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

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Missing The Warning Signs?

The Case of "Yellow Air Day" Advisories in Northern Utah

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Abstract

Using a dataset consisting of daily vehicle trips, $PM_{2.5}$ concentrations, along with a host of climactic control variables, we test the hypothesis that "yellow air day" advisories provided 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 2000s. Winter inversions occur in northern Utah when climactic conditions are such that $PM_{2.5}$ concentrations (derived mainly from vehicle emissions) become trapped in the lower atmosphere, leading to unhealthy air quality (concentrations of at least 35 $\mu g/m^3$) over a span of what are called "red air days". When concentrations rise to between 15 and 25 $\mu g/m^3$ on their way to the 35 $\mu g/m^3$ threshold, the region's residents are informed via several different media sources and road signage that the region is experiencing a yellow air day, and urged to reduce their vehicle usage during the day. Our results suggest that yellow air day advisories have been at best weak, at worst perverse, measures 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.

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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 technologies – 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 the relative price of that behavior). To 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

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[1]In their systematic review of the ecolabeling literature – encompassing studies of ecolabels presented as text, logo, or a combination of the two, and messages promoting organic, environmentally sustainable, and low-to-no greenhouse gas embodying food products – Potter et al. (2021) conclude that ecolabels help motivate consumers to choose greener products. Experimental evidence provided by 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 bids 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., monitoring compliance of marine fisheries).

[2]Hamilton (1995) was the first to show that shareholders in firms that self-reported 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 in the TRI were not always matched by similar reductions in measured concentrations from EPA monitors. With respect to the control of nonpoint source water pollution, Ribaudo and Horan (1999) find that propitious 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.

the longer-term goal of mitigating the human behaviors that cause 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 from the soft policy perspective, trigger a reduction in externality-causing behaviors? In the case of water pollution, for example, the questions are what effect does a beach advisory have on a swimmer's decision to take a plunge in contaminated water? What effect does a fish consumption advisory have on angler's decision to cast a line into a contaminated lake or river? And to what extent do changes in these individual behaviors translate into a reduction in a water source's contamination level? In terms of air pollution, what effect does an air quality advisory have on people's decisions to exercise outdoors or commute to work by bicycle, mass transit, or automobile?

In answer to the latter question, 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 2000s, when elevated $PM_{2.5}$ concentrations tied mainly to region-wide vehicle usage sporadically exceeded the EPA's National Ambient Air Quality Standards (NAAQS), causing "red air day" episodes. As elaborated on in Section 2, these episodes were often dramatic in their scope. Hence, our study area and period of analysis provide an opportune setting within which to measure the effectiveness of an air quality alert program. Furthermore, because the red air day episodes are seasonal and sporadic within a given season, intra- and inter-episode dynamic responses to an advisory, in the form of "alert fatigue", can be conveniently measured. 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, et al., 2008). The advisory programs publicize local air quality conditions on a daily basis. The conditions are typically categorized as color-coded, ordinal rankings and 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, 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 wide variety of news outlets (newspapers, television, radio, emails, and various internet sites) on the day of rather than day before measured $PM_{2.5}$ concentrations.[3] The color green indicated "good" air

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[3]Similar to Tribby et al. (2013) and Cummings and Walker (2000), Utah's advisories were disseminated "day of", and were

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 avoidance behaviors that can be taken on an individual basis, such as reducing vehicle trips or travel speeds, carpooling, or using alternative transportation modes; behaviors that alleviate the negative impacts of pollution on a personal level and simultaneously help alleviate the problem 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) and 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 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]

As Noonan (2011) points out, by their very nature air quality advisories send conflicting messages. One

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thus not as peremptory as "day-before" advisories would otherwise have been. We nevertheless test for the existence of potential day-before effects in Section 6, as their existence would suggest that vehicle users possibly base their decisions on expectations that an advisory will be issued, e.g., in response to evening news reports on the radio and television that predict 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 alter behavior uniformly in a given population; impacts vary across individuals, contexts, and activities. In fact, some of these behavioral impacts may be perverse in terms of mitigating the underlying effects of vehicle emissions, e.g., by inducing a greater reliance on automobiles on alert days in order to reduce exposure to poor air quality.

[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.

message persuades individuals to voluntarily reduce their vehicle usage in order to mitigate collective health and environmental damages associated with poor air quality, while another message prompts individuals to limit their exposure to outdoor air. 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 outdoors 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 – an unanticipated outcome we explore theoretically in Section 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 status for $PM_{2.5}$ concentrations. Based upon several different empirical specifications that inter alia control for autocorrelation in our model's error structure and potential endogeneity associated with yellow air day advisories, we find evidence of a heterogeneous relationship between yellow air day advisories and region-wide vehicle trips. In our baseline models we find that, on average, one-day lagged advisories have a negative impact on vehicle trips. However, this negative impact is greatly reduced in magnitude when the advisories are issued on weekdays and Saturdays, in some perverse cases turning positive. We also find no evidence of intra-seasonal alert fatigue. In our more disaggregated models we find additional instances of the advisory's relatively meager negative impact on vehicle usage in Cache Valley, which again under certain circumstances (specifically, during certain days of the week and later years during our study period) exhibits a perverse positive effect. The later-year effect is indicative of possible inter-seasonal alert fatigue.

The next section expounds upon three previous studies most relevant to ours – Cutter and Neidell (2009), Saberian et al. (2017), and 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 with the aim of preempting the onset of red air day episodes. This discussion is premised upon a conceptual model developed in Appendix A. Section 5 describes and summarizes our data. Section 6 presents the results of our empirical analysis, and Section 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 2000s. 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 2001-2004 to identify the effect of STA on region-wide transportation choices across days and times of day. They estimate that STA reduces total daily traffic volume by 2.5% - 3.5%, with the largest effect occurring during and just after morning commuting hours.[8] The STA has 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 interpret this latter result as evidence that discretionary trips, as opposed to commuter trips, respond to STA 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 Section 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 – in particular, that discretionary vehicle trips tend to be more responsive than commuting trips, as one would naturally expect – as underpinning an average daily effect, which is the effect we expressly 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. 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

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[8]This result – of the STA's statistically negative effect on the Bay area's traffic volume – is perhaps the most widely cited finding of statistical significance in the literature. More recently, Zou (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% to 7% (as compared with the average 1.6% gap). This evidence leads Zou to conclude that gaming by the 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 to widen the pollution gap.

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 use of the Bay area's public transport system (Bay Area Rapid Transit, or BART), Cutter and Neidell 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 provides 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 in the cancellation of public transit trips. Data limitations preclude us from measuring public transit responses to the yellow air day advisories in northern Utah.[9]

In addition to providing a benchmark for comparison with this study's empirical results, Cutter and Neidell's 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 trigger rule in the same manner as observed covariates (in their case within bands of 0.01 and 0.02 ppm of the STA trigger concentration level).[10] Hence, the RD design is suitable for causal inference in this case. In our study, we utilize the instrumental variable (IV) approach for causal inference – which is a commonly used approach to mitigate potential endogeneity in data pertaining to voluntary behavior – for two main reasons. First, as discussed in Section 6, our instruments are "strong" (Angrist et al., 1996). Second, our 'non-discontinuous' approach permits an investigation of alert fatigue, whereas the RD design does not.

Although Saberian et al. (2017) estimate the effect of day-before, city-wide air quality advisories on a different behavior than vehicle usage – strenuous outdoor activities, in specific bicycling – several aspects of their econometric strategy are worthy of emulation. As for their empirical results, the authors find a

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[9]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 ranked as the fifth busiest rapid transit system in the US (World Atlas, 2021).

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

relatively large, statistically significant reduction in cycling 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 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 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 Section 6, we also adopt this approach.

Most 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. 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 falling on Fridays and Saturdays, respectively, and almost 6% higher during Mondays-Thursdays. These results are robust to controlling for the 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.'s control variable for alert fatigue – is found to be statistically insignificant.

