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ESTIMATING THE EFFECTIVENESS OF A SEASONAL GAS TAX FOR CONTROLLING EPISODIC $PM_{2.5}$ CONCENTRATIONS IN CACHE COUNTY, UTAH

by

Leo A. Moscardini

A thesis submitted in partial fulfillment
of the requirements for the degree

of

MASTER OF SCIENCE

in

Applied Economics

Approved:

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UTAH STATE UNIVERSITY
Logan, Utah

2014

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ABSTRACT

Estimating the Effectiveness of a Seasonal Gas Tax for Controlling Episodic $PM_{2.5}$ Concentrations in Cache County, Utah

by

Leo A. Moscardini, Master of Science

Utah State University, 2014

Major Professor: Dr. Arthur J. Caplan
Department: Applied Economics

For several years, residents of Cache County, Utah have suffered from the recurrence of what has come to be known as the winter-inversion, or “red-air-day” season. Each year during this season – which occurs primarily in the months of December, January, and February – particulate matter concentrations measuring two and half micrometers or less (commonly known as $PM_{2.5}$) rise and languish (for periods of days or even weeks) above federally mandated standards, causing extensive harm to community health and confounding what have thus far been the relatively tepid control efforts undertaken by local and state policymakers.

Through time-series regression modeling, we establish a statistical relationship between $PM_{2.5}$ concentrations and vehicle use in Cache County, and further calculate a gas-price elasticity for the region. Next, we analyze the benefits and costs associated with a potential seasonal gas tax which, if set appropriately and enforced effectively, could decrease vehicle use and thereby lower health costs through concomitant decreases in $PM_{2.5}$ concentrations. Specifically, we find a relatively strong positive relationship between percentage of vehicle trips reduced and associated reductions in $PM_{2.5}$ concentrations, and a gas price elasticity of approximately -0.31 in what we call a "high price variability environment."

Based upon these results, benefit-cost analysis suggests a potentially positive social net benefit for Cache County associated with imposing a seasonal gas tax to reduce $PM_{2.5}$ concentrations during the winter-inversion season. Our benefit-cost analysis, which uses quantitative estimation techniques on both sides of the ledger, yields a first-of-its-kind social net benefit estimate for controlling elevated $PM_{2.5}$ concentrations in Cache County through the imposition of a seasonal gas tax.

(71 pages)

PUBLIC ABSTRACT

Estimating the Effectiveness of a Seasonal Gas Tax for Controlling Episodic $PM_{2.5}$ Concentrations in Cache County, Utah

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Cache County, Utah boasts an abundance of awe-inspiring natural beauty. However, at times, its air quality rivals the worst in the United States. During the winter months of December through February, particulate matter measuring two and a half micrometers or less, commonly known as $PM_{2.5}$, often concentrates to dangerously high levels causing extensive harm to public health. Lawmakers have scrambled to pass legislation aimed at mitigating the risks posed by poor air quality, recently adopting a county-wide vehicle emissions testing program designed to reduce exhaust emissions from on-road mobile sources. However, its efficacy has been hotly debated and many similar programs around the country have failed to produce significant results.

Using ten years of daily data on $PM_{2.5}$ concentrations, vehicle use, and meteorological variables to control for the climactic determinants of inversions in Cache County, we construct an econometric model which attempts to explain the variation in $PM_{2.5}$ levels caused by motor vehicles. Next, employing similar methodology using historical Cache County gas price data, we model how drivers in the county respond to substantial changes in the price of gasoline. Ultimately, these two models together enable us to estimate how increases in gas price might lower vehicle use, thereby reducing public health costs through concomitant decreases in $PM_{2.5}$ concentrations. In fact, empirical analysis indicates that a winter-time (seasonal) tax on gasoline may be a more effective control mechanism for $PM_{2.5}$ than the recently adopted vehicle emissions testing program in Cache County. Moreover, we show that the benefits of clean air in the county outweigh the costs of such a tax under the right conditions.

(71 pages)

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Over the course of my Master's education, I've received immeasurable inspiration and assistance from a great many people. Dr. Arthur J. Caplan has been a phenomenal professor, mentor, and friend, and his guidance has made my research both exciting and rewarding. I'd also like to thank my thesis committee of Dr. Ryan Bosworth, Dr. Man-Keun Kim, and Dr. Roger Coulombe for their time and valuable feedback. Additionally, Carlos Silva was instrumental in providing the statistical training necessary to conduct my analyses. However, above all, I will be forever grateful for the unwavering support and encouragement given to me by my family. This thesis is for them.

Leo A. Moscardini

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INTRODUCTION

Situated in northern Utah, Cache County boasts an abundance of awe-inspiring natural beauty (see Figure 1 for the county's location in Utah). However, at times its air quality rivals the worst in the United States (Nierenberg 2009). Particularly during the winter months, inversions trap polluted air in Cache Valley[1] for days or weeks at a time. Much of the pollution is particulate matter measuring two and half micrometers or less, or $PM_{2.5}$, a term used to describe dust, soot, dirt, or smoke particles, as well as liquid droplets (EPA 2014a). These particles pose a great risk to human health, as their small size enables them to lodge deep in lung tissues.

Fig. 1 Location of Cache Valley, Utah[2]

[1] Cache Valley is the population center and predominant area of Cache County. Hence, we use Cache County and Cache Valley (sometimes referred to as "the valley") interchangeably.
[2] Source: Utahrealestateguide.org

Both point and non-point pollution sources contribute to $PM_{2.5}$ concentrations, with agricultural and industrial processes, wood burning, and vehicle emissions contributing the most (EPA 2014a). In an effort to improve air quality in the valley, lawmakers recently adopted a vehicle emissions testing program (VETP) aimed at curbing the harmful exhaust that contributes to $PM_{2.5}$ concentrations (Anderson 2013). However, because the exact relationship between vehicle use and $PM_{2.5}$ levels is as yet unknown for the region, the efficacy of a VETP has been hotly debated (Anderson 2013).

