Environmental and Resource Economics
https://doi.org/10.1007/s10640-023-00773-7

Missing the Warning Signs? The Case of "Yellow Air Day" Advisories in Northern Utah

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Accepted: 11 March 2023

Abstract
Using a dataset consisting of daily vehicle trips, $PM_{2.5}$ concentrations, and a host of climactic control variables, we test the hypothesis that "yellow air day advisories" issued by the Utah Division of Air Quality resulted in subsequent reductions in vehicle trips taken during northern Utah's winter-inversion seasons in the early 2000 s. Winter inversions occur in northern Utah when $PM_{2.5}$ concentrations (derived mainly from vehicle emissions) become trapped in the lower atmosphere, leading to unhealthy air quality over a span of time known colloquially as "red air day episodes". When concentrations rise above 15 $\mu g/m^3$ toward the National Ambient Air Quality Standard average daily threshold of 35 $\mu g/m^3$, residents are informed via different media sources and road signage that the region is experiencing a yellow air day, and are urged to reduce their vehicle usage during the day. Our results suggest that the advisories have provided at best weak, at worst perverse, incentives for reducing vehicle usage on yellow air days and ultimately for mitigating the occurrence of red air day episodes during northern Utah's winter inversion seasons.

Keywords Air pollution advisory · Vehicle usage · $PM_{2.5}$ concentrations · Soft environmental policy

JEL Classification Q53 · Q58

1 Introduction

When it comes to protecting local environments, regulators and policymakers often find themselves in the unenviable position of having to choose between "hard" and "soft" policies aimed at altering their citizens' externality-causing behaviors. Hard policies refer to taxation, rationing of threatened resources (e.g., via a cap-and-trade program or the setting of an environmental standard), or subsidization of abatement technolgies—policies that either mandate a new, environmentally benign behavior or alter the economic tradeoff associated with the existing externality-causing behavior (e.g., via raising its relative price). To

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Published online: 17 April 2023

the contrary, soft policies rely on educating the public about an existing externality, and encouraging its mitigation through voluntary adjustments in behavior without providing an economic incentive to do so. For example, eco-labeling is a soft policy that provides consumers with pertinent information about a product's environmental impact at point of purchase (i.e., on the product's label), with the tacit encouragement that consumers choose "greener" products (c.f., Potter et al. 2021; Rihn et al. 2019; Shumacher 2010)[1] Information dissemination via a clearinghouse to both firms and consumers, or specifically to firms via demonstration projects, technical assistance, newsletters, seminars, and field days, represents another soft policy approach (c.f., Ribaudo and Horan 1999; Hamilton 1995; Terry and Yandle 1997; de Marchi and Hamilton 2006).[2]

This paper investigates the efficacy of a third type of soft policy, whereby a regulatory authority issues an environmental advisory (a.k.a., alert or warning) with the short-term goal of protecting its citizens from an existing environmental harm, and, similar to ecolabeling and information-dissemination, with the longer-term goal of mitigating the human behaviors causing the harm. As with ecolabeling and information-dissemination, empirical questions abound. To what extent might an advisory reduce citizens' exposure to environmental harm and, more importantly, trigger a reduction in externality-causing behaviors? In the case of water pollution, relevant questions are, what effect does a beach advisory have on a swimmer's decision to take a plunge in contaminated water, and what effect does a fish consumption advisory have on an angler's decision to cast a line into a contaminated lake or river? In terms of air pollution, what effect does an air quality advisory have on people's decisions to use their motor vehicles?

The current paper adds to a relatively small set of previous empirical studies by investigating the effect of repeated air quality advisories issued during northern Utah's winter inversion seasons in the early 2000 s, when elevated $PM_{2.5}$ concentrations tied mainly to region-wide vehicle usage sporadically exceeded the EPA's National Ambient Air Quality Standards (NAAQS). As elaborated on in Sect. 2, these exceedances (known as "red air day episodes") were often dramatic in scope. Our study area and period of analysis therefore provide an opportune setting within which to measure the effectiveness of an

[1] In their systematic review of the ecolabeling literature, Potter et al. (2021) conclude that ecolabels help motivate consumers to choose greener products. Experimental evidence from Rihn et al. (2019) suggests that ecolabel format (i.e., text vs. logo) influences consumers' visual attention and, concomitantly, product valuation. Logos capture relatively more visual attention than text ecolabels, which in turn increases respondents' willingness to pay for ecolabeled products. Shumacher (2010) finds that demand for ecolabeled goods is higher among environmentally conscious consumers than price-oriented consumers. Kaiser and Edwards-Jones (2006) caution that a myriad of issues bedevil the impact of ecolabeling in marine fisheries, issues pertaining to a general lack of consumer concern for marine fishes and sustainable fisheries, the absence of guaranteed, continued financial benefits to participating fishers, and difficulties associated with quality assurance (i.e., compliance of marine fisheries).

[2] Hamilton (1995) was the first to show that firms self-reporting their toxic emissions via the U.S. Environmental Protection Agency's (EPA's) Toxic Release Inventory (TRI) experienced abnormally negative returns on the day the information was first publicly released. With respect to actual firm-level emissions in response to the TRI, Terry and Yandle (1997) find that, all else equal, lower per-capita emissions levels were recorded in more densely populated areas of the country. According to de Marchi and Hamilton (2006), subsequent decreases in self-reported emissions were not always matched by similar reductions measured via EPA monitors. With respect to the control of nonpoint source water pollution, Ribaudo and Horan (1999) find that favorable conditions for information dissemination exist when (1) actions that improve water quality also increase firm profitability, (2) firms have strong altruistic or stewardship motives to begin with, or (3) the on-farm costs of water quality impairments are sufficiently large. However, none of these three conditions guarantees an expected improvement in water quality.

air quality alert program. Furthermore, because the red air day episodes are seasonal and sporadic, "alert fatigue" can be conveniently measured as it occurs across yellow air days within a given season (i.e., intra-seasonally), as well as its average occurrence, or trend, across years (i.e., inter-seasonally). Alert fatigue occurs when contemporaneous, or immediate changes in human behavior—happening in response to the issuance of an air quality advisory—fade over time, i.e., when individuals eventually revert back to their original behavior patterns (Saberian et al. 2017).

Air quality advisory programs are a common form of soft policy for metropolitan areas that are in non-attainment of the NAAQS (Fujii et al. 2009; Moser and Bamberg 2008). The programs publicize local air quality conditions on a daily basis. The conditions are categorized as color-coded, ordinal rankings accompanied by descriptions of corresponding health implications and desired public actions to mitigate the problem. In the case of northern Utah's advisory program for $PM_{2.5}$ concentrations in the early 2000 s, one of three color-coded alerts was provided daily to Utah citizens by the Utah Department of Environmental Quality (UDEQ) reflecting localized (county-wide) air quality conditions. The alerts were disseminated through a variety of news outlets (newspapers, television, and radio news shows) on the day of rather than day before measured $PM_{2.5}$2013 concentrations.[3] The color green indicated good air quality, with no action required, yellow indicated moderate air quality with voluntary reductions in the use of wood/coal stoves, vehicle travel, and industrial emissions recommended, and the color red indicated unhealthy air for sensitive groups with a mandatory ban on wood/coal stove use and voluntary reductions for vehicle travel and industrial emissions recommended (c.f., Hollenhorst 2021). Thus, during our study period, a yellow air day is clearly interpretable as an air quality advisory. It warns citizens of an impending red air day episode and recommends behavioral changes that can be taken on an individual basis, such as reducing vehicle trips or travel speeds, carpooling, or using alternative transportation modes—changes that help mitigate air pollution region-wide.

Previous studies report small or no reductions in vehicle usage (and concomitantly small or no increases in the use of alternative transportation modes) in response to soft policies such as air quality advisories, which has led Bamberg et al. (2011); Noonan (2011) to interpret the literature on soft policies as being guardedly optimistic about their effectiveness.[4] For instance, Welch et al. (2005) find no substantial increase in overall ridership on Chicago Transit Authority (CTA) trains during ozone alert days, although they

[3] Similar to Tribby et al. (2013) and Cummings and Walker's (2000), Utah's advisories were disseminated "day of", and hence were not as peremptory as "day-before" advisories would otherwise have been. We nevertheless test for the existence of potential day-before effects in Sect. 6, as their existence in our data would suggest that vehicle users base their decisions on expectations that an advisory will be issued, e.g., in response to an evening news report on the radio or television that predicts ensuing poor air quality, or information on current $PM_{2.5}$ concentrations available from various websites.

[4] Noonan (2011) argues that air quality advisories can impact behavior, mostly among sensitive groups such as the elderly, and for high-exposure activities, such as outdoor exercise. In other words, advisory programs do not uniformly alter a given population's behavior. Impacts vary across individuals, contexts, and activities. In fact, some of these behavioral impacts may be perverse, e.g., by inducing a greater reliance on automobiles on alert days in order to reduce one's exposure to poor air quality. Hence, advisory programs can instigate tension between an individual's altruistic impulses to mitigate his or her contribution to the air quality problem by reducing vehicle usage versus the perceived need to reduce the immediate health risks associated with the problem by increasing vehicle usage. As pointed out by an anonymous reviewer, the degree of this tension likely depends upon a pollutant's concentration level, i.e., the extent to which the local environment is polluted.

report increases during peak commuting periods and decreases during non-peak hours.[5] Using a quasi-experimental design, Cutter and Neidell (2009) find decreases in daily traffic counts, but no increase in public transportation ridership during alert days in the San Francisco Bay Area of California. Using a data-driven traffic forecasting model, Cummings and Walker (2000) find no significant traffic reductions in 13 non-attainment counties in the Atlanta, Georgia metropolitan area during ozone alert days.[6] Nevertheless, meta-analyses conducted by Fujii et al. (2009) and Moser and Bamberg (2008) suggest statistically significant reductions in vehicle usage in response to soft policies.[7]

More recently, Rivera (2021) has evaluated the effectiveness of a system of temporary driving bans triggered by air quality warnings in Santiago, Chile. Employing a fuzzy regression discontinuity design anchored to thresholds in the city's air quality index, Rivera (2021) finds that the bans—triggered by a three-tiered system of alerts that further tightens permanent driving restrictions on dirty vehicles, imposes new restrictions on clean vehicles, and is staggered according to the last digits of vehicles' license plate numbers—reduces overall vehicle trips by 6–9% during peak hours, and 7–8% during off-peak hours. These reductions are consistent with increases in the use of Santiago's mass-transit systems.[8]

As Noonan (2011) points out, by their very nature air quality advisories send conflicting messages. One message persuades individuals to voluntarily reduce their vehicle usage in order to mitigate collective health and environmental damages associated with poor air quality (i.e., the message appeals to one's altruistic tendencies), while another message prompts individuals to limit their exposure to outdoor air (i.e., the message appeals to one's innate desire to reduce personal risk exposure). The first message therefore encourages less vehicle use, e.g., by switching from driving automobiles to walking, riding a bicycle, or taking mass transit, while the second encourages greater vehicle usage as a means to limit exposure (taking public transportation typically requires additional time outdoors walking to and from a transit station and waiting for a bus or train to arrive). To the extent that enough individuals heed the second message more than the first, we should therefore expect an air quality advisory to increase vehicle use region-wide—a perverse outcome we explore theoretically in Sect. 4.

In this paper, we analyze daily administrative data on region-wide traffic volumes and $PM_{2.5}$ concentrations spanning northern Utah's winter-inversion seasons from 2002–2012, a decade during which the region was in non-attainment the NAAQS for $PM_{2.5}$ concentrations. Based upon different empirical specifications that control for autocorrelation in the models' error structures, we find mixed evidence regarding the relationship between yellow air day advisories and region-wide vehicle trips. Controlling for particular days of the week and holidays, as well as a host of weather conditions, we find that one-day lagged

[5] Cutter and Neidell (2009) point out that Welch et al.'s. (2005) standard errors were not adjusted to account for observing multiple stations per hour per day, and are therefore likely under-estimated.

[6] Cummings and Walker's (2000) finding was later echoed by Henry and Gordon's (2003) analysis of telephone survey responses from Atlanta residents.

[7] Moser and Bamberg (2008) estimate an 11% reduction across 141 studies spanning workplace travel plans, school travel plans, and travel awareness campaigns.

[8] As Rivera (2021) points out, by the time of her study the implementation of mandatory driving restrictions based upon license plate numbers had become a common regulatory strategy used worldwide to improve local air quality conditions and reduce traffic congestion. See Barahona et al. (2020) and Bonilla (2019) for recent studies on mandatory driving bans, and Caplan and Kim (2018), and references therein, for earlier studies.

advisories have a small negative impact on vehicle trips during weekdays and Saturdays. This general result contrasts with Tribby et al.'s (2013) finding of a perverse (i.e., positive) effect of advisories on vehicle trips in Utah's Wasatch Front region during the same time horizon, but comports with Cutter and Neidell's (2009) findings. We find no evidence that the yellow air day advisories are endogenously determined by weather conditions and lagged vehicle trips, and similarly no evidence of inter-seasonal alert fatigue (i.e., we do not find a trend in the average degree of alert fatigue across years). However, we do find mixed evidence regarding intra-seasonal alert fatigue (i.e., the occurrence of alert fatigue within a given season).

The next section elaborates on the three previous studies most relevant to ours—(Cutter and Neidell 2009; Saberian et al. 2017) Tribby et al. (2013)—with the goal of placing our study's contribution in the context of the existing literature. Section 3 describes our study area, northern Utah. Section 4 discusses the theoretical underpinnings of our main hypothesis, in particular how and under what circumstances we should expect yellow air day advisories to instigate region-wide reductions in vehicle trips. This discussion is premised upon a conceptual model developed in the technical appendix. Section 5 describes and summarizes our data. Section 6 presents the results of our empirical analysis, and Sect. 7 concludes.

2 Literature Review

Cutter and Neidell (2009) provide an early analysis of the efficacy of air quality advisory programs, in particular San Francisco Bay metropolitan area's Spare the Air (STA) program implemented in the early 2000 s. Under the STA program, advisories were issued on days when ground-level ozone was predicted to exceed the NAAQS. The authors apply a regression discontinuity (RD) design to traffic and weather data from 2001 to –2004 to identify the effect of the STA program on region-wide transportation choices across days and times of day. They estimate that the program reduced total daily traffic volume by 2.5–3.5%, with the largest effect occurring during and just after morning commuting hours.[9] The STA program had no statistical effect on total daily public transit use, but borderline statistically significant effects during peak commute times. Further, the authors find statistically significant decreases in traffic during and immediately after morning commute hours, statistically insignificant traffic responses throughout the middle of the day and into the evening rush hour, but then statistically significant decreases after 8 pm. Cutter and Neidell's (2009) interpret this latter result as evidence that discretionary trips, as opposed

[9] This result is perhaps the most widely cited finding in the literature. More recently, Zoe (2021) finds that "pollution gaps", which exist in areas of the US where pollution concentrations are measured intermittently by regulatory authorities (in specific, once every six days of the week), are excerbated when advisories accompany relatively high concentrations on days during which the concentrations are measured, i.e., on "on-days". Pollution gaps occur when, all else equal, concentrations are lower on on-days than "off-days", i.e., days when concentrations are not measured by regulatory authorities (but are measured by the researcher using satellite data). Zou's empirical model detects 1.6% less particulate pollution during on-days than off-days. Further, there is a 10% higher likelihood that an advisory is issued on on-days, and the advisories are associated with pollution gaps of 5–7% (as compared with the average 1.6% gap). This evidence leads Zou (2021) to conclude that gaming among regulatory authorities most likely reflects short-term cutbacks of polluting activities during critical times, e.g., when a county's noncompliance risk is high. Advisories are used strategically by the authorities, thus widening the pollution gap.

to commuter trips, responded to the STA program's advisories. All results are robust to alternative specifications of the RD design and the inclusion of traffic monitor and public transit station fixed effects.

As described in Sect. 5, our data for the current study is aggregated to a daily—rather than disaggregated to an hourly—time-step. As such, we do not assess advisory effects on an hourly basis. We take results such as Cutter and Neidell's (2009)—in particular, that discretionary vehicle trips tend to be more responsive to advisories than commuting trips, as one would naturally expect—as underpinning an average daily effect, which is the effect we seek to measure in our study. For one thing, focusing on the average effect reflects the full extent of northern Utah's reliance on yellow air day advisories as the sole means of regulating vehicle usage during its winter inversion seasons in the early 2000 s. The advisory's message was universal in this regard: regardless of whether you use your vehicle for commuting or discretionary purposes, drive it less often during yellow air days. Thus, measuring the advisory program's average effect is consistent with, and the most relevant test of, the regulation's main objective. Further, the nature of our data permits relatively robust estimation of an average effect. We utilize daily data for winter-inversion seasons spanning ten years, a period of time during which northern Utah residents experienced frequent yet intermittent issuance of advisories in response to significant variation in $PM_{2.5}$ concentrations.