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[11] In a series of robustness checks, Saberian et al. find a roughly 40% reduction in leisure cycling in response to an alert, compared with only a 20% reduction in commuter cycling. With respect to the measurement of alert fatigue, 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 estimate is concomitantly diminished. As described in Section 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 in northern Utah, 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.

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.[14] They find that increases in vehicle usage on yellow air days is evident throughout the region's main metropolitan area, and is concentrated along the major commuting thoroughfares. Decreased traffic volume is evident in the center of the metropolitan area. Further, Tribbey et al. 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 (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 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 2000s. 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. We develop a theoretical framework in Section 5 that provides a basis for these disparate results. In Section 6, we present empirical results for air quality advisories issued in northern Utah during the early 2000s, 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 these 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 Cache Valley during the early 2000s. Figure 1 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] Primarily 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.

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[14]Since the number and dispersion of ATRs in northern Utah is much less than in Salt Lake and Davis Counties, the need to conduct this type of disaggregated analysis is obviated in our study.

[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).

Figure 2 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.

[INSERT FIGURES 1 AND 2 HERE]

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, 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 as infant mortality and low birth weight (USEPA, 2016; Dockery et. al, 1993; Pope et. al, 1995; Pope, 1989).[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 3 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 $\mu g/m^3$ averaged over any 24-hour period (horizontal red line) from year to year. Once above the 35 $\mu g/m^3$ threshold, the concentrations trigger a red air day episode. Concentration levels rising to within the yellow bands of 15 $\mu g/m^3$ and 25 $\mu g/m^3$ trigger a yellow air day advisory.

[INSERT FIGURE 3 HERE]

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[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.

The extent to which yellow air day advisories may have induced a change in individuals' behaviors is hinted at in Figure 3. For example, in relation to the 2002-2003 winter-inversion season the advisories issued for yellow air days during the 2004-2005 inversion season did not seem to constrain subsequent increases in $PM_{2.5}$ concentrations to below the red air day threshold. Yellow air day advisories issued during the 2005-2006 and 2006-2007 inversion seasons likewise suggest at best limited success for the advisories in obviating the progression of $PM_{2.5}$ concentrations to red air day status. 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 Section 6.

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 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 consecutive-day yellow air day advisories were issued. For example, if an 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. 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 red air day episode. If instead Wednesday is not a red air day, then the two-day yellow air day

advisory did not preceed a red air day episode.[17]

[INSERT TABLE 1 HERE]

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 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.

As Moscardini and Caplan (2017) point out, during a typical inversion episode 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 valleys $PM_{2.5}$ 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 (NASA 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

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[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.

[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).

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 valleys winter inversion problem.

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, more efficiently using their vehicles via "trip chaining", carpooling, or telecommuting, then we would expect an advisory to correlate statistically with the region-wide reduction in vehicle trips. To the contrary, if too small a number of individuals respond to the advisory then we would expect to find no correlation. It is also possible that a large-enough number of individuals might 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 Appendix A that models the three polar types of individuals that comprise 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' pattern 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 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.[19]

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[19]Given its static nature, our model is precluded from explicitly accounting for potential alert fatigue among individuals. However, if we assume that alert fatigue impacts equally each of the three types of individuals we describe below, then relatively speaking the differences in individuals' behaviors identified by the model would be unaltered in the presence of fatigue.

As Appendix A shows, one type of individual (Case 1) ignores the damages associated with region-wide vehicle trips in each period altogether, even given the fact that a yellow air day advisory causes the marginal damage associated with increases in region-wide vehicle trips to increase. With only minimal assumptions placed on the structure of this individual's preferences, we show that in this case the individual responds to the issuance of the advisory by increasing his vehicle trips (refer to equations (5)-(8) in the appendix). A second type of individual (Case 2) accounts solely for the expected damages she alone incurs in any given period, i.e., the individual partially internalizes the contribution her vehicle trips makes to region-wide environmental damages. This type of individual responds to yellow air day advisories to a lesser (positive) extent than a Case 1 individual, and may in fact respond by decreasing her vehicle trips in equilibrium when the change in her perceived marginal damage (from vehicle trips) associated with the issuance of a yellow air day advisory exceeds the corresponding change in her marginal benefit (refer to equations (10)-(14) in the appendix).

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). As Appendix A demonstrates, a sufficient condition for a Case 3 individual's (henceforth "Individual 3'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 Individual 3'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 Individual 3's vehicle-trip response with a Case 1 individual's is shown to be more likely to hold (refer to equations (16)-(20) in the appendix).

Surely a given region consists not only of these three polar types of individuals, but rather a variety of convex combinations of the three. The point is, to the extent that more Case 1 type individuals comprise a region than Case 2 and Case 3 types we should expect to see less of a reduction in vehicle usage in response to a yellow air day advisory. Or, alternatively stated, the more likely we will see an increase in vehicle usage in response to the advisory. Because the data we describe in Section 5 and analyze in Section 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 sufficient conditions for responding less positively

(and perhaps negatively) to yellow air day advisories.[20] Rather, we test whether on average northern Utah residents' vehicle usage responded positively or negatively (or not all) to yellow air day advisories issued during the first decade of 2000.[21]

5 Data and Summary Statistics

The data for our empirical analysis in Section 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-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 (UDEQ 2016a, 2016b, 2016c).[22] 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 and Utah Climate Center (Weather Underground, 2016; Utah Climate Center, 2016). Lastly, hourly vehicle trip count data were obtained from the Utah Department of Transportation (UDOT, 2014), which were then aggregated to obtain daily counts. The Automatic Traffic Recorder (ATR) stations for the trip count data in Cache Valley are 303, 363, and 510, which cover the county's main north-south transportation artery. Figure 4 depicts the specific ATR locations. Stations other than 303, 363, and 510 provided insufficient data for our study period, including station 620 (demarked in the color red), which was added during the second half of our study period.

[INSERT FIGURE 4 HERE]

Specific names of and summary statistics for the variables used in our study are presented in Table 2. We see that on average over 43,000 vehicle trips (*VehicleTrips*) 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

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[20]Even household- or individual-level data would require....to enable us to distinguish the different types of individuals comprising the region.

[21]We also 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 (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.

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

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 is not systematically biasing the analysis presented in Section 6 in any apparent way.

[INSERT TABLE 2 HERE]

As indicated in Table 2, daily $PM_{2.5}$ concentration levels averaged slightly more than 19 $\mu g/m^3$ during our study period. This level rises to over 39 $\mu g/m^3$ per day in the presence of a temperature inversion, illustrating the positive relationship between northern Utah's wintertime temperature inversions and elevated $PM_{2.5}$ concentrations.[23] Yellow air day advisories (*YellowAdvisory*) were issued on roughly a third of the 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 alert fatigue (as described in Sections 2 and 3) given the advisories' relatively high frequency of issuance. Lastly, in addition to the varied controls for weather conditions, e.g., *Humidity*, *Wind*, *Humwind*, *Pressure*, *SnowFall*, and *SnowDepth*, we follow Tribbey et al. (2013) by also controlling for the potential effect of holidays on vehicle usage in the valley.[24] As indicated by the variable *Holiday*, 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 5 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 days of the week. To facilitate these comparisons, we convert each of the three variables to their respective percentage equivalents. For example, Average # Vehicle Trips for a given day of the week is measured as the percentage of total weekly vehicle trips, on average, taken during that day. Similarly, Average # Red Air Days for a given day of the week is measured as the percentage of total weekly red air days, on average, experienced during that day, and Average # Advisories for a given day of the week is measured as the percentage of total weekly yellow air day advisories, on average, experienced during that day. The comparisons are anchored by day-of-the-week due to the statistically significant, negative pairwise correlations that exist for vehicle trips across all

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[23]The negative value for *TempDiff* indicates that the average day during our study period did not experience a temperature inversion.

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

days of the week, e.g., between trips taken on Mondays vs. Tuesdays, Mondays vs. Wednesdays, Tuesdays vs. Wednesdays, etc.[25] 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 econometric analyses (Angrist et al., 1996).

[INSERT FIGURE 5 HERE]

The relatively tight, unconditional relationship existing 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.