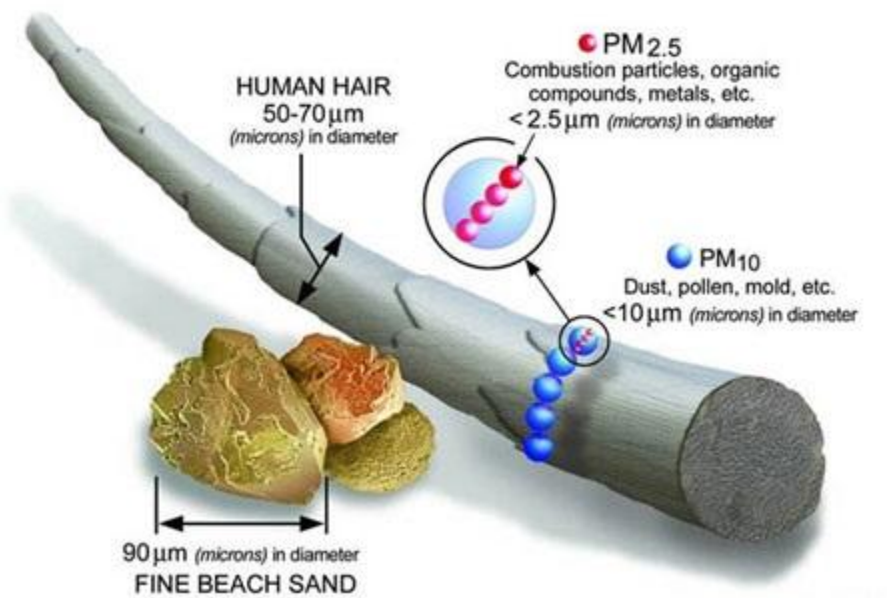

Fig. 2 Relative size of PM2.5[3]

This thesis establishes a precise statistical relationship between vehicle use (in the form of vehicle trips) – a proxy for human-induced emissions – and $PM_{2.5}$ concentrations

[3] Source: U.S. EPA

in Cache County using time-series regression analysis. The results reveal that a reduction in vehicle trips would quite dramatically decrease $PM_{2.5}$ concentrations. Furthermore, using somewhat similar regression methodology, a relationship between vehicle trips and at-the-pump gas prices is estimated, thus laying a policy foundation for a seasonal gas tax. Finally, using a variety of approaches, this paper explores the benefits and costs of such a tax and shows that, under the right conditions, the policy passes a benefit-cost analysis.

THE PROBLEM AND PROPOSED SOLUTION

For approximately 75 percent of each year, Cache County is virtually free of $PM_{2.5}$ concentrations that exceed EPA safe standards. However, in 2008, it was designated by the EPA as a nonattainment area, meaning that the valley had not complied with "the national primary or secondary ambient air quality standards" for $PM_{2.5}$ concentrations over a period of successive years (EPA 2014a). Currently, the 24-hour standard for $PM_{2.5}$ concentrations, as measured by the "three year average of the annual 98th percentile of readings," is less than or equal to 35 micrograms per cubic meter (µg/m^3).[4] For several days of the year, particularly during the winter months of December, January, and February, Cache County's $PM_{2.5}$ concentrations rise well above that level (EPA 2014a).

Figure 3 depicts the distribution of $PM_{2.5}$ concentrations during the 2010 – 2011 season (note the spikes above the 35 µg/m^3 standard (horizontal red line) in early December and early-to-mid January in that year). Figure 4 shows the distribution of monthly average $PM_{2.5}$ concentrations in Cache County for the years 2002 – 2012 (note the distribution's mass for the months of December – February).

[4] The current standard represents a drastic tightening of the previous 1997 standard of 65 µg/m^3.