With respect to the Bay area's public transport system (Bay Area Rapid Transit, or BART), Cutter and Neidell's (2009) find instances of decreases in BART use daily from 2 to 4 pm, with the 3 pm estimate statistically significant in certain specifications. They postulate that since the STA program provided information about expected air quality at a level where health concerns may arise, people may have responded to alerts by reducing their BART trips in order to lower their exposure to pollution. Ozone levels peak around 3 p.m., so the decrease in BART ridership during these hours coupled with no change in traffic volumes is demonstrative of avoidance behavior practiced by individuals having canceled public transit trips. Data limitations preclude us from measuring public transit responses to the yellow air day advisories in northern Utah. Although its bus service is free to the public, northern Utah's transit system is for the most part limited to the region's major city, Logan. The system's (Cache Valley Transit Authority's) limited service area and hours of operation and relatively slow travel speeds stands in stark contrast to the Bay area's interurban rapid-transit system, which is currently ranked as the fifth busiest rapid transit system in the US (World Atlas 2021).

In addition to providing a benchmark for comparison with this study's empirical results, Cutter and Neidell's (2009) research design also offers useful methodological comparisons. As they point out, potential confounding factors are obviated under the RD design when unobservable factors either do not vary or evolve smoothly around the STA program's trigger rule in the same manner as observed covariates (in their case within bands of 0.01 and 0.02 ppm of the STA program's trigger concentration level).[10] Hence, the RD design is suitable for causal inference. In our study, we instead test for potential endogeneity in the context of an instrumental variable (IV) model—which is a commonly used mitigation approach for data based upon voluntary behavior. Robust Durbin and Wu-Hausman tests suggest that endogeneity is not afflicting our original OLS estimates (Hausman 1978; Durbin 1954; Wu 1973).

[10] Cutter and Neidell's (2009) evidence supports the former condition, i.e., that unobservable factors do not vary around the trigger concentration level. See Lee and Lemieux (2010) for a survey of the RD method.

Although Saberian et al. (2017) estimate the effect of day-before, city-wide air quality advisories on bicycling rather than vehicle usage, several aspects of their econometric strategy are applicable to our study. The authors find a relatively large, statistically significant reduction in cycling in response to advisories among riders in Sydney, Australia during a five-year period, 2008–2013. The reduction ranges between 14 and 35%, which is larger in magnitude on weekends than on weekdays (suggesting a larger impact on leisure cyclists as opposed to commuter cyclists), and diminishes to between zero and 2% as a consequence of intra-seasonal alert fatigue.[11]

Saberian et al. (2017) estimate both OLS and IV models (their instrument for the IV model, the occurrence and proximity of bushfires, is shown to be a "strong" instrument, in that it negatively impacts Sydney's air quality index (AQI) but has no direct influence on cycling behavior other than through its effect on the AQI, i.e., bushfire activity is orthogonal to other unobservable factors affecting cycling behavior.[12] To account for potential intra-seasonal alert fatigue, they follow Zivin and Neidell's (2009) approach of introducing an interaction term consisting of contemporaneous and one-day lag dummy variables that respectively equal one if an advisory was issued on that day, zero otherwise. As discussed further in Sect. 6, we also adopt this approach and find no evidence of alert fatigue within a given season in our models.

Similar to our study, Tribby et al. (2013) integrate a decade (2001–2011) of daily traffic counter data for Salt Lake and Davis counties (located in the Wasatch Front region of Utah), with data on air quality advisory status and meteorological data to control for weather effects. The authors test for advisory effects on vehicle usage during both the winter months, when $PM_{2.5}$ concentrations tend to be elevated, and the summer months, when ground level ozone levels are elevated.[13] We henceforth discuss Tribby et al.'s results for wintertime $PM_{2.5}$ concentrations, since these are most relevant to our study's focus on northern Utah's winter-inversion season.

Tribbey et al. (2013) find evidence suggesting that yellow air day advisories have perverse effects on vehicle usage—yellow air days are associated with higher traffic volume relative to green air days. Specifically, traffic volume is 12% and 10% higher on yellow air days occurring on Fridays and Saturdays, respectively, and almost 6% higher during Mondays-Thursdays. These results are robust to variation in weather and number of days since the last green air day. The number of days since the last green air day—Tribbey et al. (2013) control variable for intra-seasonal alert fatigue—is found to be statistically insignificant.

Because of the relatively large number of automatic traffic recorders (ATRs) and their dispersed locations throughout Salt Lake and Davis Counties, the authors conduct a disaggregated analysis of their data by ATR location. They find that increases in vehicle usage on yellow air days is evident throughout the region's main metropolitan area, and is

[11] In a series of robustness checks, Saberian et al. (2017) find a roughly 40% reduction in the response of leisure cyclists due to alert fatigue, compared with only a 20% response reduction in commuter cycling. The authors caution that because the number of consecutive-day alerts in their data is minimal—occurring only seven times during the five-year study period—the precision of their alert-fatigue estimate is concomitantly diminished. As described in Sect. 6, the number of consecutive-day alerts in our data is markedly higher than Saberian et al.'s.

[12] In other words, bushfire activity satisfies the exclusion restriction (c.f., Angrist et al. 1996).

[13] Similar to Cache Valley (northern Utah's main county), Salt Lake and Davis counties were in non-compliance with the NAAQS for $PM_{2.5}$ concentrations, as well as for ozone concentrations, during their study period.

concentrated along the major commuting thoroughfares. Decreased traffic volume is evident in the center of the metropolitan area. Further, Tribbey et al. (2013) find substantial increases in vehicle trips near canyons providing access to the neighboring mountains, which the authors interpret as an increase in discretionary trips to the mountains (where the air is typically cleaner) on yellow air days.

The empirical results presented in Cutter and Neidell's (2009) and Tribbey et al. (2013) delineate the extent to which vehicle usage responds to an air quality advisory in any given area. Cutter and Neidell's (2009) find evidence supporting the efficacy of advisories, in particular that vehicle usage declined contemporaneously (albeit marginally) when air quality advisories were issued in the San Francisco Bay area during the early 2000 s. To the contrary, Tribbey et al. (2013) find that vehicle usage responded positively to advisories issued in the Wasatch Front region of Utah during the same time period, with no evidence of alert fatigue.[14] We develop a theoretical framework in Sect. 5 that provides a basis for these disparate results, and in Sect. 6 we present empirical results for air quality advisories issued in northern Utah during the early 2000 s, a region at the time experiencing sometimes dramatic surges in wintertime $PM_{2.5}$ concentrations. These results add to the mixture of evidence uncovered by previous studies.

3 Study Area

As Moscardini and Caplan (2017) point out, elevated $PM_{2.5}$ concentrations were a persistent, episodic pollution problem in northern Utah's main county, Cache Valley, during the early 2000 s. Figure B1 shows the valley's location in the northern region of the state (Cache Valley is shaded orange in the upper portion of the figure).[15] Almost exclusively during the winter months of December through February each year, temperature inversions trap $PM_{2.5}$ mostly in the form of dust and smoke particles for days or weeks at a time. These particles in turn pose an elevated risk to human health, as their small size enables them to lodge deep in human lung tissue. Figure B2 depicts the seasonality of the valley's winter-inversion problem during our study period, with the mass of the distribution of monthly average $PM_{2.5}$ concentrations occurring during the winter months.

As discussed in Acharya and Caplan (2020), short-term exposure to elevated $PM_{2.5}$ concentrations is linked to increased hospital admissions and emergency department visits for respiratory effects, such as asthma attacks, as well as increased respiratory symptoms,

[14] Although Rivera's (2021) findings align with Cutter and Neidell's (2009), recall that Santiago's advisory system is linked with varying stages of mandatory vehicle restrictions. When deteriorating air quality is less severe (and thus an initial alert is issued), temporary driving restrictions prohibit the driving of light-duty cars between 7:30 am and 9 pm. These temporary restrictions (applied discriminantly based upon license plate numbers) affect both clean and dirty vehicles (which are distinguished via green stickers affixed to the bumpers of the former type of vehicle) on any day of the week. As air quality deteriorates further, to a "pre-emergency" state, more dirty cars are banned permanently (until air quality improves) and more restrictions are placed upon the use of cleans cars. Under more adverse conditions, classified as "emergencies", bans and restictions on both types of vehicles increase further. Santiago's alert program does not rely upon voluntary self-restrictions, unlike the San Francisco Bay and Wasatch Front programs, as well as the program reported on here for northern Utah.

[15] Logan is the region's largest city, with a population in 2009 (the middle of our study period) of 46,000 people residing in 16,000 households (Census Bureau, 2010). Cache Valley's population is growing rapidly—it is expected to roughly double in size from 135,000 currently to 230,000 by 2050 (Perlich et al. 2017).

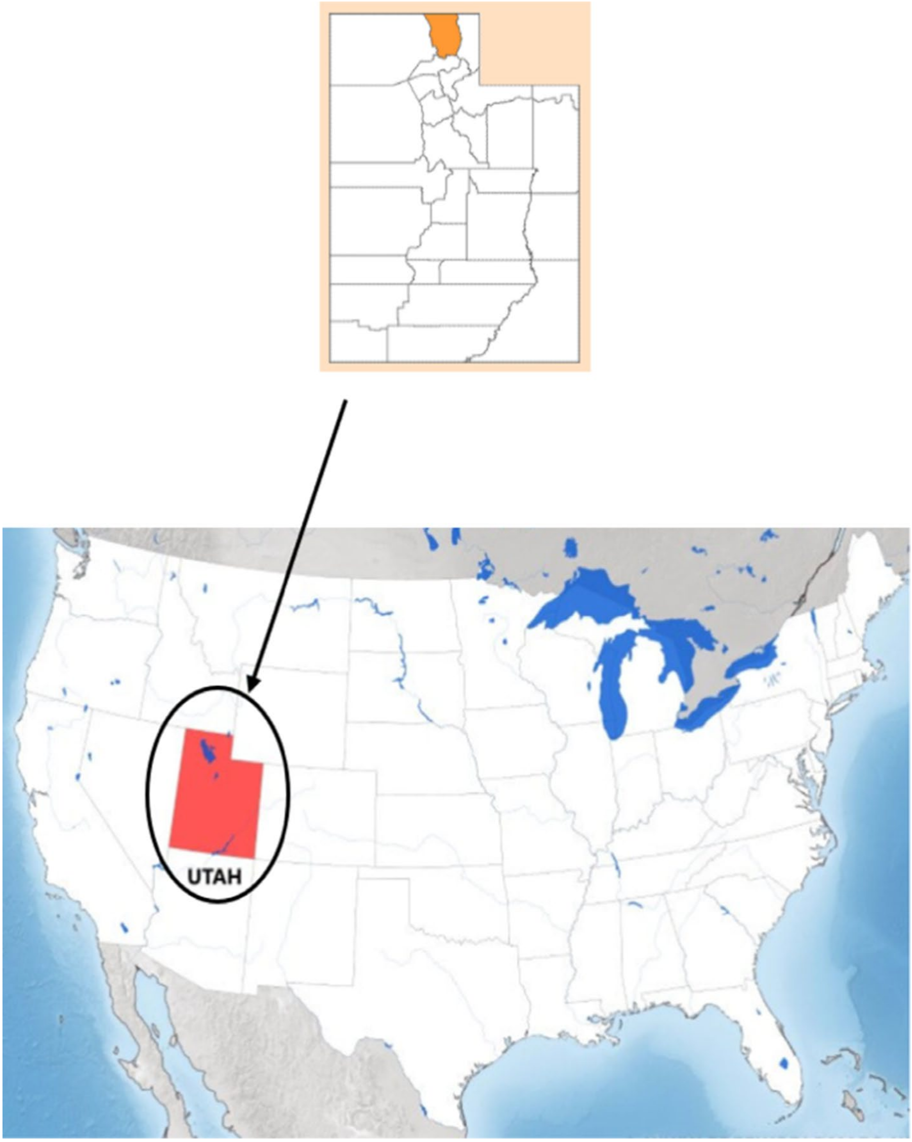

Fig. 1 Location of Cache Valley, Utah *Source* https://onlinelibrary.utah.gov/utah/counties/ and https://www.freeworldmaps.net/united-states/utah/location.html

such as coughing, wheezing and shortness of breath. Short-term exposure is also linked to reduced lung function in children and in people with asthma. Long-term exposure to elevated $PM_{2.5}$ concentrations can cause premature death due to heart and cardiovascular disease associated with heart attacks and strokes. Some studies suggest that long-term exposure can cause cancer as well as harmful developmental and reproductive defects, such

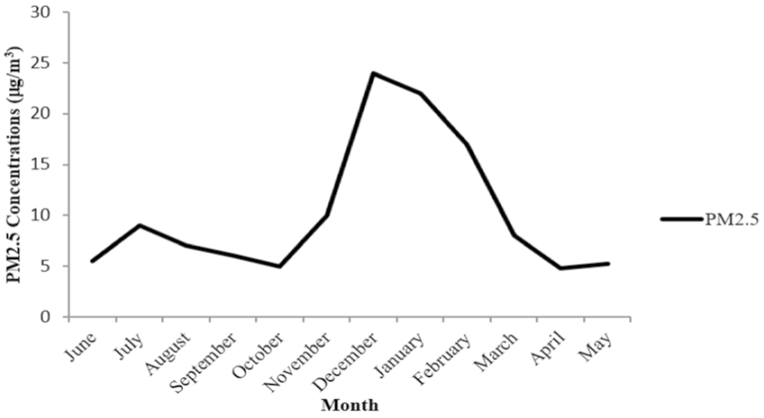

Fig. 2 Average monthly $PM_{2.5}$ concentrations in Cache Valley, Utah *Source* Moscardini and Caplan (2017)

as infant mortality and low birth weight (Utah 2016; Dockery et al. 1993; Pope 1989; Pope et al. 1995).[16]

Moscardini and Caplan (2017) also point out that residents of Cache Valley are victims of both their climatology and topography. Under certain meteorological conditions, cold air is trapped between the mountains close to the surface and is held in place by a layer of warm air above—the process creating an inversion. As elevation rises, temperature gradually decreases. Given conducive barometric-pressure, precipitation, and wind-speed conditions, descending warm air creates an inversion layer. Within this layer, temperature increases with increasing elevation, constituting the reverse of normal air patterns. The inversion layer traps $PM_{2.5}$ concentrations between geologic barriers which, in the case of Cache Valley, are the Wellsville and Bear River Mountain Ranges.

Figure B3 depicts the annual distributions of $PM_{2.5}$ concentrations in the valley during the first half our study period, 2003–2007 (the second half of the period, 2008–2012, depicts similar annual distributions). Note the variability in spikes above the Environmental Protection Agency's (EPA's) national ambient air quality (primary and secondary) standard (NAAQS) of 35 μg/m^3 averaged over any 24-hour period (horizontal red line) from year to year. Once above the 35 μg/m^3 threshold, the concentrations trigger a red air day episode. Concentration levels rising above the 15 μg/m^3 threshold trigger a yellow air day advisory.

The extent to which yellow air day advisories may have induced a change in individuals' behaviors is difficult to ascertain in Fig. B3. On the one hand, each season experienced a certain number of red air days, with the 2004–2005 season being particularly severe. It thus seems clear that yellow air day advisories were unsuccessful in eliminating any given season's red air day episodes. On the other hand, who can say whether the severity of the red air day episodes would not have been worse in any given season had the advisories not been issued? The extent to which the advisories affected region-wide vehicle usage on yellow air days, which in turn determined $PM_{2.5}$ concentrations, is explored at length in Sect. 6.

[16] Moscardini and Caplan (2017), Caplan and Acharya (2019), Acharya and Caplan (2020), and references therein elaborate on the precursors, causes, and patterns of elevated $PM_{2.5}$ concentrations in Cache valley during the winter inversion seasons of our study period.

Fig. 3 Annual distributions of $PM_{2.5}$ concentrations in Cache Valley, Utah, 2003–2007 *Source* Moscardini and Caplan (2017)

As pointed out by Caplan and Acharya (2019), a new $PM_{2.5}$ standard for Cache Valley was set in Utah's State Implementation Plan (SIP) at 40.7 $\mu g/m^3$ subsequent to our study period, calculated as an average of three running three-year averages of 98th percentile concentration levels surrounding the baseline year 2010 (known as the "baseline design value"). This new standard effectively raised the 24-hour standard by over five $\mu g/m^3$ relative to the long-standing threshold of 35 $\mu g/m^3$. The UDEQ also revised its color-coded warning system. Currently, yellow air day advisories are triggered when $PM_{2.5}$ concentrations rise to "moderate" levels between 12.1 and 35.4 $\mu g/m^3$. Unhealthy conditions prevail for sensitive groups between 35.5 and 55.4 $\mu g/m^3$, unhealthy conditions for everyone occur between 55.5 and 150.4 $\mu g/m^3$, very unhealthy between 150.5 and 250.4 $\mu g/m^3$, and hazardous at 250.5 $\mu g/m^3$ and above (see https://air.utah.gov/).