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 control for the potential effects of autocorrelation and endogeneity in our model's error structure, and to probe the robustness of our results. In general, the functional relationship between *YellowAdvisory* and *VehicleTrips* can be expressed as,

$$VehicleTrips = f(X; \Theta, \varepsilon),$$

where matrix X contains a set of explanatory variables taken from Table 2 (each set including a control for *YellowAdvisory*), Θ represents the corresponding vector of constant parameters to be estimated, and ε denotes an independently, identically distributed (i.i.d.) error term. We consider two different specifications of the variable *VehicleTrips* in the econometric model's framework – levels and natural logarithmic – as well as two specifications of *YellowAdvisory* – one as defined in Table 2 and the other redefined to

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[25]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.

include the green air day preceding each yellow air day episode.[26] For example, if during any given week of our study period a yellow air day episode began on a Wednesday with, say, a $PM_{2.5}$ concentration of 27.5 $\mu g/m^3$, and the concentration on the preceding Tuesday was less than 15 $\mu g/m^3$, then the Tuesday's *YellowAdvisory* value would also be set equal to one (from what had been zero) in the redefined version of *YellowAdvisory*. The purpose of this redefinition of *YellowAdvisory* was to test for the potential of individuals foreseeing an impending yellow air day advisory one day prior to its issuance, and adjusting their vehicle usage accordingly. In the end, this redefinition of *YellowAdvisory* had no quantitative effect on our results, suggesting that during our study period individuals responded myopically to worsening air quality conditions and concomitant issuances of yellow air day advisories.[27]

6.1 Identifying and Controlling for Autocorrelation

We henceforth report results for both the levels and log-transformed specifications of *VehicleTrips*.[28] To begin, we apply Ljung and Box's (1978) and Cumby and Huizingas (1992) Portmanteau tests for white noise error terms in each specification. Results are presented in Table 3. We find that including the first four lags of *VehicleTrips* and *Ln(VehicleTrips)*, respectively, as regressors satisfies the null hypothesis of no second-order autocorrelation in the residuals.[29] This is evidenced by the statistically insignificant χ^2 values for the Portmanteau tests. Further, the statistically insignificant Durbin χ^2 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 *VehicleTrips* and *Ln(VehicleTrips)* include the four lagged terms, respectively, as sets of controls for first- or second-order autocorrelation that would otherwise be present in the error structures.[30]

[INSERT TABLE 3 HERE]

As the results in Table 3 indicate, contemporaneous vehicle trip counts are, for the most part, positively correlated with their lagged values. For example, for every additional vehicle trip taken in the previous

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[26]A green air day occurs when its $PM_{2.5}$ concentration averages less than 15 $\mu g/m^3$ over the 24-hour period. We also estimated the model using a three-day forward moving average of *VehicleTrips* and found the results to be qualitatively similar to those for levels. The results using this specification are available from the author upon request.

[27]Results based on this redefined version of *YellowAdvisory* are also available upon request from the author.

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

[29]In other words, second-order autocorrelation is controlled for once four lags of *VehicleTrips* and *Ln(VehicleTrips)* are included as regressors in their respective models.

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

period (i.e., $VehicleTrip_{t-1}$), contemporaneous trips ($VehicleTrip_t$) are estimated to increase by 0.52. From column three of the table we see that for every one percent increase in $VehicleTrip_{t-1}$, $VehicleTrip_t$ are estimated to increase by 43 percent. 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.

6.2   Baseline and Disaggregated Regression Results

Table 4 presents our baseline results for equation (1) quantifying the relationship exhibited between $YellowAdvisory$ and the two vehicle trip measures.[31] Focusing on the model estimated for $VehicleTrips$ (whose results are closely corroborated by the model estimated for $Ln(VehicleTrips)$), we see that contemporaneous yellow air day advisories have no influence on the valley's vehicle trip counts. However, one-day lagged advisories do. On average, a lagged yellow air day advisory induces a subsequent *increase* of slightly more than 4,000 vehicle trips the next day (an increase of more than nine percent of average daily trips). Neverthe-less, as evidenced by the larger negative coefficient estimate (in magnitude) for variable $[YellowAdvisory \text{ x } NotSunday]_{t-1}$, lagged advisories occurring on days of the week other than Sundays result in a net decrease of slightly more than 140 region-wide vehicle trips. Although statistically significant, this non-Sunday effect of lagged yellow air day advisories represents a relatively small, 0.3 percent of average daily trips. The meagerness of this effect is particularly notable given that, on average, 20,500 more vehicle trips are taken in the valley on non-Sundays (the coefficient value for variable $NotSunday = 20,487.62$).[32]

[INSERT TABLE 4 HERE]

Table 4 also shows that while vehicle trips taken during three-day windows around national holidays decrease by roughly 4,500, the effect of yellow air day advisories issued during these windows of time are statistically insignificant. The annual dummy variables for years 2007 – 2012 (the latter half of our study period), denoted $Year2007 - Year2012$, each indicate higher numbers of vehicle trips relative to the former half of the study period, and thus control for trend increases in region-wide vehicle trips during the study period. The statistically significant F value indicates that the null hypothesis of jointly insignificant

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[31]The coefficient estimates corresponding to the four lagged $VehicleTrips$ and $Ln(VehicleTrips)$ variables included in these and all ensuing regressions to control for first- and second-order autocorrelation have been suppressed in order to eliminate unnecessary clutter in the tables.

[32]Vehicle trips are noticeably lower in the valley on Sundays due to the preponderance of members of the Church of Jesus Christ of Latter Day Saints (LDS), who have historically been encouraged to attend church for three-hour stints each Sunday. Church attendance in turn reduces vehicle usage on Sundays each week. The valley's population was estimated to be 83 percent LDS in 2010 (Cannon, 2015).

coefficient estimates is rejected. Together, the set of regressands explain 82 percent of the total variation in *VehicleTrips*.

Following Saberian et al. (2017), we also included a control variable for (intra-seasonal) alert fatigue in each of the models in Table 4, defined as the interaction between *YellowAdvisory* and *YellowAdvisory$_{t-1}$*. We find no evidence of intra-seasonal fatigue in either model using this approach, whether restricted to non-Sundays or not. Although our measure of alert fatigue is formulated differently than theirs, the absence of fatigue found for Cache Valley comports with Tribbey et al.'s (2013) finding for Utah's Wasatch Front, suggesting that within a given winter-inversion season the effect of Utah's yellow air day advisories on vehicle usage is not necessarily a function of when they are issued during the season. For comparison, the effect of inter-seasonal alert fatigue is tested in the next set of models. As will be shown, we find spotty evidence of this type of fatigue.

Table 5 reports more disaggregated results for the *VehicleTrips* and *Ln(VehicleTrips)* models. To eliminate unnecessary clutter in the tables, we have suppressed the coefficient estimates for the *Year*2007 – *Year*2012 dummy variables, as these are qualitatively very similar to those reported in Table 4. We have also suppressed the estimates for daily dummy variables (with Sunday as the excluded category), as these estimates correspond individually very closely with the estimates for *NotSunday* in Table 4.[33]

[INSERT TABLE 5 HERE]

We begin by noting that while the model for *Ln(VehicleTrips)* reports respective coefficient estimates of the same signs as the model for *VehicleTrips*, only the estimate for *Holiday* is statistically significant. This estimate indicates that, all else equal, the three-day windows around holidays are correlated with a nine-percent reduction in region-wide vehicle trips – a result that is corroborated by the coefficient estimate of just under -3,800 trips in the *VehicleTrips* model.[34] In contrast, the model for *VehicleTrips* reports several interesting relationships between yellow air day advisories and region-wide vehicle trips. For example, contemporaneous yellow air day advisories – as opposed to one-day lagged advisories – are associated with an average reduction in region-wide vehicle usage of just under 3,300 trips. When weighed against advisories issued during holidays, this average reduction falls to approximately 520 vehicle trips (-3,370.21 + 2,847.50). Further, advisories issued on Fridays result in an average reduction of only 150 trips (-3,370.21

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[33]We also suppress results for monthly dummy variables and monthly dummies interacted with *YellowAdvisory*, as these coefficient estimates were all statistically insignificant for both *VehicleTrips* and *Ln(VehicleTrips)*.