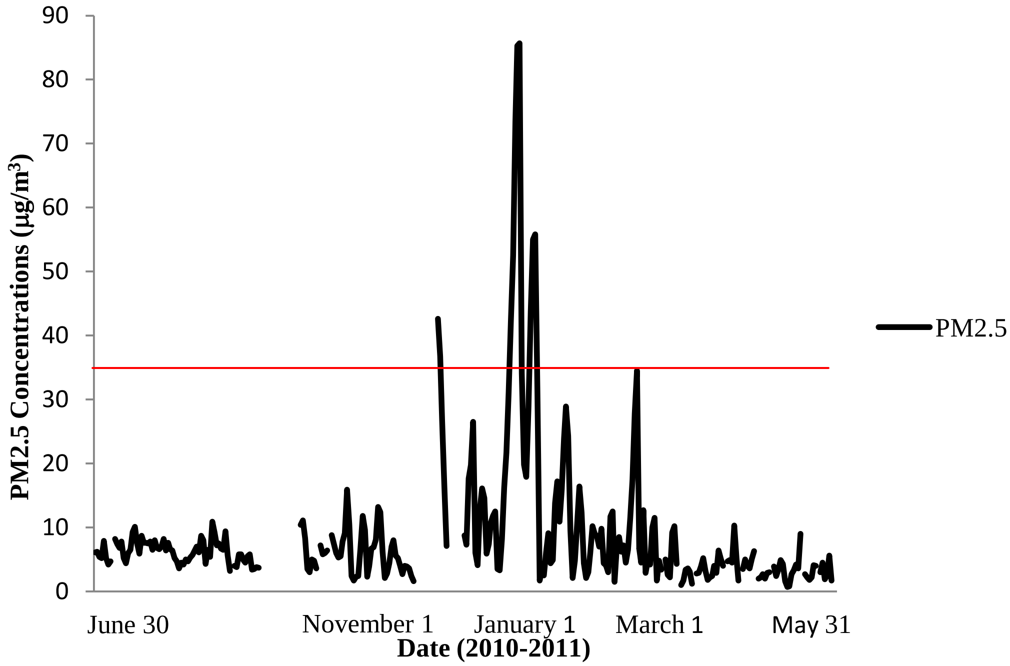

Fig. 3 PM 2.5 concentrations in Cache County for the 2010 – 2011 season

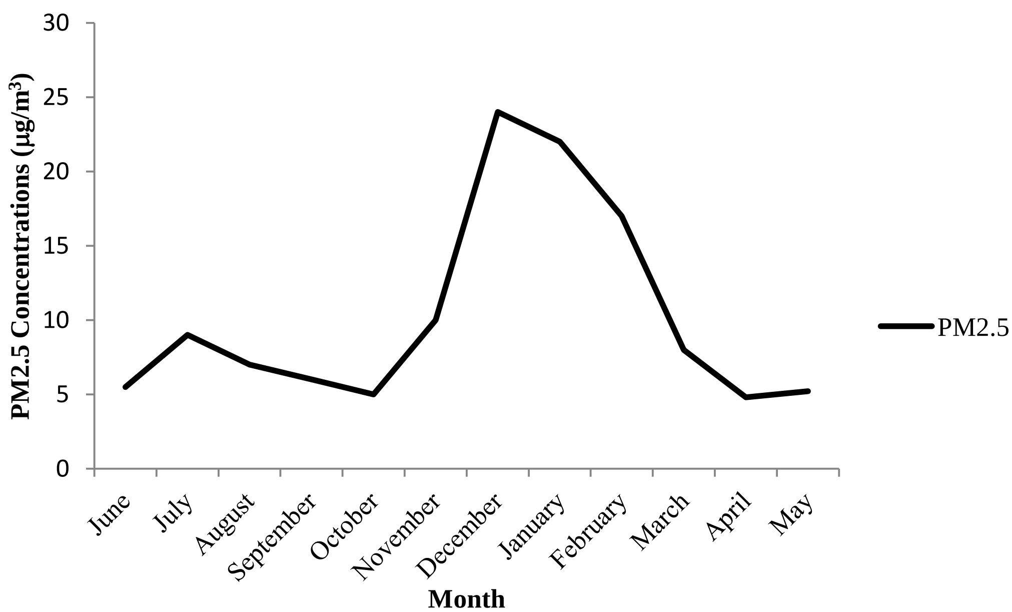

Fig. 4 Monthly average PM 2.5 concentrations for 2002 – 2012

Inversion

In no small way, residents of Cache County are victims of both their climatology and topography. Under certain meteorological conditions, cold air becomes trapped between the mountains close to the surface and is held in place by a layer of warm air above, a process known as "inversion" (State of Utah 2013).

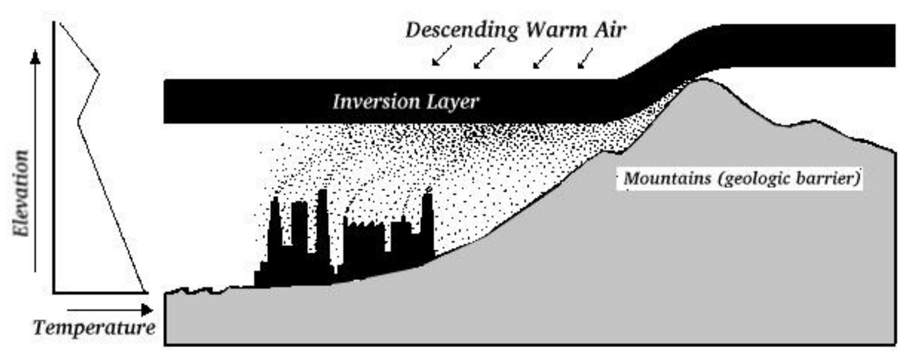

Fig. 5 Inversion[5]

Figure 5 illustrates the inversion problem. As elevation rises, temperature gradually decreases. However, given certain barometric pressure, precipitation, and wind speed conditions, descending warm air can create an inversion layer, at which point temperature increases with increasing elevation constituting the reverse of normal air patterns. This inversion layer traps $PM_{2.5}$ concentrations between geologic barriers which, around Cache County, are the Wellsville and Bear River Mountains. Figure 6 depicts the aesthetic consequences of inversion.

Heightened concentrations of $PM_{2.5}$ brought about by winter-time inversions

[5] Source: Indiana State University

carry significant consequences for human health. Data collected by Utah State Representative Ed Redd, formerly a medical doctor at the Bear River Department of Health in Logan, indicate that during the winter months of 2004, three deaths, five hospitalizations, and 109 emergency room visits were attributable to dangerous levels of the pollutant, resulting in estimated health costs of more than $23 million in four months (Coulombe 2011). This amount can be thought of as one measure of the annual cost of elevated $PM_{2.5}$ concentrations in Cache County.

Fig. 6 Absence and presence of inversion, respectively, in Cache County

Sources of and Control Mechanisms for $PM_{2.5}$

Because large industrial point sources are scarce in Cache County, researchers have linked the region's agriculturally-dominated economy to heightened $PM_{2.5}$ concentrations. When mixed with exhaust emissions, ammonium vapors from livestock waste form $PM_{2.5}$. A study conducted by researchers at Utah State University show that "the urine and manure of Cache County's 75,000 cows release about 5.3 tons of ammonia vapors into the air each winter day" (Fahys 2004). These ammonia vapors, trapped in the valley by an inversion, can concentrate between five and ten times their normal levels (Fahys 2004). Figure 7 illustrates that the largest contributor to $PM_{2.5}$ concentrations in Cache County is ammonium nitrate.