Table 1 provides the relative frequencies of yellow air day advisories occurring during our study period in each year's winter-inversion season, as well as the number of separate "yellow air day episodes", the average lengths of the episodes (with attendant standard deviations), and the percentage of yellow air day advisories that preceded a red air day episode. By yellow air day episode we mean any span of days in which (24-hour averaged) $PM_{2.5}$ concentrations remained in the range of 15–34.99 $\mu g/m^3$ for consecutive days; days during which consecutive-day yellow air day advisories were issued. For example, if an

Table 1 Yellow air day advisories

Inversion season	% Advisories (# of days)	# Episodes	Avg. episode lgth. (SD) (# of days)	% Preceed red air episode (# days)
2002–2003	38	9	3.8 (3.9)	33
2003–2004	20	10	1.8 (1.1)	60
2004–2005	30	13	2.1 (1.1)	62
2005–2006	30	10	2.7 (1.9)	40
2006–2007	34	10	3.1 (2.2)	40
2007–2008	27	11	2.2 (1.8)	18
2008–2009	24	9	2.4 (1.9)	33
2009–2010	40	9	4.0 (2.7)	89
2010–2011	20	7	2.6 (1.4)	29
2011–2012	24	5	4.4 (4.9)	0

advisory was issued on a single day (followed by a green air day), then the span of that episode is a single day. If an advisory was issued on two consecutive days (and then followed by a green air day), the span of the episode is two days, and so on. A yellow air day episode that preceeds a red air day episode is one whose final day is consecutive with the first day of an ensuing red air day episode, i.e., when the 24-hour average concentration level rises above the 35 $\mu g/m^3$ threshold. For example, if yellow air day advisories are issued consecutively on Monday and Tuesday of a given week and then a red air day episode begins on Wednesday, the two-day yellow air day advisory preceeded a red air day episode. If instead that Wednesday is not a red air day, then the two-day yellow air day advisory did not preceed a red air day episode.[17]

From Table 1 we see several instances of variation in yellow air day advisories across the yearly inversion seasons. For example, the percentage of days in which an advisory was issued reached as high as 40% during the 2009–2010 season and as low as 20% in the 2003–2004 and 2010–2011 seasons. The number of yellow air day episodes reached as high as 13 during the 2004–2005 season and as low as 5 in the 2011–2012 season. The average episode length was 4.4 days long in 2011–2012 and only 1.8 days long in 2003–2004. Lastly, the variability in the percentage of yellow air day episodes preceding red air day episodes (as high as 89% in the 2009–2010 season and as low as 0% in the 2011–2012 season) is similarly pronounced. Across seasons, there does not appear to be a noticeable decline in the precedence of yellow air day advisories prior to red air day episodes, suggesting a lack of unconditional evidence in support of the hypothesis that vehicle usage in northern Utah evolved to be more responsive to the advisories over the course of our study period.

[17] There is only one instance in the dataset where a red air day episode occurred without having been preceeded by a yellow air day advisory.

As Moscardini and Caplan (2017) point out, during a typical inversion period anywhere from 60% to 85% of all $PM_{2.5}$ is created by secondary particulate formation. Secondary particulate formation occurs when precursor emissions of nitrogen oxides (NOx), sulfur oxides (SOx), and especially volatile organic compounds (VOCs) react and combine in the atmosphere to create concentrations of $PM_{2.5}$. VOCs are highly reactive. As they break apart, they combine with other gaseous chemicals to form nitrates. These nitrates then react with ammonia to form ammonium nitrate, the leading contributor to $PM_{2.5}$ concentrations in Cache Valley. This led the UDEQ to conclude that reducing VOC emissions offered the best near-term approach to reducing the valley's $PM_{2.5}$ concentrations during winter inversions. Approximately 50% of anthropogenic VOC emissions in Cache Valley were attributable to industrial and commercial processes, 45% to motor vehicles, and 5% to consumer solvents (National 2014). Therefore, a policy aimed at reducing vehicle use represented a potentially effective way of advancing the UDEQ's goal of reducing the valley's VOC emissions.[18]

In an effort to reduce mobile-source emissions, Cache Valley's policymakers adopted a mandatory vehicle emissions testing program (VETP) during the period under study—the efficacy of which has since been hotly debated, primarily due to exemptions for diesel trucks, and subsequently later-model vehicles (Anderson 2013). In concert with yellow air day advisories issued by the UDEQ, the VETP was the sole mandatory initiative enacted by the state of Utah during our study period to control the valley's winter inversion problem.

As mentioned in Sect. 2, northern Utah's mass transit system is for the most part limited to the region's major city, Logan. The transit authority operates 16 fixed routes consisting of ten local routes, five regional connector routes, and one commuter route. Ridership increased by 334% between the system's inception in 1995 and 2012, but has declined each year since peaking in 2012. Passenger trips totaled roughly 1.9 million in 2015, representing a decline of nearly 12% between 2012 and 2015 (LSC Transportation Consultants 2017). Relative to transit systems in larger US cities, northern Utah's service area and hours of operation are limited. Future expansion of the system is hamstrung by a relatively low transit-dependent percentage of the region's population and constrained funding sources. According to LSC Transportation Consultants (2017), roughly 4% of the region's population is without private vehicle access, 17% and 8% are young (ages 10–19) and old (ages 65 and older), respectively, 3% are ambulatory disabled, and 15% are low-income. Hence, transit-dependence is not currently a driving force behind demand for expansion of the transit system. Further, the system is expected to remain tax-supported and zero-fare for the foreseeable future. Sales tax and federal and state grants account for roughly 96% of the system's revenue (the remainder coming from advertising services and interest income from investments and fund balance) (LSC Transportation Consultants 2017). The bottom line is that the region's mass transit system is not likely to be an alternative mode through which the region's mobile-source emissions can be controlled in the near future.[19]

[18] The positive link between vehicle usage and $PM_{2.5}$ concentrations is certainly not unique to Cache Valley, Utah. For example, see Chen et al. (2020).

[19] In terms of commuting to work, slightly over 75% of northern Utah workers are estimated to drive alone to work, with another 11% carpooling and slightly less than 2% using public transport. The average one-way commute time is approximately 17 min. Approximately 64% of northern Utah commuters commute within the region (LSC Transportation Consultants 2017).

4 A Theory

Human mobility often creates a tension between individual decision-making and collective outcomes. The private automobile bestows clear benefits to individuals in terms of enabling access to utility-generating consumption, but generates harms to collective well-being, as in the case of noxious tailpipe emissions contributing to poor local air quality. The extent to which yellow air day advisories impact region-wide vehicle usage ultimately traces to individual- (or household-) level decision-making. If a large-enough number of individuals heed the advisory and reduce their vehicle trips on yellow air days by, for example, switching to alternative modes of transportation such as buses or walking, or more efficiently using their vehicles via "trip chaining", carpooling, or telecommuting, then we would expect an advisory to correlate statistically with a region-wide reduction in vehicle trips. To the contrary, if too small a number of individuals respond to the advisory in these ways, then we would expect to find no correlation. It is also possible that a large-enough number of individuals will respond perversely to the advisory by increasing their vehicle usage on yellow air days e.g., to provide what they perceive as greater protection from poor air quality than walking or using mass transit, or simply to reduce their need for travel during an ensuing red air day episode Tribby et al. (2013).

To better understand these potential influences, we develop a simple conceptual framework in Technical Appendix A that models three stylized types of individuals comprising a region and that (no pun intended) drive the region's overall response to a given yellow air day advisory. Since individuals are in reality precluded from predicting the emergence of yellow air days and the days' patterns of occurrence throughout a given winter inversion season, the model presumes individuals are myopic in their decision making, in particular that they are unable to identify an optimal path of future vehicle usage at the outset of the inversion season. As a result, individuals are assumed to make vehicle-use decisions contemporaneously without the aid of foreknowledge.[20]

As the appendix shows, one type of individual (Case 1) completely ignores the damages associated with region-wide vehicle trips in each period, despite the fact that a yellow air day advisory causes the individual's perceived marginal damage associated with increases in region-wide vehicle trips to increase. A Case 1 individual is therefore prone to alter his vehicle usage in a manner consistent with avoidance, i.e., consistent with basing his vehicle-use choices solely upon the goal of reducing personal risk exposure. With only minimal assumptions placed on the structure of this individual's preferences, we show that a Case 1 individual responds to the issuance of an advisory by increasing his vehicle trips (refer to Eqs. (A.5)–(A.8) in the appendix). A second type of individual (Case 2) accounts solely for the expected damages she personally incurs in any given period, i.e., a Case 2 individual partially internalizes the contribution her vehicle trips makes to region-wide environmental damages, but only as those damages affect her own welfare. As shown in the appendix, this type of individual responds to yellow air day advisories to a lesser (positive) extent than a Case 1 individual as a result of at least partially mitigating her contribution to damages, and may in fact respond by decreasing her vehicle trips in equilibrium when the change in her perceived marginal damage (from

[20] Because individuals are assumed mypoic, our model is precluded from explicitly accounting for behavioral determinants of intra-seasonal alert fatigue among individuals. Nevertheless, if we assume that alert fatigue impacts equally each of the three types of individuals described below, then relatively speaking, the differences in individuals' behaviors identified by the model would be unaltered in the presence of fatigue.

vehicle trips) associated with the issuance of a yellow air day advisory exceeds the corresponding change in her marginal benefit (refer to Eqs. (A.10)–(A.14) in the appendix). In effect, a Case 2 individual exhibits a limited, selfish concern for the environmental consequences of her vehicle usage.

The third type of individual (Case 3) is altruistic, accounting not only for the expected damages that his vehicle trips imposes on himself and all other individuals in the region, but also the expected benefits that all other individuals in the region obtain as a result of increasing their vehicle trips in response to a yellow air day advisory (e.g., by limiting their exposure to outdoor air). In our particular context, this full accounting of expected benefits and costs represents what is commonly known as "pure altruism", a concept developed in the broader theoretical frameworks of Simon (1993), Bergstrom (1999), Antweiler (2015), and Ottoni-Wilhelm et al. (2017).[21] As the appendix demonstrates, a sufficient condition for a Case 3 individual's vehicle trip level to respond less positively to a yellow air day advisory than a Case 2 individual's is that the change in the former's perception of the added aggregate damages suffered by all other individuals in the region in response to the advisory exceeds his perception of the added aggregate benefits obtained by all other individuals. The corresponding sufficient condition comparing a Case 3 individual's vehicle-trip response with a Case 1 individual's is shown to be more likely to hold in general (refer to Eqs. (A.16)–(A.20) in the appendix). Therefore, similar to previous theoretical and experimental findings concerning altruism and voluntary contributions to a public good (which in our case is represented by reduced vehicle usage), contributions from a Case 3 individual are expected to increase only under certain conditions (c.f., Smith et al. 1995; Ley 1997; Hahn and Ritz 2014; Croson 2007).

Surely, a given region consists not only of these three stylized types of individuals, but also any convex combination of the three. The point is, to the extent that more Case 1 individuals comprise a region than Case 2 and Case 3 individuals, we should expect to see less of a reduction in vehicle usage in response to any given yellow air day advisory. Or, alternatively stated, the more likely we will see an increase in vehicle usage in response to the advisory.[22] Because the data we describe in Sect. 5 and analyze in Sect. 6 is region-, as opposed to household- or individual-level, we are precluded from directly testing whether Case 2 and Case 3 individuals in northern Utah have met their respective sufficiency

[21] The experimental literature is chockfull of studies where participants behave altruistically under certain conditions. For examples, see Fehr and Schmidt (1999), Bolton and Ockenfels (2000), Andreoni and Miller (2002), Andreoni and Rao (2011).

[22] An alternative theory could instead base individuals' vehicle-use decisions upon their subjective risk preferences concerning their own personal health. These differences could be modeled in a context of what the current model identifies as either a Case 1 or Case 2 individual, i.e., an individual who either completely ignores his own contribution to the region's PM2.5 concentrations via his vehicle usage, or who ignores his contribution to everyone else's damages. In other words, the risk-preference model would consist of non-altruistic individuals who are distinguished instead by their subjective risk preferences. In this framework, individuals who perceive relatively high risk to their personal health associated with the issuance of an advisory would be more likely to increase their vehicle usage in response to the advisory. In contrast, those who perceive relatively low risk associated with the issuance of an advisory would be more likely to decrease their vehicle usage. Hence, although there is a different interpretation of what motivates individual responses to an advisory – altruistic tendencies versus subjective risk preferences—there is a consistency in terms of what characterizes the response at a regional level. In the case of subjective risk preferences, the region-wide response depends upon the proportion of low-versus high-risk individuals in the population.

conditions for responding less positively (and perhaps negatively) to yellow air day advisories. Rather, we test whether on average northern Utah residents' vehicle usage responded positively or negatively (or not at all) to yellow air day advisories issued during the first decade of 2000.[23]

5 Data and Summary Statistics

The data for our empirical analysis in Sect. 6 are compiled from several different sources. Each variable in our dataset consists of a daily time step for the years 2002–2012. Since the problem addressed in this study occurs seasonally (from December to February) we restrict the dataset to these three months each year. $PM_{2.5}$ concentrations were recorded hourly for Cache County by the Utah Division of Air Quality (UDAQ) at EPA station code 490050004 located in downtown Logan (Utah 2016a, b, c).[24] The average concentration level recorded over a given day's 24-hour period was selected as that day's concentration level. Average daily readings of a host of weather variables—consisting of temperature gradient, wind speed, humidity, atmospheric pressure, snow depth, and snowfall level—were obtained from the Weather Underground (2016) and Utah Climate Center (2016).[25] Lastly, daily vehicle trip count data were obtained from the Utah Department of Transportation (UDOT 2014). The Automatic Traffic Recorder (ATR) stations for the trip count data in Cache Valley are #303, #363, #510, and #511, which cover the county's main north–south transportation artery. Figure B4 depicts the specific ATR locations. Stations other than #303, #363, #510, and #511 provided insufficient data for our study period, including station #620 (demarcated in the color red), which was added during the second half of our study period.

Specific names of, and summary statistics for, the variables used in our study are presented in Table 2. We see that on average over 30,000 vehicle trips ($VehicleTrips_t$) were recorded each day in Cache Valley. On the one hand, this is likely an underestimate of actual trips taken due to the finite number and specific locations of the ATR stations in the valley. On the other, at least some trips are double-counted whenever a vehicle passes more than one station during a given trip. We have no reason to believe that instances of over- and under-counting are correlated with any specific day of the week or hour of the day. Hence, the imprecision of our vehicle trip measure does not systematically bias the results presented in Sect. 6 in any apparent way.

As indicated in Table 2, daily $PM_{2.5}$ concentration levels averaged slightly more than 19 μg/m^3 during our study period. This level rises to over 39 μg/m^3 per day in the presence of a temperature inversion, illustrating the positive relationship between northern

[23] We again acknowledge that the effect of the advisory on vehicle usage in northern Utah is also averaged over commuting and discretionary trips. As Cutter and Neidell's (2009) point out, commuters generally have little flexibility when it comes to missing a work day, especially if telecommuting alternatives are limited. Hence, commuting trips have a significantly higher cost of cancellation and thus are much less likely to be delayed or substituted away from than are discretionary trips.

[24] Station 490050004 was subsequently moved five miles north of downtown Logan to the town of Smithfield shortly after the conclusion of our study period.

[25] Average daily readings for atmospheric pressure were also obtained, however this variable was consistently statistically insignificant in the regressions presented in Sect. 5.