[34]Relative to the study period's average daily trip count of 43,261, the estimate is roughly equal to nine percent.

+ 3,219.62), and advisories issued on Wednesdays result in an *increase* of 1,125 trips (-3,370.21 + 4,494.90), both relative to Sundays. Lastly, the average advisory effects for years 2008 and 2010 (relative to the average for earlier years 2002 – 2006) are both positive: an increase of 276 vehicle trips for the year 2008 (-3,370.21 + 3,646.29) and 1,336 trips for the year 2010 (-3,370.21 + 4,706.17). This is (admittedly spotty) evidence of possible inter-seasonal alert fatigue, since the negative effect of advisories are greatly reduced (to the point of exhibiting positive effects) during these two later years, or alternatively stated, the winter-inversion seasons comprising these two later years.

To summarize, our basic results suggest that a measure of heterogeneity exists in the relationship between yellow air day advisories and region-wide vehicle trips. In the baseline models we find that, on average, one-day lagged advisories have a negative impact on vehicle trips. However, this negative impact is greatly reduced in magnitude when the advisories are issued on weekdays and Saturdays, in some perverse cases turning positive. We also find no evidence of intra-seasonal alert fatigue. In our more disaggregated models we find additional instances of the advisory's relatively meager negative impact on vehicle usage in Cache Valley, which again under certain circumstances (specifically, during certain days of the week and later years during our study period) exhibits a perverse positive effect. The later-year effect is indicative of possible inter-seasonal alert fatigue.

We are unsurprised to find cases of perverse yellow air day advisories. Recall that Tribbey et al. (2013) also found a similar perverse advisory effects for Utah's Wasatch Front region. Further, as pointed out in Section 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.

6.3   Identification

In this section, we explore the potential for heretofore unexpressed factors to confound the relationship between yellow air day advisories and region-wide vehicle trips. Similar to Tribbey et al. (2013), we now incorporate a host of weather variables from Table 2 into our analysis that may conceivably identify *YellowAdvisory*. Similar to our analysis in Section 6.1, we preface this analysis with a set of Portmanteau

tests to identify and control for potential autocorrelation in the series of this variable. Results are presented in Table 6.

[INSERT TABLE 6 HERE]

We find that including the first lag of *YellowAdvisory* as a regressor is sufficient to satisfy the null hypothesis of no autocorrelation in the residuals. This is evidenced by the statistically insignificant χ^2 values for the Ljung and Box, Cumby and Huizinga, and Durbin χ^2 statistics. As the results in Table 6 indicate, contemporaneous advisories are positively correlated with their one-day lagged values – on average, an advisory issued yesterday increases the probability that an advisory will be issued today by 42 percent. Hence, the subsequent regression models explaining variation in *YellowAdvisory* each include the single lagged term as our control for first-order autocorrelation that would otherwise pervade the error structure. As will become clear below, these models are effectively first-stage regressions ultimately meant to identify instruments for second-stage regressions explaining *VehicleTrips*.

Our main results explaining variation in the issuance of yellow air day advisories are presented in Table 7. We relate this variation to changes (i.e., first differences denoted by the "D." prefix) in the weather variables.[35] The results reported in this table are derived from a linear-probability specification of the model. Results from a probit specification, which are provided in Appendix B, are qualitatively similar, albeit with generally lower levels of statistical significance reported for the coefficient estimates.[36]

[INSERT TABLE 7 HERE]

We see that, on average, the issuance of a yellow air day advisory is positively correlated with the change in the temperature gradient, and humidity and wind levels, and negatively related to changes in interaction term *Humwind* and snow depth. These results are similar to those reported in Caplan and Acharya (2019) for $PM_{2.5}$ concentrations with respect to *Humidity*'s positive and *Humwind*'s negative (statistically significant) coefficient estimates. In contrast with Caplan and Acharya (2019), the regression results reported in Table 7 indicate that changes in *TempDiff* and *Wind* are positive and statistically significant, while *SnowDepth* is negative and statistically significant.[37] Based upon the atmospheric science described in Moscardini

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[35]First-differencing mitigates potential collinearity between the weather variables and the one-day lag in *YellowAdvisory*.

[36]Since the objective in presenting our probit results is merely to compare the signs and statistical significance levels with the linear-probability specification, we report the raw coefficient estimates for the probit model rather than their associated marginal effects.

[37]As in Caplan and Acharya, *Pressure* is statistically insignificant in our regressions and therefore omitted from the table.

and Caplan (2017), the positive coefficient estimate for the change in *TempDiff* and negative estimate for change in *SnowDepth* are as expected. However, the positive coefficient estimate for change in *Wind* is unexpected, especially because it is not more than offset by *Humwind*'s negative coefficient. The absence of a statistically significant relationship between the change in *VehicleTrips* and *YellowAdvisory* is not unexpected, since the issuance of a yellow air day advisory is more directly tied to changes in weather conditions than region-wide vehicle usage per se.

To gauge whether the endogeneity of *YellowAdvisory* is of practical concern, in particular whether it could be biasing *YellowAdvisory*'s estimated relationship with *VehicleTrips* in Section 6.2, we perform two additional sets of analyses. The first set tests whether omitted variable bias could potentially be a source of endogeneity bias in our regressions (c.f., Greene, 2018). In the second set, we conduct Hausman specification tests to directly measure the extent to which endogeneity may be biasing in our earlier regressions (Hausman, 1978; Durbin, 1954; Wu, 1973).

Table 8 contains our results testing for the presence of potential omitted variable bias in the estimation of *VehicleTrips* and *Ln(VehicleTrips)*, where we again suppress the respective sets of four lagged values of the two variables (which control for first- and second-order autocorrelation in the residuals) in order to eliminate unnecessary clutter in the table. Potential omitted variables are the same weather variables as those used in Table 7 to explain variation in *YellowAdvisory*. We see that solely the change in snow depth has a statistically significant (negative) effect on vehicle trips in both specifications, which suggests scant evidence of potential omitted variable bias in the regressions reported in Section 6.2.[38]

[INSERT TABLE 8 HERE]

For the Hausman specification tests we first regressed *YellowAdvisory* on the set of weather variables included in Table 8, along with *NotSunday*, *Holiday*, the yearly dummy variables, and the four lagged terms for *VehicleTrips* and *Ln(VehicleTrips)*, respectively. Next, we included the residuals (*Residuals*) from these first-stage regressions as explanatory variables in second-stage regressions specified the same as the baseline regressions in Table 4. The *F*-statistic for *Residuals* ($F(1,308) = 3.95$) was statistically significant at the 5% level for*Ln(VehicleTrips)*, but insignificant ($F(1,308) = 0.49$) for *VehicleTrips*.

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[38]We also ran regressions with non-differenced versions of the weather variables. In these specifications *Humidity* and *Snowfall* were the sole statistically significant (negative) coefficient estimates.

We therefore instrumented for one-day lagged *YellowAdvisory* in the regression for *Ln*(*VehicleTrips*) using our set of (lagged first-differenced) weather variables.[39] Results are presented in Appendix B. We see that while the coefficient estimate for one-day lagged *YellowAdvisory* is a larger positive value than that obtained in Table 4, it is not statistically significant. All other coefficient estimates – for *NotSunday*, *Holiday*, and the annual dummy variables – conform to their corresponding values in Table 4. Hence, controlling for potential endogeneity bias weakens the perverse statistical relationship between yellow air day advisories and region-wide vehicle trips exhibited in our baseline regression in Section 6.2.