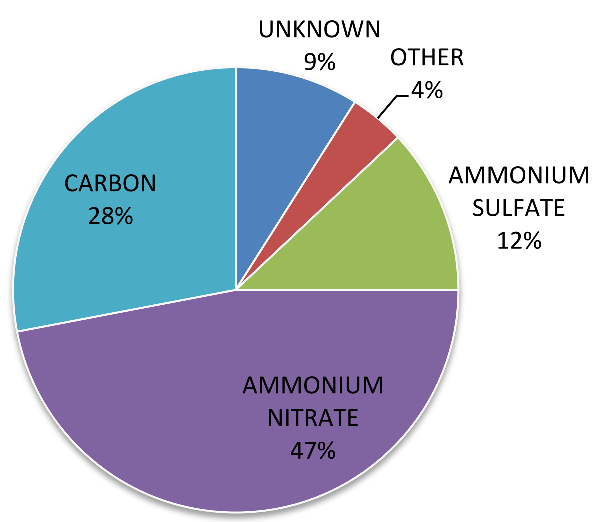

Fig. 7 PM2.5 distribution in Cache County[6]

[6] Source: UDEQ (2014b), Dec-Feb: 2000-2007, N=212.

Due to the high concentrations of ammonium vapors found in Cache County, and because ammonia is a precursor to $PM_{2.5}$ concentrations, some have proposed that stricter regulations be enforced on farms and ranches in the valley. Research has shown that there are indeed effective ways to control ammonia emissions from cattle. For example, a study conducted by Iowa State University showed that ammonia emissions "can be reduced 40-50 percent by using biofiltration" in animal housing areas (Shih et al. 2006). A biofilter, which is "simply a porous layer of organic material that supports a population of microbes," funnels dirty air from animal housing areas and converts the pollution to carbon dioxide and water (Nicolai 2011). At a cost of approximately $200 dollars per filter, and annual operating and maintenance costs typically not exceeding $5 to $10 dollars per filter, biofiltration is both an efficient and cost-effective way to control ammonia emissions (Nicolai 2011). However, local officials in Cache County have been reluctant to adopt such policies. Referring to general livestock curbs, Cache County executive Lynn Lemon stated, "I think we need to make sure we are on firm ground when we go there. The agricultural community gets really offended when we blame it on the cows" (Fahys 2004).

In March 2013, Cache County Council members voted to adopt a vehicle emissions testing program (VETP). The narrow 4-3 decision was a result of intense pressure from the EPA, as well as a reaction to studies showing that a small percentage of vehicles (around 10-15 percent) contribute the most to $PM_{2.5}$ concentrations (Fahys 2004). The VETP makes it mandatory for residents of the county to submit their vehicles for inspection every other year. However, its benefits have yet to be proven and the program's economic viability is cause for concern. Indeed, a prominent report commissioned by the National Academy of Sciences points to mounting evidence suggesting that VETPs have been much less effective than initially anticipated, on average reducing emissions by only half of promised amounts (National Research Council 2001). With an estimated implementation cost of $1.8 million and relatively low anticipated benefits, many Cache County residents have strong reservations (Anderson 2013). Cache County Council member Val Potter recently expressed his dissent, stating, “It really doesn’t solve the problem. I feel like $1.8 million for the effect that it’s going to have on air pollution in this valley really isn’t justified” (Anderson 2013). In all, the VETP is expected to reduce *total* air pollution in the valley by just three to five percent (Anderson 2013).

Due to both the high costs and relatively low predicted efficacy of Cache County’s VETP, a policy that would lower vehicle use during the inversion season may prove to be more beneficial. During an inversion, “anywhere from 60 to 85 percent of all $PM_{2.5}$ found on the Utah Department of Air Quality’s monitoring files is created by secondary particulate formation” (UDEQ 2014b). Secondary particulate formation occurs when precursor emissions of nitrogen oxides (NOx), sulfur oxides (SOx), and particularly volatile organic compounds (VOCs) react and combine in the atmosphere to create $PM_{2.5}$ (UDEQ 2014b). According to the Utah Department of Environmental Quality (UDEQ), 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 County (see figure 7).

Hence, the UDEQ concludes that reducing VOC emissions “provides the best approach to reducing $PM_{2.5}$ levels during winter inversions in Utah in the near future”

(UDEQ 2014b). Figure 8 shows that transportation accounted for the majority of anthropogenic VOC emissions from 1900-1996 (CMA 1998).

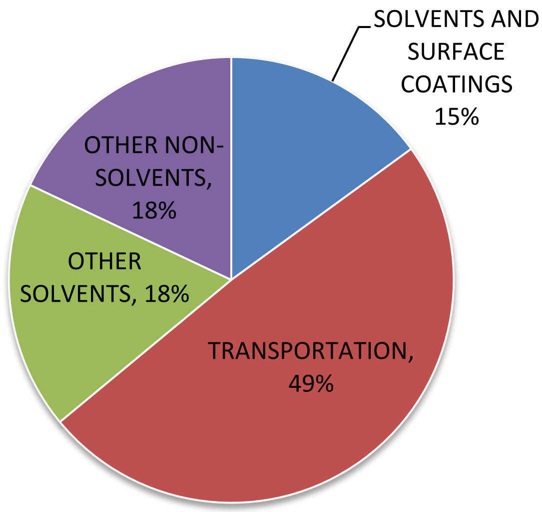

Fig. 8 Volatile organic compound (VOC) emissions inventory, 1900-1996[7]

Today, approximately 50 percent of anthropogenic VOC emissions are attributable to industrial and commercial processes, 45 percent to motor vehicles, and just five percent to consumer solvents (NASA 2014). Therefore, a policy that reduces vehicle use may be a highly effective way of advancing the UDEQ's ambition of lowering VOC emissions. If set at the appropriate level, a seasonal gas tax may be a more powerful control mechanism for $PM_{2.5}$ concentrations than the recently adopted VETP in Cache County.[8]

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[7] Source: Chemical Manufacturers Association, data from the EPA, National Air Pollutant Emission Trends, 1900-1996.