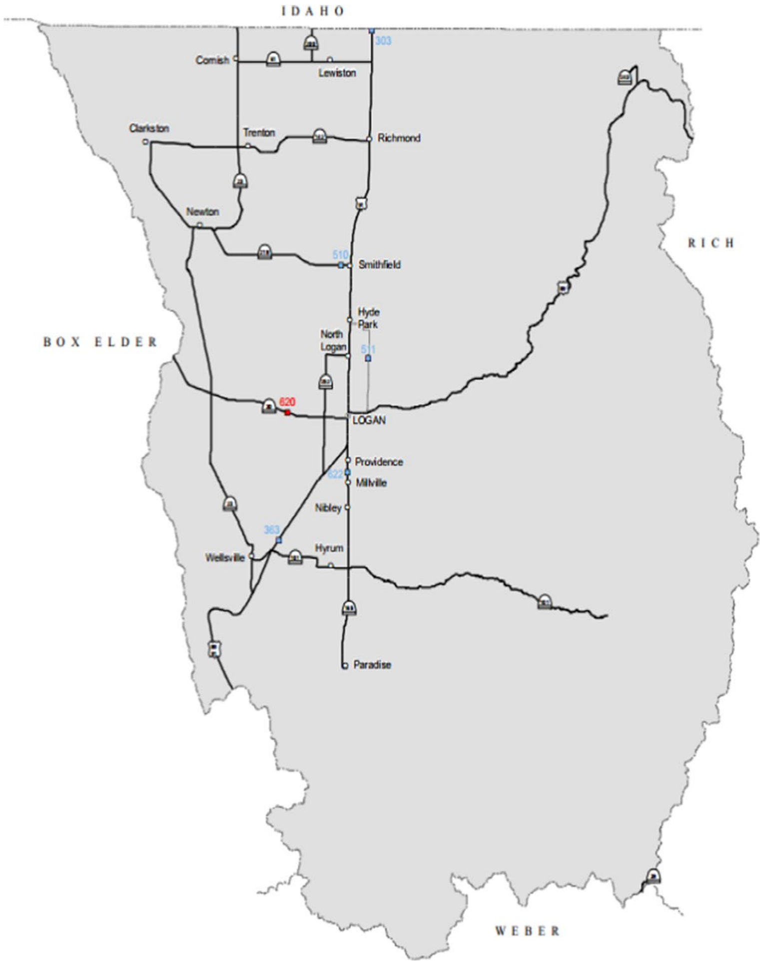

Fig. 4 Locations of automatic traffic recorder (ATR) stations in Cache Valley, Utah *Source* Moscardini and Caplan (2017)

Utah's wintertime temperature inversions and elevated $PM_{2.5}$ concentrations.[26] Yellow air day advisories ($YellowAdvisory_t$) were issued on roughly a third of the total number of days included in our study period, which suggests that if the advisories did in fact impact vehicle use in Cache Valley, vehicle owners may have been susceptible to intra-seasonal alert fatigue (as described in Sects. 2 and 3) given the advisories' relatively high frequency of issuance. To test for the possiblity of foresight on the part of the region's vehicle owners in predicting the issuance of an advisory, we redefined $YellowAdvisory_t$ to include the green air day preceding each yellow air day episode (a green air day occurs when its $PM_{2.5}$ concentration averages less than 15 μg/m^3 over the 24-hour period). This variable is labeled $YellowAdvisoryPlus1_t$. For example, if during any given week of our study

[26] The negative value for $TempDiff_t$ indicates that the average day during our study period did not experience a temperature inversion.

Table 2 Variable names, descriptions, and summary statistics

Variable	Description	Mean (St. Dev.)
$VehicleTrips_t$	Daily trip count (# of vehicle trips).	30,129 (6617)
$PM2.5_t$	Average daily $PM_{2.5}$ concentration ($\mu g/m^3$).	19.56 (19.39)
$TempDiff_t$	Temperature gradient between Logan Peak and valley floor (°F).	− 7.29 (10.24)
$PM2.5_t\|_{TempDiff_t>0}$	Average daily $PM_{2.5}$ concentration given winter-inversion conditions ($\mu g/m^3$).	39.47 (27.80)
$YellowAdvisory_t$	= 1 if yellow air day advisory is issued, 0 otherwise.	0.32 (0.47)
$YellowAdvisoryPlus1_t$	= 1 if yellow air day advisory is issued or the day prior to issuance of the advisory was a green air day, 0 otherwise.	0.57 (0.49)
$NotSunday_t$	= 1 if not Sunday, 0 otherwise.	0.86 (0.35)
$Holiday_t$	= 1 if day before, day after, or day of Christmas, New Years Day, Martin Luther King Jr. Day, or Presidents Day holidays, 0 otherwise.	0.13 (0.34)
$Fatigue$	= 1 if interaction term $YellowAdvisory_t \times YellowAdvisory_{t-1} = 1$, 0 otherwise.	0.19 (0.39)
$FatiguePlus1$	= 1 if interaction term $YellowAdvisoryPlus1_t \times YellowAdvisoryPlus1_{t-1} = 1$, 0 otherwise.	0.52 (0.50)
$Humidity_t$	Daily humidity level (%).	82.66 (8.78)
$Wind_t$	Daily wind speed (miles/hour).	3.03 (2.67)
$HumWind_t$	$Humidity_t * Wind_t$.	243.74 (203.89)
$SnowFall_t$	Daily snowfall level (mm).	14.45 (37.54)
$SnowDepth_t$	Daily snow depth (mm).	127.26 (115.87)

period a yellow air day episode began on a Wednesday with, say, a $PM_{2.5}$ concentration of 27.5 μg/m^3, and the concentration on the preceding Tuesday was less than 15 μg/m^3, then that Tuesday's $YellowAdvisory_t$ value would also be set equal to one (from what had been zero) in the formulation of $YellowAdvisoryPlus1_t$. As expected, $YellowAdvisoryPlus1_t$'s mean value exceeds $YellowAdvisory_t$'s, in this case by a factor of over 1.75. Similarly, $FatiguePlus1$'s mean value exceeds $Fatigue$'s by a factor of over 2.7.

Lastly, in addition to the varied controls for weather conditions, e.g., $Humidity_t$, $Wind_t$, $Humwind_t$, $SnowFall_t$, and $SnowDepth_t$, we depart from Tribbey et al. (2013) by explicitly controlling for the potential effect of holidays on vehicle usage in the valley.[27] As indicated by the variable $Holiday_t$, we dummy for three-day windows surrounding the respective national holidays occurring during our study period. These holiday windows account for more than a tenth of total number of days in our sample.

Figure 1 provides a glimpse of the unconditional relationship between red air days and yellow air day advisories, on the one hand, and region-wide vehicle trips on the other, across each specific day of the week. Percentage of Vehicle Trips for a given day of the week is measured as the percentage of total vehicle trips taken during that day of the week across our sample. Similarly, Percentage of Red Air Days for a given day of the week is measured as the percentage of total red air days experienced during that day, and Percentage of Advisories for a given day of the week is measured as the percentage of total yellow air day advisories experienced during that day across our sample. We anchor these comparisons by day-of-the-week due to the statistically significant, negative pairwise correlations that exist for vehicle trips across all days of the week, e.g., between trips taken on Mondays versus Tuesdays, Mondays versus Wednesdays, Tuesdays versus Wednesdays, etc.[28] Further, Moscardini and Caplan (2017), Caplan and Acharya (2019), and Acharya and Caplan (2020) found day-of-the-week to be strong instruments for vehicle trips in their $PM_{2.5}$ regressions.

The relatively tight unconditional relationship depicted in Fig. 1 between red air days and vehicle trips echoes that uncovered by the conditional analyses conducted by Moscardini and Caplan (2017); Caplan and Acharya (2019), and Acharya and Caplan (2020). To the contrary, we see that yellow air day advisories do not exhibit as tight a relationship with vehicle trips. Although it mimics that of red air days and vehicle trips on Sundays through Tuesdays of the average week, the relationship between advisories, on the one hand, and vehicle trips and red air days on the other, seems to break down across the remaining days of the week. This is an indication that if we are successful in uncovering a conditional relationship between advisories and vehicle trips in the next section, it is likely to be weak (Figs. 2, 3, 4 and 5).

6 Empirical Results

In measuring the relationship between the issuance of yellow air day advisories and region-wide vehicle trips in Cache Valley, we estimate a number of different specifications to probe the robustness of our results. In general, the functional relationship between $YellowAdvisory_t$ and $VehicleTrips_t$ can be expressed as,

[27] Tribbey et al. (2013) removed holidays from their data, thus eliminating their possible influence on individual's vehicle usage. In contrast, we explicitly control for their possible effects.

[28] Although relatively low in magnitude—the Pearson's correlation coefficients hover in the neighborhood of −0.15 for each pairwise comparison—they are each statistically different at the 5% level of significance.

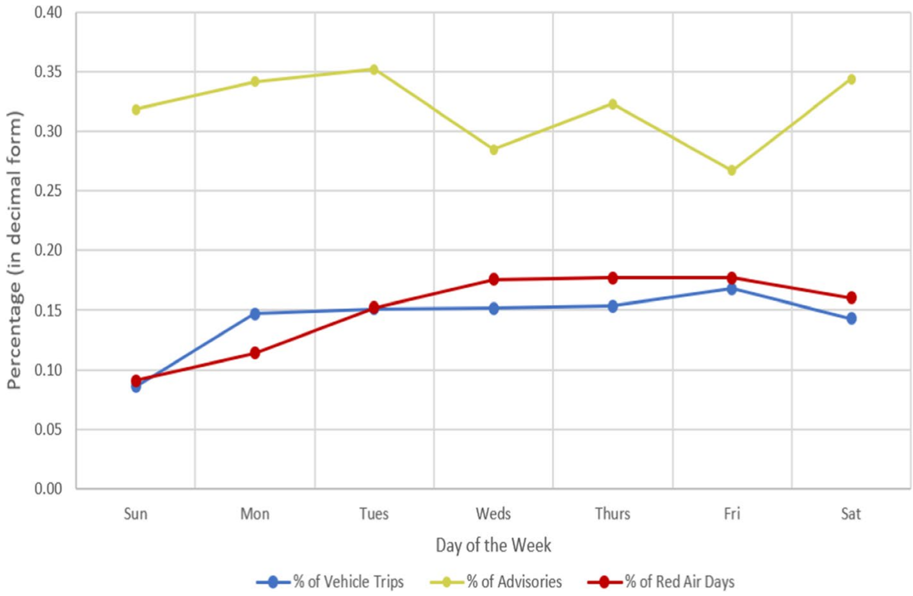

Fig. 5 Day-of-week percentages for vehicle trips, red air days, and yellow air day advisories

$$VehicleTrips_t = f\left(X; \Theta, \epsilon_t\right), \tag{1}$$

where matrix X contains a set of explanatory variables taken from Table 2 (each set including contemporary and/or lagged versions of either $YellowAdvisory_t$ or $YellowAdvisoryPlus1_t$), Θ represents the corresponding vector of parameters to be estimated, and ϵ_t is an idiosyncratic error term. We consider two different specifications of the variable $VehicleTrips_t$ in the econometric model's framework—levels and natural logarithmic—as well as separate specifications for $YellowAdvisory_t$ and $YellowAdvisoryPlus1_t$.[29]

6.1 Identifying and Controlling for Autocorrelation

We report results in this subsection for both the levels and log-transformed specifications of $VehicleTrips_t$.[30] To begin, we apply (Ljung and Box 1978; Cumby and Huizinga 1992) Portmanteau tests for white noise error terms in each specification. Results are presented in Table 3. We find that including the first three lags of $VehicleTrips_t$ and first two lags of $Ln(VehicleTrips)_t$, respectively, as regressors satisfies the null hypothesis of no second-order autocorrelation in the residuals.[31] This is evidenced by the statistically insignificant χ^2 values for the Portmanteau tests. Further, the statistically insignificant Durbin χ^2

[29] We also estimated the model using a three-day forward moving average of $VehicleTrips_t$ and found the results to be qualitatively similar to those for levels. The results using this specification are available from the author upon request.

[30] Stata/IC version 16.1 for Windows (64-bit x86-64) was used for all regression analyses reported in the paper.

[31] In other words, second-order autocorrelation is controlled for once three lags of $VehicleTrips_t$ and two lags of $Ln(VehicleTrips)_t$ are included as regressors in their respective models.

statistics for both models indicate that the regression results are consistent with an absence of first-order autocorrelation in the residuals. Hence, all ensuing regression models explaining variation in vehicle trips include the respective lagged terms as sets of controls for first- or second-order autocorrelation that would otherwise be present in the error structures.[32]

As the results in Table 3 indicate, contemporaneous vehicle trip counts are positively correlated with their first-lagged values and negatively correlated with their second-lagged values. For example, from column three of the table we see that for every one-percent increase in vehicle trips taken in the previous period (i.e., $Ln(VehicleTrips)_{t-1}$), contemporaneous trips ($Ln(VehicleTrips)_t$) are estimated to increase by 0.14 percent. Since these regressions serve the sole purpose of purging our subsequent regressions in Sect. 6.2 of potential first- and second-order autocorrelation, rather than explaining variation in vehicle trip counts per se, there is no need to estimate non-linear distributed-lag versions of the models presented in Table 3. We do, however, test for non-linearities in the distributed-lag effects of yellow air day advisories on vehicle trip counts in Sect. 6.2's models. For these and all ensuing regressions, observations for January and February of 2002, December of 2004, and all of 2005 and 2006 were dropped due to missing data—primarily missing values for the variable $VehicleTrips_t$.

6.2 Regression Results

Table 4 presents our main results for Eq. (1) quantifying the relationship exhibited between our two yellow air day advisory measures on the one hand, and $Ln(VehicleTrips)_t$ on the other. The models based on $VehicleTrips_t$ were qualitatively similar to those for $Ln(VehicleTrips)_t$. Hence, we report results solely for the latter specification in this and the next subsection. In concert with the results in Table 4, Eq. (1) takes the specific form,

$$\begin{aligned} Ln(VehicleTrips)_t = \theta_0 &+ \sum_{i=1}^{2} \theta_i Advisory_{t-i-1} + \theta_3 NotSunday_t \\ &+ \sum_{i=4}^{5} \theta_i \left(Advisory_{t-i-4} x NotSunday_{t-i-4}\right) + \theta_6 Holiday_t \\ &+ \sum_{i=7}^{8} \theta_i \left(Advisory_{t-i-7} x Holiday_{t-i-7}\right) + \sum_{i=9}^{14} \theta_i Year_{200i-2} \\ &+ \beta_{15} D.TempDiff_t + \beta_{16} D.Humidity_t + \beta_{17} D.Wind_t \\ &+ \beta_{18} D.HumWind_t + \beta_{19} D.SnowFall_t + \beta_{20} D.SnowDepth_t + \epsilon_t, \end{aligned} \tag{2}$$

where $Ln(VehicleTrips)_t$ and $Holiday_t$ are as defined in Sect. 5, and we specify $Advisory_t$ as a placeholder for $YellowAdvisory_t$ and $YellowAdvisoryPlus1_t$, both of which are also as defined in Sect. 5. The variable $NotSunday_t$ controls for potential effects on travel behavior associated with Cache Valley's dominant faith, the Church of Jesus Christ of Latter Day Saints (LDS) (the valley's population was estimated to be 83 percent LDS in 2010 Cannon 2015). LDS members have historically been encouraged to attend church for three-hour stints each

[32] Residual plots also indicate the existence of white-noise error terms at the respective lags. The plots are available upon request from the author.

Table 3 Controlling potential autocorrelation in $VehicleTrips_t$ and $Ln(VehicleTrips)_t$

Explanatory variables	Dependent variable	
	$VehicleTrips_t$	$Ln(VehicleTrips)_t$
Constant	29,321.52***	10.74***
	(2,114.89)	(0.554)
$VehicleTrips_{t-1}$	0.22***	–
	(0.041)	
$VehicleTrips_{t-2}$	− 0.22***	–
	(0.041)	
$VehicleTrips_{t-3}$	0.07*	–
	(0.042)	
$Ln(VehicleTrips)_{t-1}$	–	0.14***
		(0.040)
$Ln(VehicleTrips)_{t-2}$	–	− 0.18***
		(0.040)
F	15.91***	14.18***
$Adj.R^2$	0.07	0.04
Cumby-Huizinga χ^2	0.051	1.536
Modified Ljung-Box χ^2	0.005	0.129
Durbin χ^2	0.012	0.088
N	583	605

***Significant at 1% level, **Significant at 5% level, *Significant at 10% level

Sunday, which in turn reduces region-wide vehicle usage on Sundays each week.[33] Variable $Year_t$ controls for a potential annual trend in $Ln(VehicleTrips)_t$. Following Caplan and Acharya (2019), the weather variables are first-differenced versions of those defined in Table 2 (denoted by the "D." prefixes).[34] To reduce unnecessary detail in Table 4, both $D.Wind_t$ and $HumWind_t$ are excluded due to their statistical insignificance across both models.

We see from Table 4 that contemporaneous yellow air day advisories have no influence on the valley's vehicle trip counts in either of the $YellowAdvisory_t$ and $YellowAdvisoryPlus1_t$ models.[35] However, one-day lagged advisories do. On average, a lagged yellow air day

[33] To test whether dummying for weekdays (= 1 if a weekday, 0 otherwise) rather than $NotSunday_t$ is more appropriate, we conducted a series of means tests (assuming both paired and unpaired data). The results support what eyeballing the median and mean values of vehicle trip counts for each respective day of the week would suggest. The median and mean values reveal a starkly lower trip count for Sundays (20,030 and 19,553, respectively) vis-a-vis every other day of the week than do Saturdays (32,432 and 31,498, respectively). The means tests reveal strongly negative, statistically significant differences (p-value = 0.000) between mean vehicle trip counts on Sunday versus each day of the week, including Saturday. Saturday's mean trip count is not statistically different than Tuesday's, Wednesday's, and Thursday's. It is statistically larger than Monday's (p-value = 0.032) and statistically lower than Friday's (p-value = 0.000). Thus, there is some statistical justification to report the results for models including the *NotSunday* dummy variable rather than a weekday dummy.

[34] First-differencing also mitigates potential collinearity between the weather variables and one-day lags in our two advisory measures, as well as these measures each interacted with $NotSunday_t$.

[35] The coefficient estimates corresponding to the two lagged $Ln(VehicleTrips)_t$ variables included in these and all ensuing regressions to control for first- and second-order autocorrelation are not shown in order to eliminate unnecessary detail in the tables.