As a final note, we assess the strength of our instrumental variables (weather variables), i.e., the extent to which they satisfy the three assumptions delineated in (Angrist et al., 1996; Lousdal, 2018): relevance, exclusion, and exchangeability. The relevance assumption is met due to the overall statistical significance of the set of instruments explaining *YellowAdvisory* in Table 7, as well as the individual significance levels of the coefficient estimates for *D.TempDiff*, *D.Humidity*, *D.Wind*, *D.Humwind*, and *D.SnowDepth*. The relative lack of statistical significance of the coefficients for these same variables in directly explaining variation in *VehicleTrips* and *Ln*(*VehicleTrips*) (in Table 8) provides evidence that the exclusion assumption is also provisionally met. The exchangeability assumption is trivially satisfied by virtue of our data limitations – we are unable to control for potential confounding factors other than those associated with our set of climate variables. As a result, we are confident that our instrumented approach adequately controls for potential endogeneity bias in our estimated coefficients.

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 2000s. During this period, when $PM_{2.5}$ concentrations (derived mainly from vehicle emissions) rose to between 15 and 25 $\mu g/m^3$, on their way to the 35 $\mu g/m^3$ 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

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[39]We instrumented for lagged rather than contemporaneous *YellowAdvisory* to be as consistent as possible with the results in Table 4 for *Ln*(*VehicleTrips*).

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 evidence of a heterogeneous relationship between yellow air day advisories and region-wide vehicle trips. On average, one-day lagged advisories have a negative impact on vehicle trips. However, this negative impact is greatly reduced in magnitude when the advisories are issued on weekdays and Saturdays, in some perverse cases turning positive. Further, we have found no evidence of intra-seasonal alert fatigue. In our more disaggregated models we have found additional instances of the advisory's relatively meager negative impact on vehicle usage in Cache Valley, which again under certain circumstances (specifically, during certain days of the week and later years during our study period) exhibits a perverse positive effect.

As mentioned in the Introduction section, yellow air day advisories are an example of a "soft" environmental policy, which 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. 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 the improve social welfare. In some cases the incentives may provoke perverse behaviors that instead diminish welfare. Clearly, our results affirm the need for "harder" environmental policies, such as taxation, subsidization, or the establishment of permit markets, to accompany soft policies in redressing behaviors that contribute to negative externalities. This is particularly the case in locations where substitutes for the externality-causing behavior are not readily available.

For example, in Cache Valley, Utah, viable transportation alternatives – particularly during the winter months – are relatively scarce. While a free bus service run by the Cache Valley Transit District offers relatively convenient and timely transportation within select areas of the valley, its reach is not frequent enough in time and broad enough in space to substitute for private vehicle usage among most residents. Hence, if a hard policy, such as the seasonal gas tax proposed by Moscardini and Caplan (2017) or the issuance of a municipal clean air bond proposed by Acharya and Caplan (2020) were to be imposed, it is likely the former would simply raise the revenue via taxation that the bond would raise by fiat, and vehicle-based contributions to $PM_{2.5}$ concentrations would not necessarily be ameliorated, at least in the short term. Until the revenue generated by the tax or bond is used to create viable transportation alternatives

at a scale large enough to make $PM_{2.5}$-generating vehicle usage redundant, soft policies such as the issuance of advisories are unlikely to spur the behavioral changes necessary to mitigate negative externalities, whether they be local, regional, or global in scale.

Appendices

A Appendix for Section 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.[40] We specify i's benefit function in period t, u_{it}, as,

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

where z_{it} represents the amount of a composite good obtained as a function of vehicle usage, denoted as q_{it}, and x_{it} is 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 to within the $15-25$ μ/m^3 interval.[41] 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 $\beta_i^q(\theta_t) \equiv 1 - \beta_i^z(\theta_t)$ 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 Section 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

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

[41]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}.

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, regardless of the tradeoff s/he makes between z_{it} and x_{it} on yellow air days – a tradeoff accounted for in benefit function u_{it}. We represent these expected damages with function $E[d_{it}]$,

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

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, marginal damages suffered by each individual i in period t increase in response to the issuance of a yellow air day advisory, i.e., $(\partial^2 \bar{d}_{it}/\partial Q_t \partial \alpha_i)(\partial \alpha_i/\partial \theta_t) > 0$. 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,

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

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).[42]

Next, we consider three cases reflecting three polar types of individuals comprising the region.[43] Case 1 pertains to individuals who ignore the damages associated with region-wide vehicle trips in each period t, Q_t, altogether, even given $\partial \alpha_i/\partial \theta_t \neq 0$. Case 2 pertains to individuals who account solely for the expected damages that they alone incur in period t, i.e., individual i dissects function $\bar{d}_{it}$ as $\bar{d}_{it}(q_{it} + Q_{-it}; \alpha_i(\theta_t))$,

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[42]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 $\sum_t w_{it} = \sum_t (p_t^z z_{it}(q_{it}) + p_t^q q_{it} + x_{it})$.

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

where Q_{-it} represents the aggregate trip count across all individuals in the region except individual i. 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.

A.1 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,

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

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

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

The left-hand side of (4) represents the marginal benefit of an additional vehicle trip and the right-hand side represents the corresponding marginal cost. Together with (3) and function $z_{it}\left(q_{it}\right)$, optimality condition (4) solves for $q_{it}^*=q_{it}\left(w_{it},p_t^z,p_t^q,\alpha_i\left(\theta_t\right),\beta_i^z\left(\theta_t\right),\beta_i^x\left(\theta_t\right)\right)$, $z_{it}^*=z_{it}\left(w_{it},p_t^z,p_t^q,\alpha_i\left(\theta_t\right),\beta_i^z\left(\theta_t\right),\beta_i^x\left(\theta_t\right)\right)$, and $x_{it}^*=x_{it}\left(w_{it},p_t^z,p_t^q,\alpha_i\left(\theta_t\right),\beta_i^z\left(\theta_t\right),\beta_i^x\left(\theta_t\right)\right)$.

Substituting q_{it}^*, z_{it}^*, and x_{it}^* into (4) and differentiating allows us to solve for the marginal effect of a change in θ_t on q_{it}^* relative to x_{it}^*.[44] The expression for this marginal effect is,

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

where

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

and

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

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[44]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 (3) and (4).

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

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

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

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

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

Clearly, the result in (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).

A.2 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,

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

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

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

As with Case 1, the left-hand side of (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

expected marginal damage associated with an additional vehicle trip, $\partial \bar{d}_{it}/\partial Q_t$. Similar to Case 1, equation (3), function $z_{it}(q_{it})$, and optimality condition (9) solve for q_{it}^{**}, z_{it}^{**}, and x_{it}^{**}, which when substituted back into (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,

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

where

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

and

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

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

$$\frac{\partial q_{it}^{**}}{\partial \theta_t} < \frac{\partial q_{it}^*}{\partial \theta_t} > 0. \tag{13}$$

Further, we find that,

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

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 i's marginal benefit associated with the change in information-conditioned parameter β_i^z. Our result for Case 2 therefore depicts the predilection of 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 equations (13) and (14) demonstrate, Case 2 individuals may choose to decrease the number of their vehicle trips in response to a yellow air day advisory.