[8] To our knowledge, Cropper et al. (2014) is the only extant study that investigates the use of a market-based policy to control what it calls "episodic pollution" attributable to mobile sources (i.e., vehicle

Furthermore, questions arise as to the benefits (in the form of induced medical cost savings) and costs associated with such a tax. The research and results presented in the following sections are aimed at empirically evaluating the potential role a gas tax may play in reducing $PM_{2.5}$ concentrations in Cache County, and in exploring attendant questions concerning the benefits and cost associated with reducing these concentrations in the valley during the winter months.

emissions), in specific ground-level ozone in Washington, DC. The authors propose a permit scheme that they estimate would – after accounting for non-compliance – result in approximately one million vehicles removed from the road during high-ozone days, which in turn would result in the reduction of more than 30 tons of NO_x emissions per day (reductions in percentage terms not provided by the authors) and raise an estimated $111 million in revenue per ozone season.

DATA SOURCES

To analyze the merits of a seasonal gas tax in Cache County, two separate regression models are required to (1) establish a statistical relationship between $PM_{2.5}$ concentrations and vehicle travel (a "$PM_{2.5}$ regression"), and (2) to establish a statistical relationship between vehicle travel and gas prices (a "gas-price regression"). In doing this, a correlation between gas prices and $PM_{2.5}$ concentrations can be estimated.

The $PM_{2.5}$ regression models are built around three key measures: daily $PM_{2.5}$ concentrations, daily vehicle trip counts, and a vector of daily weather variables to control for inversion-inducing meteorological conditions in Cache County. Data for these models are collected from three primary sources, and have a date range from 2002 to 2012. Note that because inversions are solely a wintertime phenomenon, only data from winter months are used for analysis (December through February). $PM_{2.5}$ concentrations are recorded by the Utah Division of Air Quality at EPA station code 490050004 located in downtown Logan, Cache County's largest city (UDEQ 2014a). This data is collected hourly, and we aggregate these readings and divide by 24 to obtain daily averages.

Trip count data were obtained from the Utah Department of Transportation (UDOT). UDOT has six automatic traffic recorder (ATR) stations located strategically throughout Cache County (UDOT 2014b). However, only four stations have been in service since 2002. Data collection at the two additional ATR stations began in 2005 and 2008, respectively. To preserve continuity in the data, only readings from the first four stations are used. Figure 8 shows the locations of all six active ATR stations in the valley. For our study, data from ATR stations #303, #363, #510, and #511 are used. Station #303 borders Idaho, while station #363 lies central to Wellsville and Hyrum.

Station #510 is located in Smithfield, and station #511 lies in North Logan, located next to Utah State University. We aggregate the trip counts from these four stations in order to generate an estimation of the total vehicle trips taken in the valley per day.

Daily measurements for temperature, wind speed, humidity, and precipitation are recorded at a weather station based at Logan-Cache Airport. The data for Cache County was obtained from Weather Underground and is certified by the National Weather Service (Weather Underground 2013).

Similar to the $PM_{2.5}$ regressions, the gas-price regressions are built around several crucial variables: trip count, gas price, temperature, and household income. Note that while trip count appears as an explanatory variable in the $PM_{2.5}$ regression, it becomes the dependent variable in the gas-price regression.[9] Gas price data is obtained from GasBuddy.com, which compiles statistics from consumers, credit card transaction records, and gas stations themselves (GasBuddy 2013). Household income is proxied by a dummy variable for pre- and post-recession years (year ≤ 2008=0, year >2008=1). Unlike the $PM_{2.5}$ regressions, the gas-price regressions use data from all months (year-round). Unfortunately, adequate gas price data for Cache County is unavailable prior to 2006. Therefore, the gas price regression models are restricted to the date range 2006-2012.

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[9] This creates a scenario in which there is a potential for endogeneity in our $PM_{2.5}$ regressions. We explore this problem at length in the following section.