Table 4 Regression results for $Ln(VehicleTrips)_t$

Explanatory variables	Advisory model	
	$YellowAdvisory_t$	$YellowAdvisoryPlus1_t$
Constant	6.75***	6.54***
	(0.436)	(0.441)
$Advisory_t$	− 0.001	0.002
	(0.022)	(0.023)
$Advisory_{t-1}$	0.046*	0.057**
	(0.025)	(0.024)
$NotSunday_t$	0.504***	0.517***
	(0.020)	(0.019)
$Advisory_t \times NotSunday_t$	0.000	− 0.015
	(0.021)	(0.020)
$Advisory_{t-1} \times NotSunday_{t-1}$	− 0.051**	− 0.060**
	(0.025)	(0.025)
$Holiday_t$	− 0.116***	− 0.156***
	(0.040)	(0.053)
$Advisory_t \times Holiday_t$	0.100**	0.115**
	(0.049)	(0.055)
$Advisory_{t-1} \times Holiday_{t-1}$	− 0.032	− 0.007
	(0.036)	(0.026)
D.TempDiff	0.001	0.001*
	(0.001)	(0.0008)
D.Humidity	− 0.003***	− 0.003***
	(0.001)	(0.001)
D.SnowFall	− 0.0002	− 0.0003*
	(0.0001)	(0.0002)
D.SnowDepth	− 0.001***	− 0.001***
	(0.0002)	(0.0002)
$Year2007$	0.028*	0.023
	(0.015)	(0.015)
$Year2008$	− 0.025	− 0.021
	(0.020)	(0.018)
$Year2009$	0.018	0.010
	(0.015)	(0.014)
$Year2010$	0.053**	0.046**
	(0.022)	(0.020)
$Year2011$	0.067***	0.065***
	(0.015)	(0.016)
$Year2012$	0.031**	0.029*
	(0.014)	(0.015)
F	176.46***	180.70***
$Adj.R^2$	0.82	0.83
AIC	− 666.33	− 687.99
BIC	− 578.13	− 599.46
N	342	347

Robust standard errors in parentheses (Huber 1967; White 1980, 1982)

***Significant at 1% level, **Significant at 5% level, *Significant at 10% level advisory induces a subsequent *increase* in the next day's vehicle trips of 4.7 percent from the daily average in the case of the $YellowAdvisory_t$ model and 5.9 percent in the case of the $YellowAdvisoryPlus1_t$ model. This positive effect seems to suggest that at least some individuals are substituting their driving inter-temporally in response to the advisories in order to avoid having to drive more on an impending red air day, and/or are self-protecting themselves from the effects of pollution (although this latter supposition would seem to better explain a positive contemporaneous effect of the advisory).

In contrast, the larger negative coefficient estimates (in magnitude) for the two lagged advisory variables interacted with $NotSunday_{t-1}$ suggest that lagged advisories occurring on days of the week other than Sundays result in net decreases in vehicle trips of 0.5 and 0.3 percent, respectively. The meagerness of these net negative effects is particularly notable given that, on average, roughly 66 percent more vehicle trips are taken in the valley on non-Sundays. Nevertheless, the net negative effects denote the existence of inertia on the part of at least some households, i.e., that these households delay reducing their vehicle use in response to an advisory.

Table 4 also shows that while vehicle trips taken during three-day windows around national holidays decrease by 12.3 percent from average in the case of the $YellowAdvisory_t$ model and 16.9 percent in the case of the $YellowAdvisoryPlus1_t$ model, yellow air day advisories issued during holidays have perverse contemporaneous effects, inducing estimated increases of 10.5 and 12.2 percent in vehical trips from average, respectively. Relative to the advisory's negative lagged non-Sunday effect, this perverse holiday effect is quite large. Further, both models indicate that changes in humidity and snow-depth levels correlate negatively with vehicle trips (we also find a statistically significant negative effect for change in snowfall level in the $YellowAdvisoryPlus1_t$ model, as well as a positive effect for the change in temperature difference). The dummy variables for years 2007—2012 (the second half of our study period) indicate higher numbers of region-wide vehicle trips relative to the first half of the study period for years 2010 – 2012. Thus, the annual dummies control for what appears to be an increasing trend in region-wide vehicle trips during the final three years of the study period. The statistically significant F values indicate that the null hypothesis of jointly insignificant coefficient estimates is rejected for each model, and the sets of regressands in each model explain over 80 percent of total variation in $Ln(VehicleTrips)_t$. Lastly, both the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) indicate that the $YellowAdvisoryPlus1_t$ model explains the data best (Wooldridge 2020).[36]

To test the robustness of the results in Table 4, particularly with respect to the contemporaneous and lagged effects of yellow air day advisories on vehicle trip counts, we ran alternative sets of regressions for the $YellowAdvisory_t$ and $YellowAdvisoryPlus1_t$ models.[37] For one set, we added additional lagged terms to each respective model linearly, i.e.,

[36] We also ran the $YellowAdvisory_t$ and $YellowAdvisoryPlus1_t$ models with *NotSunday* broken out by specific day-of-the-week in order to trace the non-Sunday effect to any specific days. As expected, both models report statistically significant positive coefficients for each day of the week relative to Sundays. Results for the year dummy variables and the set of weather variables are qualitatively similar to those reported in Table 4. Both models also report positive coefficients for contemporaneous advisories issued on holidays and lagged advisories generally, although the lagged coefficient for $YellowAdvisoryPlus1_t$ is statistically insignificant. Advisories interacted with specific (non-Sunday) days of the week are each negative but statistically insignificant in the $YellowAdvisory_t$ model. The interaction term for Tuesday is significant in the $YellowAdvisoryPlus1_t$ model. Again, the AIC and BIC values indicate that the $YellowAdvisoryPlus1_t$ model better explains the data.

[37] These full set of results is available from the author upon request.

$YellowAdvisory_{t-2}$ (and its associated interaction terms) were added to the $YellowAdvisory_t$ model, and $YellowAdvisoryPlus1_{t-2}$ (and its associated interaction terms) were added to the $YellowAdvisoryPlus1_t$ model. In each case, the second-lagged terms were statistically insignificant, and the signs of the remaining variables (including the weather variables and annual dummy values) remained the same. The AIC and BIC goodness-of-fit measures for the $YellowAdvisory_t$ model including the second-lagged terms increased by 3.6% and 6%, respectively, and the same measures for the $YellowAdvisoryPlus1_t$ model increased by 4.9% and 7.5%, respectively, indicating that the models with second-lagged terms performed worse overall than the models in Table 4.

Following (Burkhardt et al. 2019), we also tested for non-linear (quadratic) lagged effects of $YellowAdvisory_t$ and $YellowAdvisoryPlus1_t$ on vehicle trip counts. Similar to the models with second-lagged terms added linearly, the AIC and BIC measures for these models indicate a deterioration in goodness-of-fit. Regarding the $YellowAdvisory_t$ model, the measures increased by 3.6% and 6.1%, respectively, for the quadratic model with two lags of $YellowAdvisory_t$, and by 6.2% and 8.9%, respectively, for the model with three lags.[38] For the $YellowAdvisoryPlus1_t$ model, the AIC and BIC measures for the two-lag model increased by 4.9% and 7.5%, respectively, and by 9.5% and 12.8% for the three-lag model, respectively, again indicating a deterioration in goodness-of-fit.[39]

Lastly, when we dropped the contemporaneous effects from the linear models (and thus estimated the models solely with $YellowAdvisory_{t-1}$ and $YellowAdvisoryPlus1_{t-1}$ and their associated interaction terms, respectively), the coefficient estimates on these lagged terms remained the same and the AIC and BIC measures all decreased. Although the goodness-of-fit measures indicated an improvement in overall fit in these models, we no longer capture the contemporaneous interaction effect between the advisory and the three-day holiday window, which is important given that these holiday windows encompass 13% of all days in our sample (see Table 2). Dropping the lagged effects from the linear models likewise reduced the AIC and BIC measures, but in this case we no longer capture the multiple lagged effects that help explain variation in vehicle trip counts. For these reasons, we believe the models presented in Table 4 best represent the gamut of the advisory's contemporaneous and lagged effects on trip counts.

Technical Appendix B contains coefficient plots of the advisory variables for these different specifications of the model. Figures 6 and 7 display the coefficients corresponding

[38] With respect to the non-linear two-lag model's specific coefficients, estimates of the advisory's contemporaneous and second-lag effects on vehicle trips remain statistically insignificant, while the estimate for the first-lag effect remains positive but now marginally insignificant. The first-lag interaction effect $YellowAdvisory_{t-1} \times NotSunday_{t-1}$ remains negative and statistically significant, while the contemporaneous interaction effect $YellowAdvisory_t \times Holiday_t$ remains positive but marginally insignificant. Results for the non-linear three-lag model are similar. Estimates of the advisory's contemporaneous and second-lag effects on vehicle trips remain statistically insignificant, while the estimate for the first-lag effect is positive but marginally insignificant. Interestingly, the estimate of the third-lag effect is negative and statistically significant. The first-lag interaction effect $YellowAdvisory_{t-1} \times NotSunday_{t-1}$ remains negative and statistically significant, while the third-lag effect is positive and significant. Lastly, none of the contemporaneous and lagged estimates for the $YellowAdvisory_t \times Holiday_t$ interaction term are statistically significant.

[39] Results for two- and three-lag models' coefficients closely mimic those for both the two-lag and three-lag $YellowAdvisory_t$ models, respectively, with a few exceptions. In the two-lag model, the positive contemporaneous effect of $YellowAdvisoryPlus1_t \times Holiday_t$ is now statistically significant. In the three-lag model, both the first- and second-lag advisory effects are positive and significant, while the third-lag effect is negative and significant. Both $YellowAdvisoryPlus1_{t-1}$ x $NotSunday_{t-1}$ and $YellowAdvisoryPlus1_{t-2}$ x $NotSunday_{t-2}$ are negative and significant, and while $YellowAdvisoryPlus1_t \times Holiday_t$ remains positive and significant, $YellowAdvisoryPlus1_{t-2} \times Holiday_{t-2}$ in now negative and significant.

Table 5 Regression results for alert fatigue (dependent variable is $Ln(VehicleTrips)_t$)

Explanatory variables	Advisory model	
	$YellowAdvisory_t$	$YellowAdvisoryPlus1_t$
Constant	6.75***	6.56***
	(0.439)	(0.441)
$Fatigue_t$	− 0.017	–
	(0.029)	
$Fatigue_t \times NotSunday_t$	0.047	–
	(0.029)	
$FatiguePlus1_t$	–	0.058**
		(0.029)
$FatiguePlus1_t \times NotSunday_t$	–	− 0.001
		(0.027)
$Advisory_t$	0.014	− 0.023
	(0.023)	(0.022)
$Advisory_{t-1}$	0.062*	0.026
	(0.033)	(0.032)
$NotSunday_t$	0.504***	0.520***
	(0.020)	(0.019)
$Advisory_t \times NotSunday_t$	− 0.026	− 0.020
	(0.024)	(0.026)
$Advisory_{t-1} \times NotSunday_{t-1}$	− 0.077**	− 0.059**
	(0.031)	(0.028)
$Holiday_t$	− 0.115***	− 0.156***
	(0.040)	(0.053)
$Advisory_t \times Holiday_t$	0.102**	0.112**
	(0.050)	(0.055)
$Advisory_{t-1} \times Holiday_{t-1}$	− 0.035	− 0.002
	(0.036)	(0.025)
F	162.19***	170.48***
$Adj.R^2$	0.82	0.83
AIC	− 664.42	− 688.64
BIC	− 568.55	− 592.41
N	342	347

Robust standard errors in parentheses (Huber 1967; White 1980, 1982)

***Significant at 1% level, **Significant at 5% level, *Significant at 10% level

to the contemporaneous effects of $YellowAdisory_t$ and $YellowAdvisoryPlus1_t$ on vehicle trip counts. We see that the contemporaneous effects of both advisory variables themselves, and their interactions with $NotSunday_t$ are all statistically insignificant ($YellowAdvisoryPlus1_t \times NotSunday_t$ is marginally significant in Model 5, the quadratic model with three-day lag effects). To the contrary, both advisory variables are statistically significant at the five-percent level when interacted with $Holiday_t$ in Models 1 and 2 (Model 2 being the model presented in Table 4). The interaction term is statistically significant at the ten-percent level for each of the remaining models, except for $YellowAdvisory_t \times Holiday_t$ in Model 5.

Figures 8 and 9 in Technical Appendix B similarly display the coefficients corresponding to the one-day lag effects of $YellowAdisory_t$ and $YellowAdvisoryPlus1_t$ on vehicle trip counts. Here, we see that the coefficients for $YellowAdvisoryPlus1_{t-1}$ and $YellowAdvisoryPlus1_{t-1} \times NotSunday_{t-1}$ are each statistically significant at the five-percent level across all model specifications. The coefficients for $YellowAdvisoryPlus1_{t-1} \times Holiday_{t-1}$ are each statistically insignificant across all specifications. The only coefficient for the $YellowAdvisory_{t-1}$ model that is statistically significant at the five-percent level is the coefficient associated with $YellowAdvisory1_{t-1} \times NotSunday_{t-1}$ in Model 2. This coefficient is statistically significant at the ten-percent level in each of the remaining model specifications. The coefficient for $YellowAdvisory_{t-1}$ is likewise statistically significant at the ten-percent level in Models 1, 2, and 5, and the interaction term $YellowAdvisory_{t-1} \times Holiday_{t-1}$ is not statistically significant in any of the model specifications.

Following (Zivin and Neidell's 2009; Saberian et al. 2017), we also tested for the effects of possible intra-seasonal alert fatigue in our models (again, by "intra-seasonal alert fatique" we mean the occurrence of fatigue across yellow air days within a given season). Results are presented in Table 5. Since the coefficient estimates for the differenced weather variables and yearly dummies are qualitatively similar to those reported in Table 4, we exclude them from the table. As Table 5 indicates, we find no evidence of intra-seasonal fatigue in the $YelloAdvisory_t$ model. Although both are larger in magnitude, the negative coefficient for $YellowAdvisory_{t-1} \times NotSunday_{t-1}$ continues to offset the positive coefficient for $YelloAdvisory_{t-1}$ in this model. In contrast, we do find potential intra-seasonal alert fatigue in the $YelloAdvisoryPlus1_t$ model at a high enough level to almost completely offset the negative advisory effect on non-Sundays (note that the coefficient estimate for $YelloAdvisoryPlus1_{t-1}$ del).

It is important to note that multicollinearity is likely affecting these results. Correlation coefficients for $Fatigue_t$, on the one hand, and $YellowAdvisory_t$ and $YellowAdvisory_{t-1}$ on the other, exceed 0.7. They exceed 0.87 in the case of $FatiguePlus1_t$ versus $YellowAdvisoryPlus1_t$ and $YellowAdvisoryPlus1_{t-1}$. Further, Variance Inflation Factors (VIFs) for $Fatigue_t$ and $Fatigue_t \times NotSunday$ in Table 5 are 8.82 and 6.97, well above the next highest value of 2.56 for *SnowDepth*. The VIFs for $FatiguePlus1_t$ and $FatiguePlus1_t \times NotSunday$ are 18.16 and 16.88, likewise well above the next highest value of 2.76 for *NotSunday*. Hence, our results for intra-seasonal alert fatigue should be interpreted with caution. We tested both models for inter-seasonal fatigue in more disaggregated specifications by interacting $YellowAdvisory_{t-1}$ and $YellowAdvisoryPlus1_{t-1}$, respectively, with annual dummy variables. Coefficient estimates for these interaction terms were consistently statistically insignificant, indicating no evidence of this type of fatigue.

To summarize our findings in this section, regression results presented in Table 4 suggest, on average, that one-day lagged advisories have an overall small positive impact on vehicle trips. We are not necessarily surprised by this result, since Tribbey et al. (2013) likewise found a perverse advisory effect for Utah's Wasatch Front region. Further, as pointed out in Sect. 4 (and explored further in Appendix A), when a large-enough number of individuals respond perversely to the advisory by increasing their vehicle usage on yellow air days e.g., to provide what they perceive as greater protection from poor air quality than walking or using mass transit, or simply to reduce their need for travel during an ensuing red air day episode, we should expect to see a perverse advisory effect. Nevertheless, we find that this positive impact is outweighed by the negative impact advisories have when they are issued on weekdays and Saturdays, resulting in small negative impacts on vehicle trips of between 0.3 and 0.5 percent. We find questionable evidence for intra-seasonal alert fatigue and no evidence of inter-seasonal fatigue.