A.3   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,

$$u_{it}\left(z_{it}\left(q_{it}\right),x_{it},\sum_{j\neq i}\bar{u}_{jt}\left(z_{jt}\left(q_{jt}\right),x_{jt};\beta_{j}^{z}\left(\theta_{t}\right),\beta_{j}^{x}\left(\theta_{t}\right)\right);\beta_{i}^{z}\left(\theta_{t}\right),\beta_{i}^{x}\left(\theta_{t}\right)\right)-\bar{d}_{it}\left(q_{it}+Q_{-it};\alpha_{i}\left(\theta_{t}\right)\right)$$

$$-\sum_{j\neq i}\bar{d}_{jt}\left(q_{it}+Q_{-it};\alpha_{j}\left(\theta_{t}\right)\right)+\phi_{it}\left(w_{it}-p_{t}^{z}z_{it}(q_{it})-p_{t}^{q}q_{it}-x_{it}\right)$$

where $\phi_{it}>0$ represents i's period t Lagrangian multiplier. An altruistic individual i accounts for the effect of a yellow air day advisory on the expected benefits that all other individuals j, $j\neq i,i,j=1,...,I$ 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 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,

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

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 (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, equation (3), function $z_{it}\left(q_{it}\right)$, and optimality condition (15) solve for q_{it}^{***}, z_{it}^{***}, and x_{it}^{***}, which when substituted back into (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,

$$\frac{\partial q_{it}^{***}}{\partial\theta_{t}}=-\frac{\Psi_{3}}{\Omega_{3}},i=1,...,I,t=1,...,T, \tag{16}$$

where

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

and

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

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 (10)–(12) with (16)–(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 $i, j = 1, ..., I$, and $t = 1, ..., T$,[45]

$$\frac{\partial q_{it}^{***}}{\partial \theta_t} < \frac{\partial q_{it}^{**}}{\partial \theta_t} \quad \text{if} \quad \sum_{j \neq i} \left(\frac{\partial^2 \bar{d}_{jt}}{\partial Q_t^{***} \partial \alpha_j} \frac{\partial \alpha_j}{\partial \theta_t} \right) >$$

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

The left-hand side of the second inequality in (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 (5)–(7) with (16)–(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 $i, j = 1, ..., I$, and $t = 1, ..., T$,

$$\frac{\partial q_{it}^{***}}{\partial \theta_t} < \frac{\partial q_{it}^*}{\partial \theta_t} \quad \text{if} \quad \frac{\partial^2 \bar{d}_{it}}{\partial Q_t^{***} \partial \alpha_i} \frac{\partial \alpha_j}{\partial \theta_t} + \sum_{j \neq i} \left(\frac{\partial^2 \bar{d}_{jt}}{\partial Q_t^{***} \partial \alpha_j} \frac{\partial \alpha_j}{\partial \theta_t} \right) >$$

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[45]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 (16), i.e., in Ω_3.

$$\sum_{j\neq i}\left(\frac{\partial^2 u_{it}}{\partial z_{it}^{***}\partial \bar{u}_{jt}}\frac{\partial \bar{u}_{jt}}{\partial \beta_j^z}\frac{\partial \beta_j^z}{\partial \theta_t}\frac{\partial z_{it}^{***}}{\partial q_{it}^{***}}\right)-\sum_{j\neq i}\left(\frac{\partial^2 u_{it}}{\partial x_{it}^{***}\partial \bar{u}_{jt}}\frac{\partial \bar{u}_{jt}}{\partial \beta_j^z}\frac{\partial \beta_j^z}{\partial \theta_t}\left(p_t^z\frac{\partial z_{it}^{***}}{\partial q_{it}^{***}}+p_t^q\right)\right), \tag{20}$$

where the left-hand and right-hand sides of the second inequality in (20) have the same interpretations as those in the second inequality in equation (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.

B   Appendix for Section 6.3

1. Identification of *YellowAdvisory* (Probit Model).

Explanatory Variables	Dependent Variable: *YellowAdvisory*
Constant	-0.94***
	(0.097)
YellowAdvisory$_{t-1}$	1.27***
	(0.159)
D.VehicleTrips	0.000
	(0.000)
D.TempDiff	0.015
	(0.011)
D.Humidity	0.04**
	(0.016)
D.Wind	0.39
	(0.246)
D.HumWind	-0.005*
	(0.003)
D.SnowFall	0.001
	(0.003)
D.SnowDepth	-0.009***
	(0.003)
$LR\chi^2(8)$	88.97***
$PseudoR^2$	0.19
N	378

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

2. Instrumented Results for *Ln*(*VehicleTrips*).

Explanatory Variables[a]	Dependent Variable: *Ln*(*VehicleTrips*)
Constant	2.90***
	(0.799)
YellowAdvisory$_{t-1}$[b]	0.17
	(0.108)
NotSunday	0.61***
	(0.022)
Holiday	-0.10**
	(0.041)
*Year*2007	0.09**
	(0.039)
*Year*2008	0.14***
	(0.039)
*Year*2009	0.17**
	(0.075)
*Year*2010	0.05
	(.054)
*Year*2011	0.23***
	(0.057)
*Year*2012	0.21***
	(0.042)
Wald χ^2(13)	2,228.86***
R^2	0.81
N	348

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

b Instrumented with lagged, first-differenced weather variables from Table 2. *** Significant at 1% level, ** Significant at 5% level, * Significant at 10% level.

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Figure 1: Location of Cache Valley, Utah

Source: https://onlinelibrary.utah.gov/utah/counties/

and https://www.freeworldmaps.net/united-states/utah/location.html.

Figure 2: Average Monthly $PM_{2.5}$ Concentrations in Cache Valley, Utah.
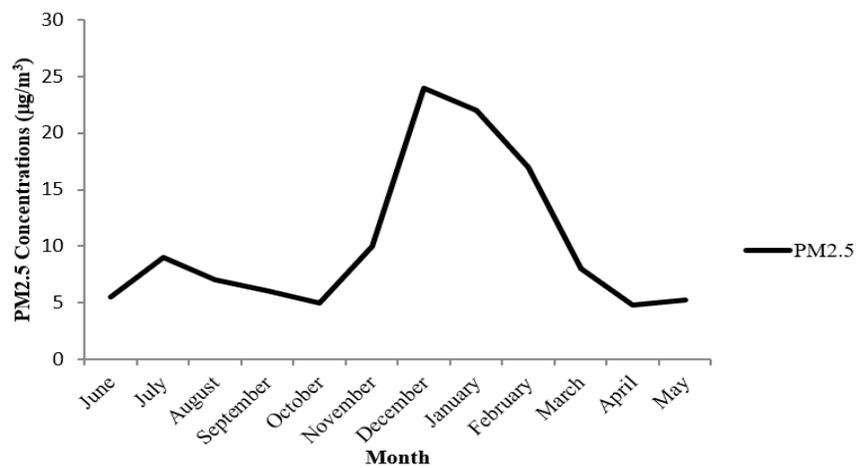

Source: Moscardini and Caplan (2017)

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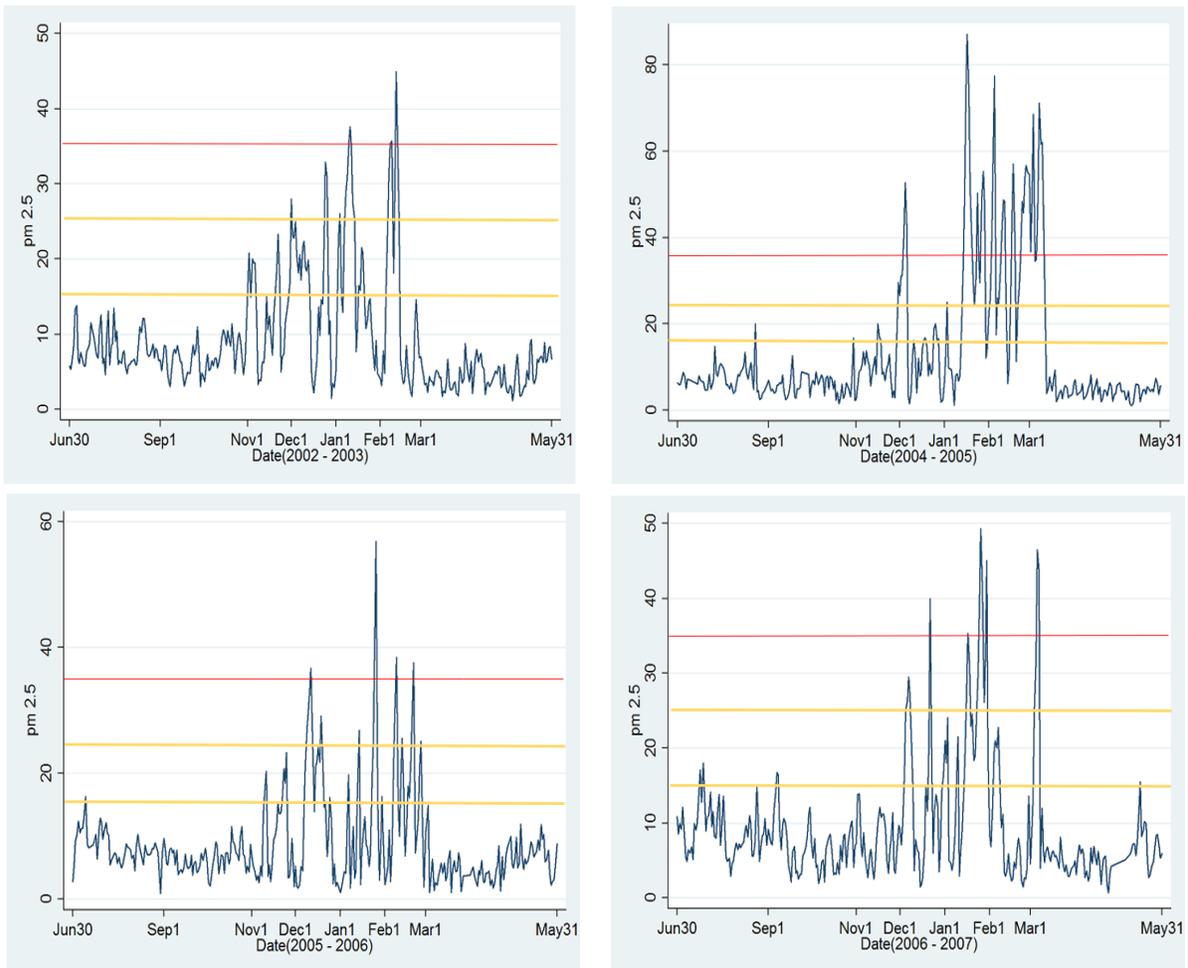
Source: Moscardini and Caplan (2017)