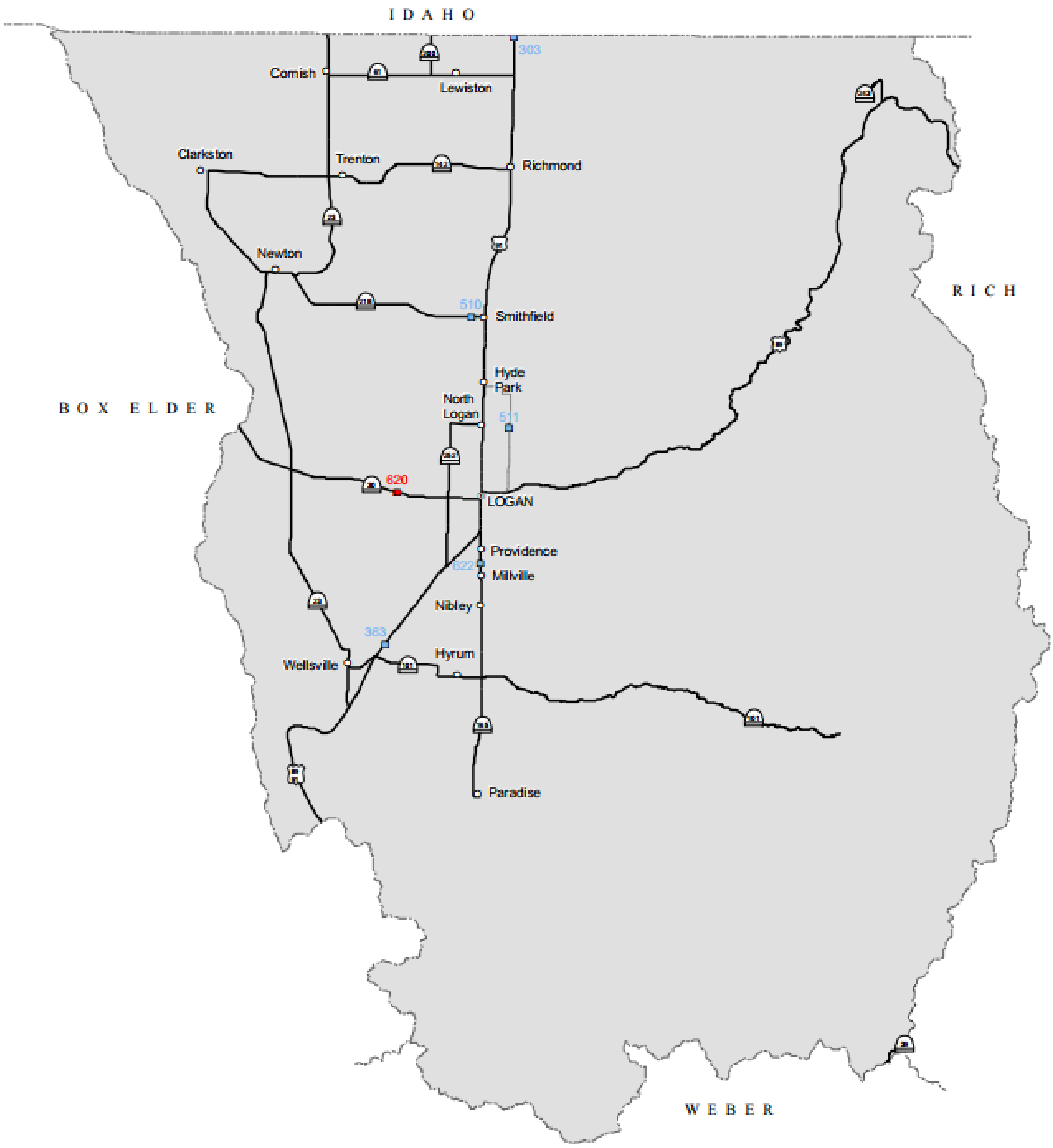

Fig. 9 ATR locations in Cache County, Utah[10]

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[10] Source: Utah Department of Transportation (2014b)

Table 1 provides descriptions and summary statistics for the variables used in both the $PM_{2.5}$ and gas-price regressions.[11] The variable *PM2.5* is calculated as the natural log of the average daily value of $PM_{2.5}$ concentrations (taking the antilog shows this average to be approximately 12.76 µg/m³) and *Trip_Count* the natural log of the three-day rolling average of total trip count in Cache County (indicating an average of approximately 31,000). A rolling average is used to control for any lingering vehicle emissions from two days lagged.[12] *Wind*, *Temp*, *Humid*, and *Precip* measure the average daily wind speed, temperature, humidity, and total precipitation in the valley, respectively. Similar to $PM_{2.5}$ concentrations, these averages are for hourly readings.

Table 1 Variable Definitions and Summary Statistics

Variable	Description	Mean	(SD)
PM2.5	Natural log of daily average $PM_{2.5}$ concentrations in Cache Valley, UT	2.546	(0.971)
Trip_Count	Natural log of the three-day rolling average of daily vehicle trips taken in Cache County, UT	10.346	(0.116)
Wind	Average daily wind speed (MPH) in Cache Valley, UT	3.029	(2.667)
Temp	Average daily temperature (°F) in Cache Valley, UT	46.118	(19.225)
Humid	Average daily relative humidity (%) in Cache Valley, UT	82.664	(8.782)
Precip	Total daily precipitation (in) in Cache Valley, UT	0.04	(0.107)
HumWind	Interaction term of *Humid* and *Wind* (*Humid* x *Wind*)	243.736	(203.886)
GPrice	Natural Log of daily average at-the-pump gas price for Cache County, UT	1.061	(0.216)
Recession	Dummy variable for pre- and post-recession years; (year ≤ 2008=0, year >2008=1)	0.455	0.498

[11] Augmented Dickey Fuller tests were performed on each variable to ensure stationarity.
[12] We tried various lag lengths for *Trip_Count* and the regressions results were qualitatively unchanged.

REGRESSION ANALYSIS

This section describes the various empirical models tested in this thesis, and discusses the ensuing results from our regression analyses. To ultimately establish a link between gas prices and $PM_{2.5}$ concentrations, we start by regressing $PM_{2.5}$concentrations *(PM2.5)* against vehicle trips *(Trip_Count)* along with a variety of meteorological variables that control for the various climactic determinants of a typical winter inversion. Next, we analyze the effect that gas prices (*GPrice*) have on *Trip_Count* using a regression configuration based upon a simple household-production model. The following empirical results suggest that a seasonal gas tax may be an effective tool in reducing vehicle travel in Cache County (and thereby $PM_{2.5}$ concentrations) during the winter inversion season.

Methodology

$PM_{2.5}$ *Estimation*

Our $PM_{2.5}$ regression models are built to explain the variation in $PM_{2.5}$ concentrations caused by vehicle use. We start with an admittedly "naïve" $PM_{2.5}$ regression: one that ignores the issue of potential endogeneity brought about by *Trip_Count*'s possible statistical relationship with *GPrice*. Equation (1) shows our initial $PM_{2.5}$ regression used to model *Trip_Count*'s effect on *PM2.5*,

$$PM2.5_t = C + \boldsymbol{\beta_n X_t} + \varepsilon_t \tag{1}$$

where C is a constant term, $\boldsymbol{\beta_n}$ is the vector of (constant) coefficients to be estimated, and $\boldsymbol{X_t}$ is a matrix of the explanatory variables *Trip_Count*, *Temp*, *Wind*, *Humid*, *Precip*, and *HumWind* for time period(s) t.[13]