Table 6 Explaining variation in $YellowAdvisory_t$ and $YellowAdvisoryPlus1_t$

Explanatory variables	Dependent variable	
	$YellowAdvisory_t$	$YellowAdvisoryPlus1_t$
Constant	0.189***	0.118***
	(0.025)	(0.030)
$D.Ln(VehicleTrips)_t$	0.018	− 0.066
	(0.083)	(0.068)
$D.TempDiff$	0.004	0.004
	(0.003)	(0.003)
$D.Humidity$	0.008**	0.005*
	(0.004)	(0.003)
$D.Wind$	0.089*	0.018
	(0.047)	(0.041)
$D.HumWind$	− 0.001**	− 0.0004
	(0.0005)	(0.0005)
$D.SnowFall$	0.000	− 0.002***
	(0.001)	(0.0006)
$D.SnowDepth$	− 0.002***	0.001*
	(0.0007)	(0.0007)
$F(8, 369)$	13.77***	85.35***
$Adj.R^2$	0.20	0.58
AIC	390.58	199.59
BIC	425.53	241.58
Durbin χ^2	2.13	1.17
Wu-Hausman F	2.07	1.13
Wooldridge robust χ^2 (endogeneity)	1.58	0.98
Montiel and Wang robust F	4.37	1.80
Wooldridge robust χ^2 (validity)	7.03	5.14
Sargan χ^2	9.60*	8.33
Basmann χ^2	9.40*	8.13
N	359	336

***Significant at 1% level, **Significant at 5% level, *Significant at 10% level

6.3 Potential Endogeneity

Because of their exogeneity with respect to error term disturbances in our models and likely correlation with our two yellow air day advisory measures, we investigated the extent to which our weather variables may be confounding the relationship between the advisories and region-wide vehicle trips found in Sect. 6.2. Ultimately, based upon Durbin χ^2, Wu-Hausman F, and Wooldridge robust χ^2 tests, we were unable to reject the null hypotheses that our *Advisory* measures—$YellowAdvisory_{t-1}$ and $YellowAdvisoryPlus1_{t-1}$ (along with $YellowAdvisory_{t-1} \times NotSunday_{t-1}$ and $YellowAdvisoryPlus1_{t-1} \times NotSunday_{t-1}$)—behave as exogenous explanatory variables in the models presented in Tables 4 and 5 (Durbin 1954;

Wu 1973; Hausman 1978; Wooldridge 1995).[40] Consistent with these results, Pflueger and Wang (2015) robust F tests indicate that the set of first-differenced weather variables are weak instruments (IVs). Results concerning the validity of the weather variables as instruments are mixed. While each of Wooldridge's, Sargan's and Basmann's respective χ^2 tests indicate that the weather variables are valid IVs in the $YellowAdvisoryPlus1_t$ model, i.e., that they are not over-identified, the Sargan and Basmann tests marginally indicate invalidity in the $YellowAdvisory_t$ model (Wooldridge 1995; Sargan 1958; Basmann 1960). These results are compiled in Table 6, where we also include coefficient estimates for the first-differenced weather variables from first-stage, ordinary least squares (OLS) regressions explaining variation in $YellowAdvisory_t$ and $YellowAdvisoryPlus1_t$, respectively (coefficient estimates and statistics testing for endogeneity, IV weakness, and IV validity from regressions explaining variation in $YellowAdvisory_t$ and $YellowAdvisoryPlus1_t$ each interacted with $NotSunday_t$ are qualitatively similar).[41] Although not an instrument itself, first-differenced vehicle trips are also included in these regressions due the variable's theoretical correlation with $PM_{12.5}$ concentrations, which in turn drive the issuance of an advisory.[42]

We see that, on average, the issuance of a yellow air day advisory is positively correlated with a change in *D.Humidity* across both models. This result is similar to that reported in Caplan and Acharya (2019) for the relationship between $PM_{2.5}$ concentrations and *D.Humidity*. In the $YellowAdvisory_t$ model, the estimates for *D.Humwind* and *D.SnowDepth* are negative, and the estimate for *D.Wind* is positive, while the estimate for *D.SnowFall* is negative and that for *D.SnowDepth* is positive in the $YellowAdvisoryPlus1_t$ model. These results for the $YellowAdvisoryPlus1_t$ model comport with the atmospheric science described in Moscardini and Caplan (2017) Interestingly, the coefficient estimates for $D.Ln(VehicleTrips)_t$ are statistically insignificant in each model. Similar to results in Tables 4 and 5, the AIC and BIC measures point to the $YellowAdvisoryPlus1_t$ model as explaining the data better. We also notice an adjusted R^2 value for the $YellowAdvisoryPlus1_t$ model that is more than twice the value for the $YellowAdvisory_t$ model.

As mentioned previously, the Durbin, Wu-Hausman, and Wooldridge tests do not reject the null hypothesis that the weather variables are exogenous, and thus the coefficient estimates presented in Table 4 are unbiased and consistent. The Montiel and Wang F values of 4.37 and 1.80 are well-below their respective critical value of 24.42 and 22.23, indicating that the weather variables are weak instruments in the $YellowAdvisory_t$ and $YellowAdvisoryPlus1_t$ models, respectively (Pflueger & Wang 2015). Statistical

[40] The Wooldridge (1995) test tolerates heteroskedastic and autocorrelated errors, while Durbin's and Wu-Hausman's do not (Baum et al. 2007; Wooldridge 1995).

[41] The coefficient estimates are obtained from a model of the form,

$$Advisory_t = \beta_0 + \beta_1 D.VehicleTrips_t + \beta_2 D.TempDiff_t + \beta_3 D.Humidity_t + \beta_4 D.Wind_t \\ + \beta_5 D.HumWind_t + \beta_6 D.SnowFall_t + \beta_7 D.SnowDepth_t + \mu_t.$$

where again $Advisory_t$ serves as a placeholder for $YellowAdvisory_t$ and $YellowAdvisoryPlus1_t$. Also included as regressors in these respective models (but not shown) are the first lag of $YellowAdvisory_t$ and first three lags of $YellowAdvisoryPlus1_t$, which were sufficient to satisfy the null hypotheses of no autocorrelation in the residuals.

[42] We also ran a logistic regression for this model, which assumes that the probability of an advisory being issued is a non-linear combination of the regressors. The results, which are available from the author upon request, were qualitatively similar to those from the linear probability model. This similarity between models was anticipated (c.f., Hellevik 2007; Long 1997). We therefore report the estimates from the linear probability model due to their ease of interpretation.

insignificance of the Wooldridge's, Sargan's and Basmann's χ^2 each indicate that the set of weather variables serve as valid instruments. Note that the Sargan and Basmann values for the $YellowAdvisory_t$ indicate invalidity, but only at marginal significance levels.

7 Summary and Conclusions

We have tested the hypothesis that yellow air day advisories issued by Utah's Department of Environmental Quality resulted in subsequent reductions in vehicle trips taken during northern Utah's winter-inversion seasons in the early 2000 s. During this period, when $PM_{2.5}$ concentrations (derived mainly from vehicle emissions) rose above 15 μg/m^3, on their way to the 35 μg/m^3 national-standard threshold for red air days, the study area's residents were informed via several different media sources that the region was experiencing a yellow air day, and urged to reduce their vehicle usage during the day. Our results suggest that yellow air day advisories provided at best weak, at worst perverse, incentives for reducing vehicle usage on yellow air days and ultimately for mitigating the occurrence of red air day episodes during northern Utah's winter inversion season. Because these episodes were often dramatic in their scope, our study area and period of analysis have provided an opportune setting within which to measure the effectiveness of an air quality alert program.

In specific, we have found weak evidence of an overall positive relationship between yellow air day advisories and region-wide vehicle trips. However, this perverse impact is outweighed by a larger negative impact in magnitude when the advisories are issued on weekdays and Saturdays, i.e., non-Sundays. As a result, advisories issued on non-Sundays (i.e., days of the week during which members of the study area's dominant religious faith are not observing their faith in local churches) induce a small negative impact on vehicle trips on average. Further, we have found mixed evidence regarding intra-seasonal alert fatigue (i.e., fatique within any given season) and no evidence of inter-seasonal fatigue (i.e., the trend in the average intra-seasonal fatigue over time). All else equal, humidity and snowdepth exhibit negative effects on vehicle trips. Tests for endogeneity of yellow air day advisories in explaining variation in vehicle trips suggest that from a statistical standpoint the advisories can be considered exogenous, issued by the regulatory authorities independently of the weather conditions and region-wide vehicle usage that contribute to elevated $PM_{2.5}$ concentration levels.

As mentioned in the Introduction section, yellow air day advisories are an example of a "soft" environmental policy, which relies on educating the public about an existing externality and encouraging its mitigation through voluntary adjustments in behavior, without providing an economic incentive to do so. Our findings echo those of previous studies in that these types of policies typically provide relatively weak incentives for indviduals to adjust their behaviors in ways that improve social welfare. In some cases the incentives may provoke perverse behaviors that instead diminish welfare. This said, scope still remains to better understand how different types of individuals respond to the issuance of air quality alerts, which in turn requires more granualar data than has heretofore been available to aid this understanding. The analysis conducted in this paper serves as a case in point. Its main limitations center on the constraints of the data—the lack of both air quality and traffic monitors in the existing dataset, and the general unavailability of individual-level data with which to directly test the conditions identified in our theoretical model. As importantly, granular data would enable an investigation of the role that behavioral determinants such as inertia play in governing individuals' responses to air quality advisories, as well as the extent to which strategic considerations such as inter-temporal substitution and self-protection impact these behaviors.

Technical Appendix

Mathematical Derivations for the Theoretical Model in Sect. 4

Consider myopic individual (or household) i in a given time period t, who derives benefit from making vehicle trips (e.g., commuting to work, shopping, traveling to recreation sites, etc.), but also incurs costs associated with the aggregate amount of trips taken in i's community or region during time t (to which individual i contributes atomistically), e.g., in the form of elevated $PM_{2.5}$ concentrations.[43] We specify i's benefit function in period t, u_{it}, as,

$$u_{it} = u_{it}\left(z_{it}\left(q_{it}\right), x_{it}; \beta_i^z\left(\theta_t\right), \beta_i^x\left(\theta_t\right)\right), i = 1, \ldots, I, t = 1, \ldots, T, \tag{A.1}$$

where z_{it} represents the amount of a composite good obtained as a function of vehicle usage, denoted as q_{it}, and x_{it} denotes the composite amount of all other goods not obtained via vehicle usage, i.e., household-produced goods. Information-conditioned parameters $0 < \beta_i^z(\theta_t) < 1$ and $0 < \beta_i^x(\theta_t) < 1$, respectively, parameterize z_{it} and x_{it} in function u_{it} such that $\beta_i^x(\theta_t) \equiv 1 - \beta_i^z(\theta_t)$, and θ_t is an information parameter representing issuance of a yellow air day advisory when $PM_{2.5}$ concentrations rise above the 15 μ/m^3 threshold.[44] For ease of exposition and without loss of generality, we assume all variables z_{it}, q_{it}, and x_{it}, and parameters $\beta_i^z(\theta_t)$, $\beta_i^x(\theta_t)$, and θ_t are measured continuously. In particular, increases in θ_t imply that the region's individuals are being supplied with more information (via an advisory) about the onset of a yellow air day.

In addition to standard curvature conditions specified for function u_{it}, i.e., $\partial u_{it}/\partial z_{it} > 0$, $\partial^2 u_{it}/\partial z_{it}^2 \leq 0$, $\partial u_{it}/\partial x_{it} > 0$, $\partial^2 u_{it}/\partial x_{it}^2 \leq 0$, and $\partial^2 u_{it}/\partial z_{it}\partial x_{it} = \partial^2 u_{it}/\partial x_{it}\partial z_{it} > 0$, and for function z_{it}, i.e., $\partial z_{it}/\partial q_{it} > 0$ and $\partial^2 z_{it}/\partial q_{it}^2 \leq 0$, we specify a key curvature condition for the ensuing analysis: $\partial \beta_i^z/\partial \theta_t > 0$. This condition indicates that, all else equal, the marginal value of z_{it} (relative to that of x_{it}) increases with the issuance of a yellow air day advisory, i.e., $\left(\partial^2 u_{it}/\partial z_{it}\partial \beta_i^z\right)\left(\partial \beta_i^z/\partial \theta_t\right) > 0$. Note that identity $\beta_i^x(\theta_t) \equiv 1 - \beta_i^z(\theta_t)$ in turn implies $\left(\partial^2 u_{it}/\partial x_{it}\partial \beta_i^z\right)\left(\partial \beta_i^z/\partial \theta_t\right) < 0$. These conditions underlie the intuition expressed in Sect. 4 that, given the issuance of a yellow air day advisory, an individual derives added benefit from any given vehicle trip, since making the trip using the next-best alternative, e.g., walking or riding a bus, involves greater exposure to the yellow air. Furthermore, given that a yellow air day advisory signals the onset of a subsequent red air day episode, individuals could perceive added benefit associated with intertemporally substituting vehicle trips forward in time to reduce the need for making future vehicle trips during the episode itself.

Individual i forms an expectation over the health and environmental damages s/he suffers with respect to aggregate $PM_{2.5}$ concentrations accumulated in the atmosphere during period t. We represent these expected damages with function $E\left[d_{it}\right]$,

$$E\left[d_{it}\right] = \bar{d}_{it}\left(Q_t; \alpha_i\left(\theta_t\right)\right), i = 1, \ldots, I, t = 1, \ldots, T, \tag{A.2}$$

[43] As we will see below, assuming myopic decision-making among individuals simplifies our model without compromising its relevance to the problem at hand.

[44] Assuming $\beta_i^x(\theta_t) \equiv 1 - \beta_i^z(\theta_t)$ is a convenient way to embed the assumption that an increase in β_i^z in response to an increase in θ_t increases the value of an additional unit of z_{it} relative to x_{it}.

where region-wide vehicle trips $Q_t = \sum_i q_{it}$, $\alpha_i(\theta_t)$ is an information-conditioned parameter distinct from β_i^z, and standard curvature conditions are specified for expected damage function $E[d_{it}]$, i.e., $\partial\bar{d}_{it}/\partial Q_t > 0$, $\partial^2\bar{d}_{it}/\partial Q_t^2 \geq 0$, and $\partial\bar{d}_{it}/\partial\alpha_i > 0$. Similar to the relationship between β_i^z and θ_t we assume $\partial\alpha_i/\partial\theta_t > 0$, which in turn indicates that, all else equal, perceived marginal damages suffered by each individual i in period t increase in response to the issuance of a yellow air day advisory, i.e., $\left(\partial^2\bar{d}_{it}/\partial Q_t\partial\alpha_i\right)\left(\partial\alpha_i/\partial\theta_t\right) > 0$. This condition accounts for an overall increase in expected marginal damages to an individual's health due to the issuance of a yellow air day advisory.

The individual's budget constraint in any given period t is given by,

$$w_{it} = p_t^z z_{it}(q_{it}) + p_t^q q_{it} + x_{it}, i = 1, \ldots, I, t = 1, \ldots, T, \tag{A.3}$$

where w_{it} represents individual i's given wealth level in period t, and per-unit prices p_t^z and p_t^q are taken as given for good z_{it} and vehicle trips q_{it}, respectively (the price of x_{it} is normalized to one).[45]

Next, we consider three cases reflecting three stylized types of individuals comprising the region.[46] Case 1 pertains to individuals who completely ignore the expected damages associated with region-wide vehicle trips in each period t, Q_t, even though $\partial\alpha_i/\partial\theta_t \neq 0$, i.e., even though they are informed about elevated $PM_2.5$ concentrations via yellow air day advisories. Case 2 pertains to individuals who account solely for the expected damages that they personally incur in period t, i.e., individual i dissects function $\bar{d}_{it}$ as $\bar{d}_{it}\left(q_{it} + Q_{-it};\alpha_i(\theta_t)\right)$, where Q_{-it} represents the aggregate trip count across all individuals in the region except individual i, and thereby accounts soley for the q_{it} in $\bar{d}_{it}(\cdot)$ in his decision problem. Case 3 pertains to altruistic individuals who account not only for the expected damages that their vehicle trips impose on themselves and all other individuals in the region, but also the expected benefits that all other individuals obtain as a result of increasing their vehicle trips in response to a yellow air day advisory, i.e., these individuals are "pure altruists" (c.f., Antweiler 2015; Ottoni-Wilhelm et al. 2017).

Case 1

An individual i who fits the description of Case 1 myopically chooses q_{it} and x_{it} to solve the following Lagrangian in each period t,

$$\begin{aligned} &u_{it}\left(z_{it}\left(q_{it}\right), x_{it};\beta_i^z\left(\theta_t\right), \beta_i^x\left(\theta_t\right)\right) - \bar{d}_{it}\left(Q_t;\alpha_i\left(\theta_t\right)\right) \\ &+ \lambda_{it}\left(w_{it} - p_t^z z_{it}(q_{it}) - p_t^q q_{it} - x_{it}\right) \end{aligned}$$

where $\lambda_{it} > 0$ represents i's period t Lagrangian multiplier. First-order conditions for this problem result in,

$$\frac{\partial u_{it}}{\partial z_{it}}\frac{\partial z_{it}}{\partial q_{it}} = \frac{\partial u_{it}}{\partial x_{it}}\left(p_t^z\frac{\partial z_{it}}{\partial q_{it}} + p_t^q\right), i = 1, \ldots, I, t = 1, \ldots, T. \tag{A.4}$$

The left-hand side of (A.4) represents the marginal benefit of an additional vehicle trip and the right-hand side represents the corresponding marginal cost. Together with (A.3)

[45] Because individuals are assumed myopic in their decision-making, we could just as well aggregate the individual's budget constraint over all periods t, i.e., express the constraint instead as $\sum_t w_{it} = \sum_t \left(p_t^z z_{it}(q_{it}) + p_t^q q_{it} + x_{it}\right)$.