Figure 4: Locations of Automatic Traffic Recorder (ATR) stations in Cache Valley, Utah
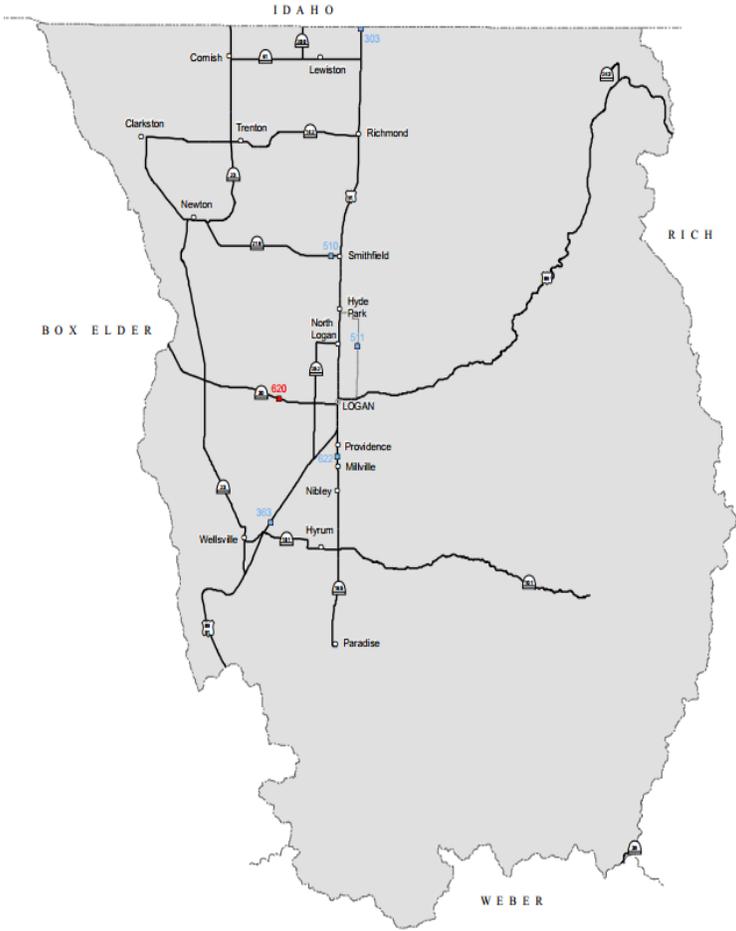
Source: Moscardini and Caplan (2017).

Figure 5: Daily averages for vehicle trips, red air days, and yellow air day advisories.
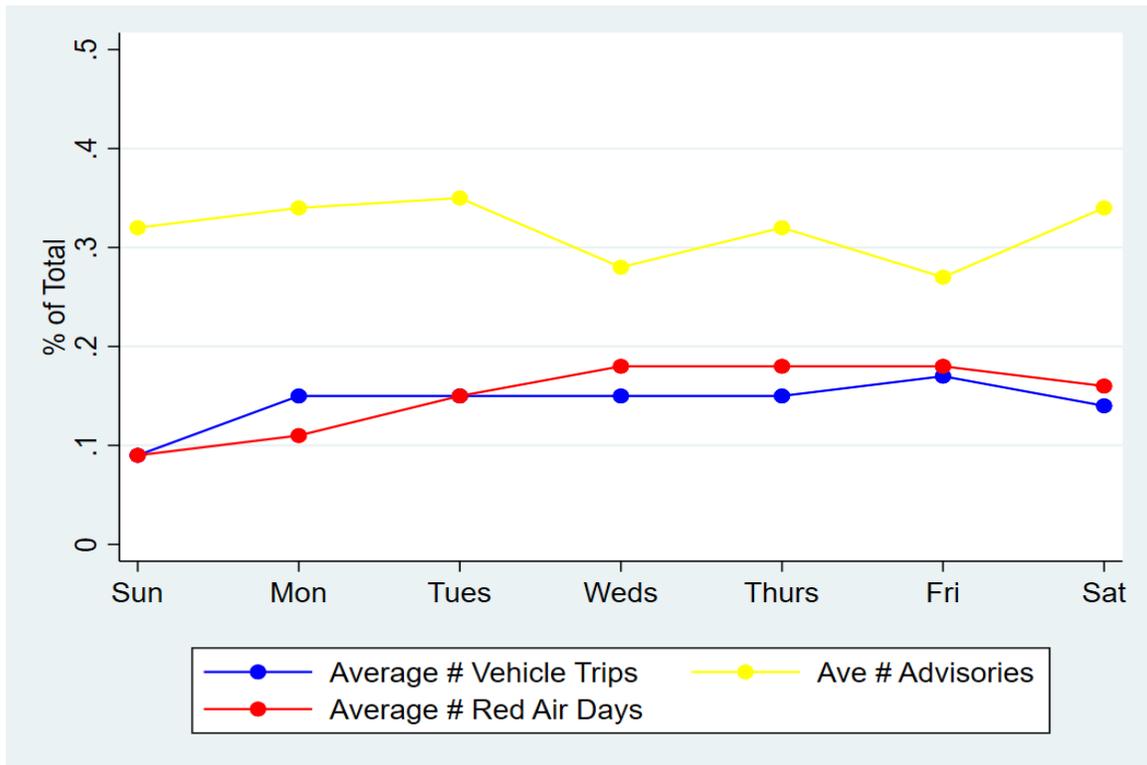
Table 1: Yellow air day advisories.

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

Table 2: Variable names, descriptions, and summary statistics.

Variable	Description	Mean (St. Dev.)
VehicleTrips	Daily trip count (# of vehicle trips).	43,261 (14,928)
PM2.5	Average daily $PM_{2.5}$ concentration ($\mu g/m^3$).	19.56 (19.39)
TempDiff	Temperature gradient between Logan Peak and valley floor ($^\circ F$).	-7.29 (10.24)
$PM2.5\|_{TempDiff>0}$	Average daily $PM_{2.5}$ concentration given winter-inversion conditions ($\mu g/m^3$).	39.47 (27.80)
YellowAdvisory	=1 if yellow air day advisory is issued, 0 otherwise.	0.32 (0.47)
Humidity	Daily humidity level (%).	82.66 (8.78)
Wind	Daily wind speed (miles/hour).	3.03 (2.67)
HumWind	*Humidity* $*$ *Wind*.	243.74 (203.89)
Pressure	Daily atmospheric pressure (p.s.i.).	30.19 (0.27)
SnowFall	Daily snowfall level (mm).	14.45 (37.54)
SnowDepth	Daily snow depth (mm).	127.26 (115.87)
Holiday	=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)
NotSunday	=1 if not Sunday, 0 otherwise.	(?) (?)

