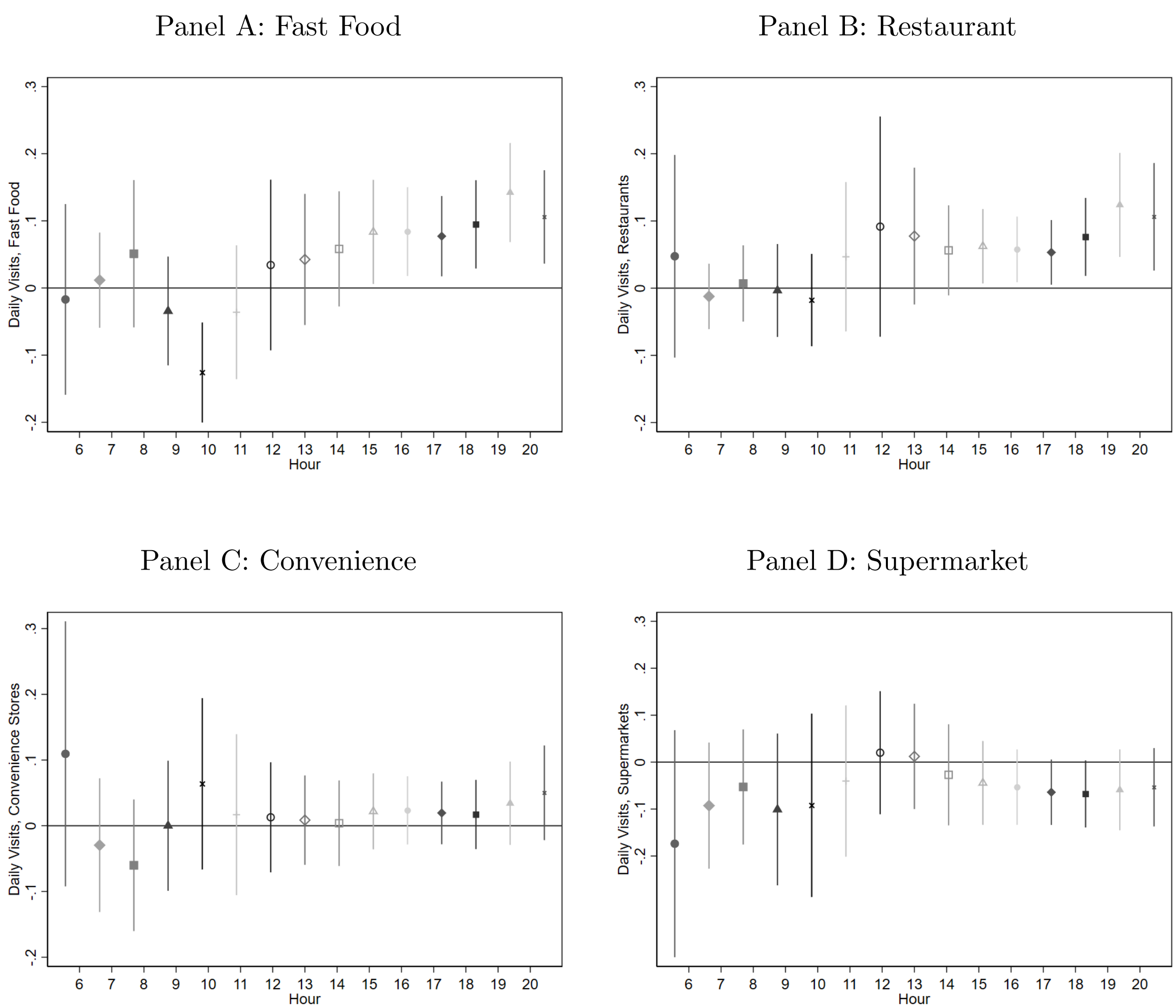
Note: Store, day, month-year, and day-of-the-week fixed effects. Controls for holidays and daily mean temperature. Weekdays only. Stores within 5 miles of highway monitors. 95% confidence errors using standard errors clustered at the highway monitor ID. Poisson model.

Figure A4: Effect of traffic delay, by each hour of day, on daily store visits - Nearest Inbound Station



Note: Store, day, month-year, and day-of-the-week fixed effects. Controls for holidays and daily mean temperature. Weekdays only. Stores within 5 miles of highway monitors. 95% confidence errors using standard errors clustered at the highway monitor ID.

Figure A5: Effect of traffic delay, by each hour of day, on daily store visits - Nearest Outbound Station



Note: Store, day, month-year, and day-of-the-week fixed effects. Controls for holidays and daily mean temperature. Weekdays only. Stores within 5 miles of highway monitors. 95% confidence errors using standard errors clustered at the highway monitor ID.