[46] Again, we acknowledge that in reality the set of individuals in any given region are likely a convex combination of these three types.

and function $z_{it}(q_{it})$, Eq. (A.4) solves for $q_{it}^* = q_{it}\left(w_{it}, p_t^z, p_t^q, \alpha_i(\theta_t), \beta_i^z(\theta_t), \beta_i^x(\theta_t)\right)$, $z_{it}^* = z_{it}\left(w_{it}, p_t^z, p_t^q, \alpha_i(\theta_t), \beta_i^z(\theta_t), \beta_i^x(\theta_t)\right)$, and $x_{it}^* = x_{it}\left(w_{it}, p_t^z, p_t^q, \alpha_i(\theta_t), \beta_i^z(\theta_t), \beta_i^x(\theta_t)\right)$.

Substituting q_{it}^*, z_{it}^*, and x_{it}^* into (A.4) and differentiating allows us to solve for the marginal effect of a change in θ_t on q_{it}^* relative to x_{it}^*.[47] The expression for this marginal effect is,

$$\frac{\partial q_{it}^*}{\partial \theta_t} = -\frac{\Psi_1}{\Omega_1} > 0, i = 1, \ldots, I, t = 1, \ldots, T, \tag{A.5}$$

where

$$\Psi_1 = \frac{\partial^2 u_{it}}{\partial z_{it}^* \partial \beta_i^z} \frac{\partial \beta_i^z}{\partial \theta_t} \frac{\partial z_{it}^*}{\partial q_{it}^*} - \frac{\partial^2 u_{it}}{\partial x_{it}^* \partial \beta_i^z} \frac{\partial \beta_i^z}{\partial \theta_t} \left(p_t^z \frac{\partial z_{it}^*}{\partial q_{it}^*} + p_t^q \right) > 0 \tag{A.6}$$

and

$$\Omega_1 = \frac{\partial^2 u_{it}}{\partial z_{it}^{*2}} \left(\frac{\partial z_{it}^*}{\partial q_{it}^*} \right)^2 + \frac{\partial u_{it}}{\partial z_{it}^*} \frac{\partial^2 z_{it}^*}{\partial q_{it}^{*2}} - \frac{\partial^2 u_{it}}{\partial x_{it}^* \partial z_{it}^*} \frac{\partial z_{it}^*}{\partial q_{it}^*} \left(p_t^z \frac{\partial z_{it}^*}{\partial q_{it}^*} + p_t^q \right) - \frac{\partial u_{it}}{\partial x_{it}^*} p_t^z \frac{\partial^2 u_{it}}{\partial z_{it}^{*2}} < 0. \tag{A.7}$$

Note that $\Psi_1 > 0$ in (A.6) follows directly from the curvature conditions specified above for $u_{it}(\cdot)$. To see why $\Omega_1 < 0$ in (A.7), first rewrite (A.4) as,

$$\frac{\partial u_{it}}{\partial z_{it}} - \frac{\partial u_{it}}{\partial x_{it}} p_t^z = \frac{p_t^q}{\frac{\partial z_{it}}{\partial q_{it}}} > 0, i = 1, \ldots, I, t = 1, \ldots, T. \tag{A.8}$$

Now note from (A.7) that $\Omega_1 < 0$ when

$$\left(\frac{\partial u_{it}}{\partial z_{it}^*} - \frac{\partial u_{it}}{\partial x_{it}^*} p_t^z \right) \frac{\partial^2 z_{it}^*}{\partial q_{it}^{*2}} < 0 \Longrightarrow \frac{\partial u_{it}}{\partial z_{it}^*} - \frac{\partial u_{it}}{\partial x_{it}^*} p_t^z > 0,$$

which coincides with the result in (A.8). Thus, $\Omega_1 < 0$.

Clearly, the result in (A.5) is driven by the assumptions underlying our problem, in particular the separability of u_{it} and $\bar{d}_{it}$ in individual i's Lagrangian function. In a more general specification of i's welfare, e.g., $u_{it}\left(z_{it}(q_{it}), x_{it}; Q_t, \beta_i^z(\theta_t), \beta_i^x(\theta_t), \beta_i^Q(\theta_t)\right)$, where $\beta_i^Q(\theta_t) < 0$ parameterizes Q_t in u_{it}, we cannot definitively sign $\partial q_{it}^* / \partial \theta_t$ without specifying additional assumptions governing the tradeoff between z_{it} and x_{it} in response to an increase in θ_t. As is, our result for Case 1 depicts the predilection of certain types of individuals who weight the private benefit associated with their vehicle trips during yellow air days more than the correlative public damages to which their trips contribute (which, according to our particular welfare specification, are completely ignored in this case).

Case 2

An individual i who fits the description of Case 2 myopically chooses q_{it} and x_{it} to solve the following Lagrangian in each period t,

[47] Solving for the relative change in q_{it}^* is sufficient for the analysis at hand. Deriving the absolute change in q_{it}^* in response to a change in θ_t requires simultaneous differentiation of (A.3) and (A.4).

$$u_{it}\left(z_{it}\left(q_{it}\right), x_{it}; \beta_i^z\left(\theta_t\right), \beta_i^x\left(\theta_t\right)\right) - \bar{d}_{it}\left(q_{it} + Q_{-it}; \alpha_i\left(\theta_t\right)\right)$$
$$+ \gamma_{it}\left(w_{it} - p_t^z z_{it}(q_{it}) - p_t^q q_{it} - x_{it}\right)$$

where $\gamma_{it} > 0$ represents i's period t Lagrangian multiplier. First-order conditions for this problem result in,

$$\frac{\partial u_{it}}{\partial z_{it}} \frac{\partial z_{it}}{\partial q_{it}} = \frac{\partial u_{it}}{\partial x_{it}} \left(p_t^z \frac{\partial z_{it}}{\partial q_{it}} + p_t^q \right) + \frac{\partial \bar{d}_{it}}{\partial Q_t}, i = 1, \ldots, I, t = 1, \ldots, T. \tag{A.9}$$

As with Case 1, the left-hand side of (A.9) represents the marginal benefit of an additional vehicle trip and the right-hand side represents the corresponding marginal cost, which in this case now accounts for the individual's expected marginal damage associated with an additional vehicle trip, $\partial \bar{d}_{it} / \partial Q_t$. Similar to Case 1, Eq. (A.3), function $z_{it}\left(q_{it}\right)$, and optimality condition (A.9) solve for q_{it}^{**}, z_{it}^{**}, and x_{it}^{**}, which when substituted back into (A.9) and differentiated allows us to solve for the marginal effect of a change in θ_t on q_{it}^{**} relative to x_{it}^{**}. The expression for this marginal effect is,

$$\frac{\partial q_{it}^{**}}{\partial \theta_t} = -\frac{\Psi_2}{\Omega_2}, i = 1, \ldots, I, t = 1, \ldots, T, \tag{A.10}$$

where

$$\Psi_2 = \Psi_1 - \frac{\partial^2 \bar{d}_{it}}{\partial Q_t^{**} \partial \alpha_i} \frac{\partial \alpha_i}{\partial \theta_t} \tag{A.11}$$

and

$$\Omega_2 = \Omega_1 - \frac{\partial^2 \bar{d}_{it}}{\partial Q_t^{**2}} < 0. \tag{A.12}$$

Comparing (A.10)–(A.12) with (A.5)–(A.7) we see that,

$$\frac{\partial q_{it}^{**}}{\partial \theta_t} < \frac{\partial q_{it}^{*}}{\partial \theta_t}. \tag{A.13}$$

Further, we find that,

$$\frac{\partial q_{it}^{**}}{\partial \theta_t} \gtrless 0 \text{ as } \frac{\partial^2 \bar{d}_{it}}{\partial Q_t^{**} \partial \alpha_i} \lessgtr \frac{\partial^2 u_{it}}{\partial z_{it}^{**} \partial \beta_i^z} \frac{\partial \beta_i^z}{\partial \theta_t} \frac{\partial z_{it}^{**}}{\partial q_{it}^{**}} - \frac{\partial^2 u_{it}}{\partial x_{it}^{**} \partial \beta_i^z} \frac{\partial \beta_i^z}{\partial \theta_t} \left(p_t^z \frac{\partial z_{it}^{**}}{\partial q_{it}^{**}} + p_t^q \right), \tag{A.14}$$

where the term $\frac{\partial^2 \bar{d}_{it}}{\partial Q_t^{**} \partial \alpha_i}$ represents the change in individual i's perceived marginal damage (from vehicle trips) associated with the change in information-conditioned parameter α_i as a result of the issuance of a yellow air day advisory (i.e., change in θ_t). The term $\frac{\partial^2 u_{it}}{\partial z_{it}^{**} \partial \beta_i^z} \frac{\partial \beta_i^z}{\partial \theta_t} \frac{\partial z_{it}^{**}}{\partial q_{it}^{**}} - \frac{\partial^2 u_{it}}{\partial x_{it}^{**} \partial \beta_i^z} \frac{\partial \beta_i^z}{\partial \theta_t} \left(p_t^z \frac{\partial z_{it}^{**}}{\partial q_{it}^{**}} + p_t^q \right)$ represents the corresponding change in individual i's marginal benefit associated with the change in information-conditioned parameter β_i^z. Our result for Case 2 therefore depicts a different type of individual than Case 1. In this case, the individual explicitly accounts for the (private effect of) the public damage to which his trips contribute, which leads to a lower increase in vehicle usage in response to a yellow air day advisory than for Case 1 individuals, all else equal. As Eqs. (A.13) and (A.14) demonstrate, Case 2 individuals may choose to decrease the number of their vehicle trips in response to a yellow air day advisory.

Case 3

An individual i who fits the description of Case 3 myopically chooses q_{it} and x_{it} to solve the following Lagrangian in each period t,

$$
\begin{aligned}
&u_{it}\left(z_{it}\left(q_{it}\right), x_{it}, \sum_{j\neq i} \bar{u}_{jt}\left(z_{jt}\left(q_{jt}\right), x_{jt}; \beta_j^z\left(\theta_t\right), \beta_j^x\left(\theta_t\right)\right); \beta_i^z\left(\theta_t\right), \beta_i^x\left(\theta_t\right)\right) \\
&\quad - \bar{d}_{it}\left(q_{it} + Q_{-it}; \alpha_i\left(\theta_t\right)\right) \\
&\quad - \sum_{j\neq i} \bar{d}_{jt}\left(q_{it} + Q_{-it}; \alpha_j\left(\theta_t\right)\right) \\
&\quad + \phi_{it}\left(w_{it} - p_t^z z_{it}(q_{it}) - p_t^q q_{it} - x_{it}\right)
\end{aligned}
$$

where $\phi_{it} > 0$ represents i's period t Lagrangian multiplier. An altruistic individual i therefore fully accounts for the effect of a yellow air day advisory on the expected benefits that all other individuals $j,\ j \neq i, i, j = 1, \ldots, I$ obtain from their vehicle usage, represented by inclusion of the term $\sum_{j\neq i} \bar{u}_{jt}\left(z_{jt}\left(q_{jt}\right), x_{jt}; \beta_j^z\left(\theta_t\right), \beta_j^x\left(\theta_t\right)\right)$ in i's own utility function u_{it}. Altruistic individual i also fully accounts for the effects of both the yellow air day advisory and her vehicle usage on the expected damages incurred by all other individuals, represented by inclusion of the separate term $\sum_{j\neq i} \bar{d}_{jt}\left(q_{it} + Q_{-it}; \alpha_j\left(\theta_t\right)\right)$ in her Lagrangian function. First-order conditions for this problem result in,

$$
\frac{\partial u_{it}}{\partial z_{it}} \frac{\partial z_{it}}{\partial q_{it}} = \frac{\partial u_{it}}{\partial x_{it}} \left(p_t^z \frac{\partial z_{it}}{\partial q_{it}} + p_t^q\right) + \frac{\partial \bar{d}_{it}}{\partial Q_t} + \sum_{j\neq i} \frac{\partial \bar{d}_{jt}}{\partial Q_t}, i, j = 1, \ldots, I, t = 1, \ldots, T. \tag{A.15}
$$

where $\partial \bar{d}_{jt}/\partial Q_t > 0 \forall j \neq i$, i.e., individual i perceives all other members of the region as suffering positive marginal damages from additional vehicle trips made within the region.

As with Cases 1 and 2, the left-hand side of (A.15) represents the marginal benefit of an additional vehicle trip and the right-hand side represents the corresponding marginal cost, which in this case now accounts for i's expected private marginal damage associated with taking an additional vehicle trip as well as i's expectation of the impact that that additional vehicle trip has on the damages incurred by all other individuals in the region, represented by the term $\sum_{j\neq i} \frac{\partial \bar{d}_{jt}}{\partial Q_t}$. Similar to Cases 1 and 2, Eq. (A.3), function $z_{it}\left(q_{it}\right)$, and optimality condition (A.15) solve for q_{it}^{***}, z_{it}^{***}, and x_{it}^{***}, which when substituted back into (A.15) and differentiated allows us to solve for the marginal effect of a change in θ_t on q_{it}^{***} relative to x_{it}^{***}. The expression for this marginal effect is,

$$
\frac{\partial q_{it}^{***}}{\partial \theta_t} = -\frac{\Psi_3}{\Omega_3}, i = 1, \ldots, I, t = 1, \ldots, T, \tag{A.16}
$$

where

$$
\begin{aligned}
\Psi_3 =& \Psi_2 + \sum_{j\neq i} \left(\frac{\partial^2 u_{it}}{\partial z_{it}^{***} \partial \bar{u}_{jt}} \frac{\partial \bar{u}_{jt}}{\partial \beta_j^z} \frac{\partial \beta_j^z}{\partial \theta_t} \frac{\partial z_{it}^{***}}{\partial q_{it}^{***}} \right. \\
&\left. - \frac{\partial^2 u_{it}}{\partial x_{it}^{***} \partial \bar{u}_{jt}} \frac{\partial \bar{u}_{jt}}{\partial \beta_j^z} \frac{\partial \beta_j^z}{\partial \theta_t} \left(p_t^z \frac{\partial z_{it}^{***}}{\partial q_{it}^{***}} + p_t^q\right) - \frac{\partial^2 \bar{d}_{jt}}{\partial Q_t^{***} \partial \alpha_j} \frac{\partial \alpha_j}{\partial \theta_t} \right)
\end{aligned} \tag{A.17}
$$

and

$$\Omega_3 = \Omega_2 - \sum_{j \neq i} \frac{\partial^2 \bar{d}_{jt}}{\partial Q_t^{***2}} < 0. \tag{A.18}$$

We note that $\frac{\partial^2 u_{it}}{\partial z_{it}^{***} \partial \bar{u}_{jt}} > 0$ and $\frac{\partial^2 u_{it}}{\partial x_{it}^{***} \partial \bar{u}_{jt}} > 0$ across all individuals j as a reflection of individual i's altruism, and $\frac{\partial \bar{u}_{jt}}{\partial \beta_j^z} \frac{\partial \beta_j^z}{\partial \theta_t} \leq 0$, which reflects the fact that before any given yellow air day advisory individuals j are assumed to have optimally set their respective $\beta_j^z(\theta_t)$ parameter values.

Comparing (A.10)–(A.12) with (A.16)–(A.18) leads to a sufficient condition governing the relationship between $\partial q_{it}^{***}/\partial \theta_t$ and $\partial q_{it}^{**}/\partial \theta_t$ across all $i, j = 1, \ldots, I$, and $t = 1, \ldots, T$,[48]

$$\frac{\partial q_{it}^{***}}{\partial \theta_t} < \frac{\partial q_{it}^{**}}{\partial \theta_t} \quad \text{if} \quad \sum_{j \neq i} \left(\frac{\partial^2 \bar{d}_{jt}}{\partial Q_t^{***} \partial \alpha_j} \frac{\partial \alpha_j}{\partial \theta_t} \right) > \sum_{j \neq i} \left(\frac{\partial^2 u_{it}}{\partial z_{it}^{***} \partial \bar{u}_{jt}} \frac{\partial \bar{u}_{jt}}{\partial \beta_j^z} \frac{\partial \beta_j^z}{\partial \theta_t} \frac{\partial z_{it}^{***}}{\partial q_{it}^{***}} \right) - \sum_{j \neq i} \left(\frac{\partial^2 u_{it}}{\partial x_{it}^{***} \partial \bar{u}_{jt}} \frac{\partial \bar{u}_{jt}}{\partial \beta_j^z} \frac{\partial \beta_j^z}{\partial \theta_t} \left(p_t^z \frac{\partial z_{it}^{***}}{\partial q_{it}^{***}} + p_t^q \right) \right). \tag{A.19}$$

The left-hand side of the second inequality in (A.19) represents the change in individual i's perceived marginal damage associated with the added aggregate damage suffered by individuals $j \neq i$ (from their vehicle trips) brought about by the respective changes in their information-conditioned parameters α_j as a result of the issuance of a yellow air day advisory (i.e., change in θ_t). The right-hand side of the second inequality represents the corresponding change in i's perceived marginal benefit associated with the added aggregate benefit obtained by individuals $j \neq i$ brought about by the respective changes in their information-conditioned parameters β_j^z.