This initial $PM_{2.5}$ regression tests an autoregressive integrated moving average, or ARIMA model. ARIMA models can correct for serial correlation in time series data and "produce better explanations of the residuals from an existing regression equation" (Studenmund 2011). These models are specified with the shorthand notation (#p, #d, #q), where "the dependent variable and any independent variables are differenced #d times, and 1 through #p lags of autocorrelations and 1 through #q lags of moving averages are included in the model" (STATA 2013a). To show how an autoregressive process may correct for possible first-order serial correlation, we estimate a generalized least squares (GLS) version of (1) following Studenmund (2011). In general, we can think of a regression equation with serial-correlated error terms as,

$$Y_t = C + \boldsymbol{\beta_1 X_{1t}} + \varepsilon_t, \text{ where } \varepsilon_t = \rho\varepsilon_{t-1} + \mu_t. \tag{2}$$

In (2), ε_t is a serially correlated error term, ρ is the associated correlation coefficient, and $\mu_t$is a classical error term. In order to effectively remove the $\rho\varepsilon_{t-1}$term from (2), we first multiply both sides of the equation by ρ and then lag the new equation by one time period, resulting in equation (3) (Studenmund, 2011),

$$\rho Y_{t-1} = \rho C + \rho\boldsymbol{\beta_1 X_{1t-1}} + \rho\varepsilon_{t-1}. \tag{3}$$

Subtracting (3) from (2) we have:

---

[13] We tested several alternative specifications (with different combinations and transformations of the explanatory variables listed in Table 1) of the model described in (1). We did not include stationary-source emissions as a separate explanatory variable for two reasons. First and foremost, we were unable to obtain these emissions estimates on a daily basis from the UDEQ. Second, because our *PM2.5* measure is effectively incorporating the effects of stationary-source emissions (in terms of their contributions to concentration levels), the coefficient on our *Trip_Count* variable can effectively be interpreted as the percentage of $PM_{2.5}$ concentrations that are explained by mobile sources, on average.

$$Y_t - \rho Y_{t-1} = C(1\text{-}\ \rho) + \boldsymbol{\beta_1}(\boldsymbol{X_{1t}} -\ \rho \boldsymbol{X_{1t-1}}) + \mu_t \tag{4}$$

which is re-written as:

$$Y_t^* = C^* + \boldsymbol{\beta_1}\boldsymbol{X_{1t}^*} + \mu_t \tag{5}$$

where $Y_t^* = Y_t - \rho Y_{t-1}$, $\boldsymbol{X_{1t}^*} = \boldsymbol{X_{1t}}$ - $\rho \boldsymbol{X_{1t-1}}$, and $C^* = C$ - ρC.

Equation (5) is a GLS version of equation (2). Note that (i) the error term μ_t is not serially correlated, and (ii) the slope coefficients $\boldsymbol{\beta_1}$ are identical to the respective slope coefficients of the original serially correlated equation (2), meaning that the $\boldsymbol{\beta_1}$ coefficients may be interpreted identically across equations. In all, the autoregressive process "expresses the dependent variable Y_t as a function of past values of the dependent variable" (Studenmund 2011).

In contrast, the moving-average component of the ARIMA model "expresses the dependent variable Y_t as a function of past values of the error term" (Studenmund 2011). Both the autoregressive and moving-average processes are shown in (6), where the θs and the ϕs are the coefficients of the autoregressive and moving-average processes, respectively, and p and q are the number of past values used of Y and ε, respectively (Studenmund 2011).

$$\begin{aligned} Y_t = C_t + \overbrace{\theta_1 Y_{t-1} + \theta_2 Y_{t-2} + \ldots + \theta_p Y_{t-p}}^{\text{Autoregressive process}} + \varepsilon_t \\ \underbrace{+\ \phi_1 \varepsilon_{t-1} + \phi_2 \varepsilon_{t-2} + \ldots + \phi_q \varepsilon_{t-q}}_{\text{Moving-average process}} \end{aligned} \tag{6}$$

While our initial $PM_{2.5}$ regression is corrected for serial correlation, it ignores the potential endogeneity associated with the *Trip_Count* variable. Endogeneity is the violation of a basic assumption of regression analysis which occurs when the error term is correlated with an explanatory variable. Without testing for potential endogeneity in the $PM_{2.5}$ regression, we assume that a shock in gas prices would be captured solely by the regression's error term, not *Trip_Count*. To test for endogeneity of the *Trip_Count* variable, a standard Hausman test is used. For this test, a gas-price regression model is estimated. Next, the residuals from this regression are added as an explanatory variable to the $PM_{2.5}$ regression. Should the residuals be statistically significant, we can conclude that *Trip_Count* is behaving as an endogenous variable in the $PM_{2.5}$ regression.

To control for endogeneity, we shift focus away from our original ARIMA model and test a more sophisticated instrumented variable (IV) regression model. This configuration essentially replaces the potentially endogenous variable, *Trip_Count*, with a set of instrumental variables, or instruments. In theory, the instruments used should be both independent of the error term and highly correlated with the endogenous variable (Studenmund 2011). The IV model can be corrected for heteroskedasticity and serial correlation through a heteroskedasticity- and autocorrelation-consistent (HAC) weighting matrix. The appropriate number of lags is determined using Newey and West's (1994) automatic lag-selection algorithm (STATA 2013b).

Gas-Price Estimation

This section describes the methodology used to calculate the statistical relationship between *GPrice* and *Trip_Count* in Cache Valley, and is divided into two subsections. The first presents a simple household-production model upon which we base our gas-price regression, and the second discusses the specification of our empirical models.