Table 3: Controlling potential autocorrelation in *VehicleTrips* and *Ln(VehicleTrips)*.

	Dependent Variable:	
Explanatory Variables	*VehicleTrips*	*Ln(VehicleTrips)*
Constant	7,524.65***	2.10***
	(1,540.802)	(0.399)
VehicleTrips$_{t-1}$	0.52***	—
	(0.041)	
VehicleTrips$_{t-2}$	-0.09*	—
	(0.046)	
VehicleTrips$_{t-3}$	0.25***	—
	(0.046)	
VehicleTrips$_{t-4}$	0.14***	—
	(0.042)	
Ln(VehicleTrips)$_{t-1}$	—	0.43***
		(0.041)
Ln(VehicleTrips)$_{t-2}$	—	-0.01
		(0.044)
Ln(VehicleTrips)$_{t-3}$	—	0.21***
		(0.044)
Ln(VehicleTrips)$_{t-4}$	—	0.17***
		(0.042)
$F(27,378)$	165.79***	122.30***
$Adj.R^2$	0.53	0.45
Cumby-Huizinga χ^2	1.394	1.576
Modified Ljung-Box χ^2	1.846	1.628
Durbin χ^2	1.383	1.565
N	594	594

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

Table 4: Baseline regression results for *VehicleTrips* and *Ln*(*VehicleTrips*).[a]

| Explanatory Variables | Dependent Variable: | |
	VehicleTrips	*Ln*(*VehicleTrips*)
Constant	-6,459.01***	3.21***
	(2,063.97)	(0.485)
YellowAdvisory	-1,407.67	0.002
	(1,478.12)	(0.029)
YellowAdvisory$_{t-1}$	4,085.61**	0.09**
	(1,825.69)	(0.038)
NotSunday	20,487.62***	0.58***
	(965.09)	(0.017)
YellowAdvisory x *NotSunday*	1,810.39	0.02
	(1,560.47)	(0.030)
[*YellowAdvisory* x *NotSunday*]$_{t-1}$	-4,226.90**	-0.09**
	(1,846.39)	(0.040)
Holiday	-4,481.26***	-0.11***
	(1,405.04)	(0.036)
YellowAdvisory x *Holiday*	1,429.71	0.02
	(2,121.36)	(0.052)
[*YellowAdvisory* x *Holiday*]$_{t-1}$	-411.11	-0.002
	(2,186.60)	(0.052)
*Year*2007	3,963.85***	0.11***
	(805.16)	(0.020)
*Year*2008	4,429.69***	0.12***
	(1,083.56)	(0.026)
*Year*2009	7,854.87***	0.19***
	(2,010.60)	(0.047)
*Year*2010	2,338.49*	0.06*
	(1,355.46)	(0.032)
*Year*2011	9,159.68***	0.22***
	(1,638.39)	(0.034)
*Year*2012	7,446.30***	0.19***
	(1,388.49)	(0.031)
$F(18,503)$	145.49***	276.79***
$Adj.R^2$	0.82	0.86
N	537	522

a Robust standard errors in parentheses (Huber, 1967; White 1980, 1982). *** Significant at 1% level, ** Significant at 5% level, * Significant at 10% level.

Table 5: Disaggregated regression results for *VehicleTrips* and *Ln*(*VehicleTrips*).[a]

	Dependent Variable:	
Explanatory Variables	*VehicleTrips*	*Ln*(*VehicleTrips*)
Constant	-8,401.84***	1.70***
	(1996.72)	(0.612)
YellowAdvisory	-3,370.21**	-0.02
	(1,613.19)	(0.033)
YellowAdvisory$_{t-1}$	825.45	0.01
	(612.48)	(0.014)
Holiday	-3,811.17***	-0.09***
	(1,348.71)	(0.035)
YellowAdvisory x *Holiday*	2,847.50*	0.05
	(1,774.03)	(0.048)
[*YellowAdvisory* x *Holiday*]$_{t-1}$	-1,106.42	-0.01
	(1,862.83)	(0.049)
YellowAdvisory x *Monday*	1,754.70	0.01
	(1814.94)	(0.031)
YellowAdvisory x *Tuesday*	1,665.07	0.01
	(1,468.49)	(0.029)
YellowAdvisory x *Wednesday*	4,494.90**	0.07
	(2,008.36)	(0.044)
YellowAdvisory x *Thursday*	3,111.26	0.06
	(2,273.50)	(0.030)
YellowAdvisory x *Friday*	3,219.62*	0.04
	(1,657.01)	(0.029)
YellowAdvisory x *Saturday*	2,391.73	0.03
	(1,629.99)	(0.032)
YellowAdvisory x 2007	1,046.64	0.01
	(933.31)	(0.022)
YellowAdvisory x 2008	3,646.29**	0.05
	(1,756.27)	(0.038)
YellowAdvisory x 2009	-1,050.14	-0.06
	(2,387.35)	(0.061)
YellowAdvisory x 2010	4,706.17*	0.08
	(2,424.06)	(0.055)
YellowAdvisory x 2011	-500.01	-0.02
	(1,460.05)	(0.027)
YellowAdvisory x 2012	1,078.93	0.00
	(1,588.79)	(0.034)
$F(37,484)$	144.70***	249.43***
$Adj.R^2$	0.88	0.90
N	522	522

a Robust standard errors in parentheses (Huber, 1967; White 1980, 1982). *** Significant at 1% level, ** Significant at 5% level, * Significant at 10% level.

Table 6: Controlling potential autocorrelation in *YellowAdvisory*.

Explanatory Variables	Dependent Variable: *YellowAdvisory*
Constant	0.18***
	(0.021)
YellowAdvisory$_{t-1}$	0.42***
	(0.036)
$F(1,638)$	137.85***
$Adj.R^2$	0.18
Cumby-Huizinga χ^2	0.088
Modified Ljung-Box χ^2	0.018
Durbin χ^2	0.087
N	640

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

Table 7: Identification of *YellowAdvisory*.

Explanatory Variables	Dependent Variable: *YellowAdvisory*
Constant	0.19***
	(0.025)
YellowAdvisory$_{t-1}$	0.43***
	(0.051)
D.VehicleTrips	-0.00
	(0.00)
D.TempDiff	0.005*
	(0.003)
D.Humidity	0.009**
	(0.004)
D.Wind	0.098**
	(0.048)
D.HumWind	-0.001**
	(0.0006)
D.SnowFall	0.003
	(0.005)
D.SnowDepth	-0.002***
	(0.0006)
$F(8,369)$	14.52***
$Adj.R^2$	0.22
N	378

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

Table 8: Testing for the Presence of Omitted Variable Bias in *VehicleTrips* and *Ln(VehicleTrips)*.[a]

| | Dependent Variable: | |
Explanatory Variables	*VehicleTrips*	*Ln(VehicleTrips)*
Constant	5,788.50***	1.51***
	(1,821.305)	(0.466)
D.TempDiff	86.58	0.003
	(70.24)	(0.002)
D.Humidity	-142.03	-0.002
	(103.96)	(0.003)
D.Wind	-497.43	0.01
	(1,869.40)	(0.046)
D.Humwind	0.46	-0.0003
	(23.01)	(0.0006)
D.SnowFall	-13.72	-0.0004
	(13.13)	(0.0003)
D.SnowDepth	-42.27***	-0.001***
	(15.36)	(0.0004)
$F(10,365)$	69.27***	51.58***
$Adj.R^2$	0.58	0.51
N	376	376

a Robust standard errors in parentheses (Huber, 1967; White 1980, 1982). *** Significant at 1% level, ** Significant at 5% level, * Significant at 10% level.