Similarly, comparing (A.5)–(A.7) with (A.16)–(A.18) leads to a sufficient condition governing the relationship between $\partial q_{it}^{***}/\partial \theta_t$ and $\partial q_{it}^{*}/\partial \theta_t$ across all $i, j = 1, \ldots, I$, and $t = 1, \ldots, T$,

$$\frac{\partial q_{it}^{***}}{\partial \theta_t} < \frac{\partial q_{it}^{*}}{\partial \theta_t} \quad \text{if} \quad \frac{\partial^2 \bar{d}_{it}}{\partial Q_t^{***} \partial \alpha_i} \frac{\partial \alpha_j}{\partial \theta_t} + \sum_{j \neq i} \left(\frac{\partial^2 \bar{d}_{jt}}{\partial Q_t^{***} \partial \alpha_j} \frac{\partial \alpha_j}{\partial \theta_t} \right) > \sum_{j \neq i} \left(\frac{\partial^2 u_{it}}{\partial z_{it}^{***} \partial \bar{u}_{jt}} \frac{\partial \bar{u}_{jt}}{\partial \beta_j^z} \frac{\partial \beta_j^z}{\partial \theta_t} \frac{\partial z_{it}^{***}}{\partial q_{it}^{***}} \right) - \sum_{j \neq i} \left(\frac{\partial^2 u_{it}}{\partial x_{it}^{***} \partial \bar{u}_{jt}} \frac{\partial \bar{u}_{jt}}{\partial \beta_j^z} \frac{\partial \beta_j^z}{\partial \theta_t} \left(p_t^z \frac{\partial z_{it}^{***}}{\partial q_{it}^{***}} + p_t^q \right) \right), \tag{A.20}$$

[48] The corresponding necessary condition for this result is less strict due to the inclusion of the term $\sum_{j \neq i} \frac{\partial^2 \bar{d}_{jt}}{\partial Q_t^{***2}}$ in the denominator of the expression for $\partial q_{it}^{***}/\partial \theta_t$ in (A.16), i.e., in Ω_3.

where the left-hand and right-hand sides of the second inequality in (A.20) have the same interpretations as those in the second inequality in Eq. (A.19). However, in this case the sufficient condition is now more likely to hold because of the addition of the $\frac{\partial^2 \bar{d}_{it}}{\partial Q_t^{***} \partial \alpha_i} \frac{\partial \alpha_j}{\partial \theta_t} > 0$ term on the left-hand side of the second inequality.

Coefficient Plots for the Empirical Analysis in Sect. 6.2

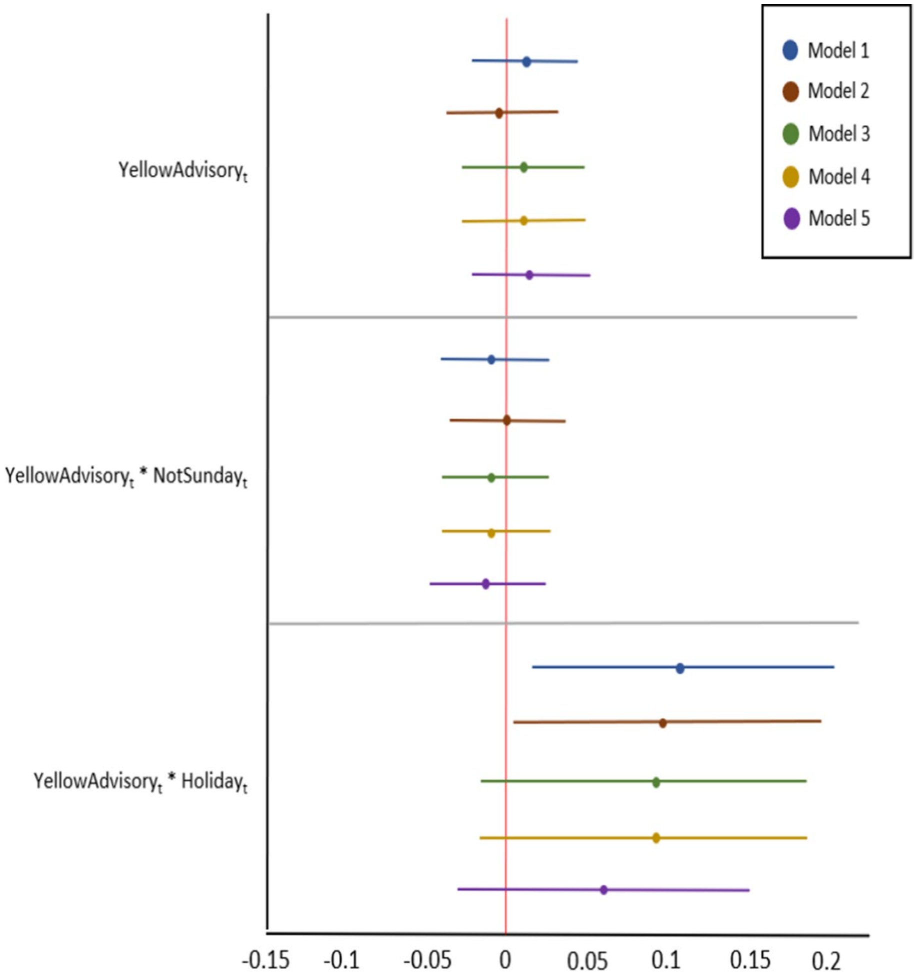

Fig. 6 Coefficient plots for $YellowAdvisoryPlus1_t$

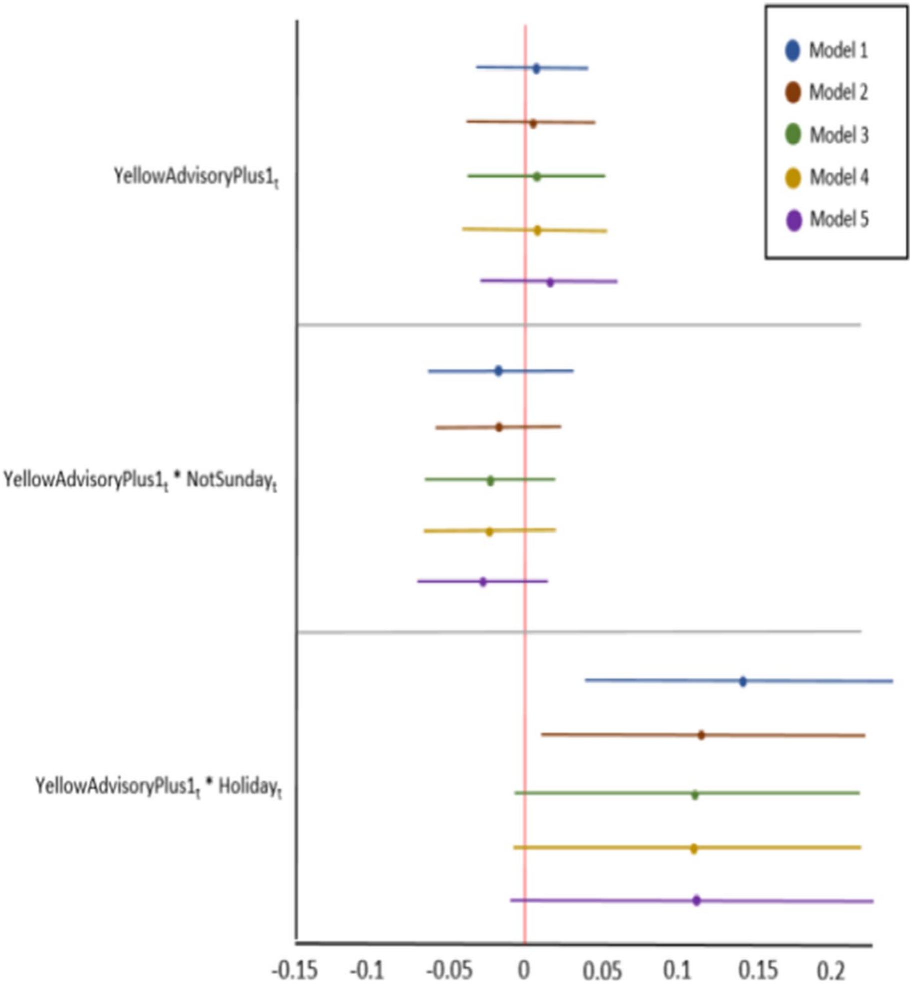

Fig. 7 Coefficient plots for $YellowAdvisory_{t-1}$

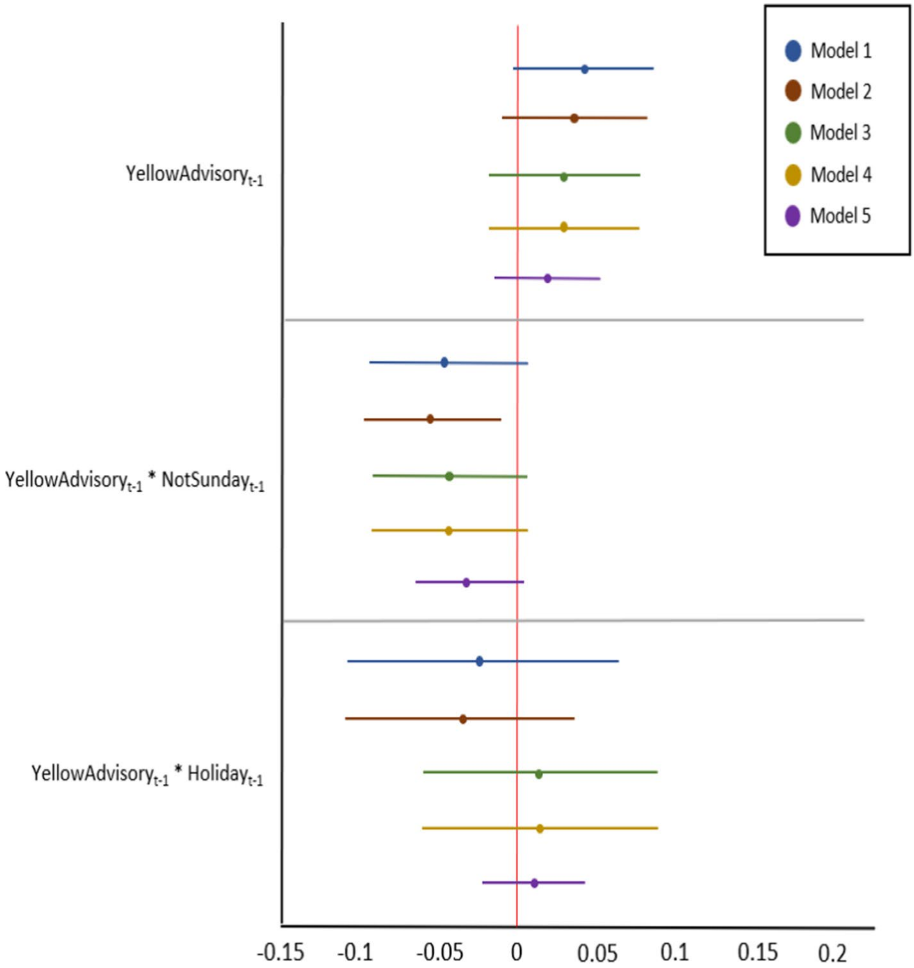

Fig. 8 Coefficient plots for $YellowAdvisoryPlus1_{t-1}$

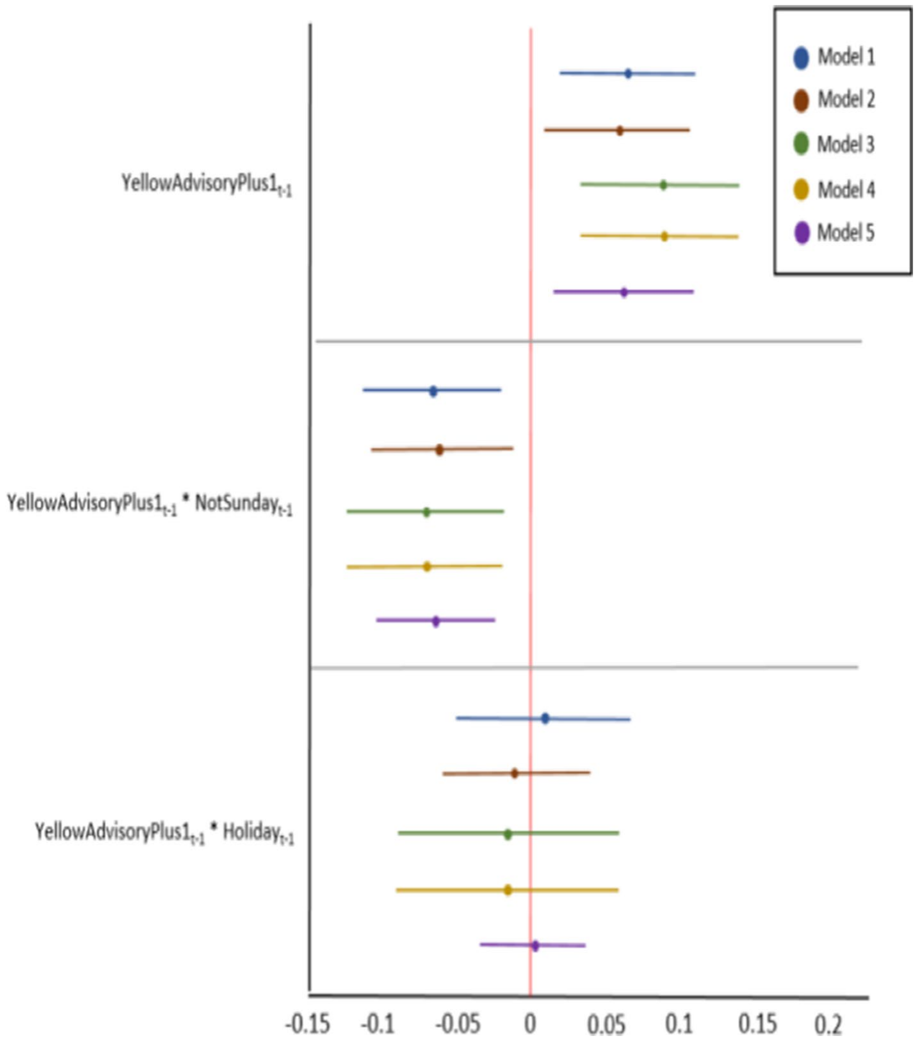

Fig. 9 Location of Cache Valley, Utah *Source* https://onlinelibrary.utah.gov/utah/counties/ and https://www.freeworldmaps.net/united-states/utah/location.html

Model 1 includes only contemporaneous effects associated with $YellowAdvisory_t$.

Model 2 includes both contemporaneous and single-day lag effects associated with $YellowAdvisory_t$.

Model 3 adds a second-day lag effect to Model 2.

Model 4 is the quadratic model with two-day lag effects.

Model 5 is the quadratic model with three-day lag effects.

Model 1 includes only contemporaneous effects associated with $YellowAdvisoryPlus1_t$.

Model 2 includes both contemporaneous and single-day lag effects associated with $YellowAdvisoryPlus1_t$.

Model 3 adds a second-day lag effect to Model 2.

Model 4 is the quadratic model with two-day lag effects.

Model 5 is the quadratic model with three-day lag effects.

Model 1 includes only single-day lag effects associated with $YellowAdvisory_{t-1}$.

Model 2 includes both contemporaneous and single-day lag effects associated with $YellowAdvisory_t$.

Model 3 adds a second-day lag effect to Model 2.

Model 4 is the quadratic model with two-day lag effects.

Model 5 is the quadratic model with three-day lag effects.

Model 1 includes only single-day lag effects associated with $YellowAdvisoryPlus1_{t-1}$.

Model 2 includes both contemporaneous and single-day lag effects associated with $YellowAdvisoryPlus1_t$.

Model 3 adds a second-day lag effect to Model 2.

Model 4 is the quadratic model with two-day lag effects.

Model 5 is the quadratic model with three-day lag effects.

Funding This study is funded in part by the Utah Agricultural Experiment Station, UTA0-1646. First-round revisions to the paper were made during the author's sabbatical leave in 2021–2022, while serving as a U.S. Fulbright Scholar at Ben Gurion University of the Negev, Israel, award 11545-IS. The author thanks Ramjee Acharya for assistance in obtaining the data used in this study, and two anonymous reviewers who helped improve the paper's final version

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