Theoretical framework

The theoretical framework for our gas-price regressions can be represented most conveniently by a variation of Becker's (1965) household production model, where a household i's welfare in time period t is a function of a composite good obtained via vehicle trips (Z_1), a numeraire good (Z_2), and parameterized by the study area's $PM_{2.5}$ concentration level ($\bar{G}$), and a vector of seasonal variables proxied by temperature (Θ) (time subscripts t are removed from the variables and functions for convenience),[14]

$$U^i(Z_{1i}, Z_{2i}; \bar{G}, \Theta) \quad (7)$$

which we assume exhibits standard curvature conditions for Z_{1i}, Z_{2i}, and $\bar{G}$. In particular, we note that $U_G^i < 0$ and $U_{GG}^i < 0$. Equation (7) can be re-written as:

$$U^i(F^{1i}(X_{1i}, T_{1i})\ Z_{2i}; \bar{G}, \Theta) \quad (8)$$

where X_{1i} represents total amount of gas used to obtain Z_{1i}, T_{1i} represents household i's time spent obtaining Z_{1i}, and F^{1i} is the household production function for Z_{1i}. Similar to function U^i, we assume F^{1i} exhibits standard production-function curvature conditions.

Household i maximizes (8) subject to its budget constraint,

$$P_1 X_{1i} + Z_{2i} + T_{1i}\overline{w}_i = \mathrm{T}\overline{w}_i, \quad (9)$$

[14] Our empirical estimation of the gas price regression assumes that function U^i is additively separable in Z_1 and Z_2.

where P_1 represents the per-unit price of Z_{1i}, $\overline{w}_i$ represents household i's composite wage rate, and T represents total work time available to household. Solving the corresponding maximization problem yields the following four first order conditions (FOC's):

$$\frac{\partial}{\partial x_{1i}} : U^i_{Z1i} F^{1i}_{X1i} - \lambda_i P_1 = 0 \tag{10}$$

$$\frac{\partial}{\partial Z_{2i}} : U^i_{Z2i} - \lambda_i = 0 \tag{11}$$

$$\frac{\partial}{\partial T_{1i}} : U^i_{Z1i} F^{1i}_{T1i} - \lambda \overline{w}_i = 0 \tag{12}$$

$$\frac{\partial}{\partial \lambda_i} : \mathrm{T}\overline{w}_i - P_1 X_{1i} - Z_{2i} - T_{1i}\overline{w}_i = 0 \tag{13}$$

where λ represents the problem's Lagrangian multiplier (marginal utility of income). FOC's (10) – (13) can be solved for household i's demand for gas, the numeraire good, and time spent obtaining Z_{1i}, i.e., $X_{1i}(\overline{w}_i, P_1, \Theta, \bar{G})$, $Z_{2i}(\overline{w}_i, P_1, \Theta, \bar{G})$, and $T_{1i}(\overline{w}_i, P_1, \Theta, \bar{G})$, respectively. The demand for goods obtained via vehicle trips can then be written as $Z_{1i} = F^{1i}(X_{1i}(\cdot), T_{1i}(\cdot))$. For future reference, the household's gas price elasticity is shown by (14),

$$\varepsilon^i_{X_{1i}P_1} = \frac{\partial X_{1i}}{\partial P_1} \frac{P_1}{X_{1i}(\cdot)} \tag{14}$$

To establish the benchmark, socially optimal allocation of the household's demands, assume a social planner maximizes the sum of all individual's utilities over the sum of individual incomes and expenditures (i.e., an economy-wide resource constraint). Hence, the optimization problem becomes:

$$\max_{\{X_{1i}, T_{1i}, Z_{2i}\}} \sum_i U^i(F^{1i}(X_{1i}, T_{1i}), Z_{2i}, \sum_i F^{1i}(X_{1i}, T_{1i}); \Theta) \tag{15}$$

where now $\bar{G}$ is explicitly recognized by the planner as variable $G = \alpha \sum_i F^{1i}(X_{1i}, T_{1i})$, where α represents an emissions factor, subject to the economy-wide resource constraint:

$$\sum_i \left(-P_1 X_{1i} - Z_{2i} - T_{1i}\bar{w}_i + T\bar{w}_i \right) = 0 \tag{16}$$

Solving the maximization problem yields the following FOC's for i=1,...,N, where μ is this problem's Lagrangian multiplier representing the marginal social utility of aggregate income:

$$\frac{\partial}{\partial x_{1i}} : U^i_{Z1i} F^{1i}_{X1i} + \alpha \sum_i U^i_G F^{1i}_{X1i} - \mu P_1 = 0 \tag{17}$$

$$\frac{\partial}{\partial z_{2i}} : U^i_{Z2i} - \mu = 0 \tag{18}$$

$$\frac{\partial}{\partial T_{1i}} : U^i_{Z1i} F^{1i}_{T1i} + \alpha \sum_i U^i_G F^{Ti}_{T1i} - \mu \bar{w}_i = 0 \tag{19}$$

$$\frac{\partial}{\partial \mu_{1i}} : \sum_i (T\bar{w}_i - P_1 X_{1i} - Z_{2i} - T_{1i}\bar{w}_i) = 0 \tag{20}$$

The social planner is tasked with implementing a socially optimal gas tax. To accomplish this, the planner sets the tax according to (21), where t^*_{X1i} represents the optimal, (Pigovian), individualistic tax rate on gas used to obtain Z_1.

$$t^*_{X1i} = - \frac{\alpha \sum_i U^i_G F^{1i}_{X1i}}{\lambda_i} \tag{21}$$

The optimal gas tax is added to P_1, and the social planner further normalizes P_1 by $\frac{\mu}{\lambda_i}$ so that (10) becomes $U^i_{Z1i} F^{1i}_{X1i} - \lambda_i [(\frac{\mu}{\lambda_i}) P_1 + \frac{\alpha \sum_i U^i_G F^{1i}_{X1i}}{\lambda_i}]$ which collapses to (17). Similarly, the social planner sets a socially optimal tax on individual i's time spent obtaining Z_1, shown by (22), also normalizing $\bar{w}_i$ by $\frac{\mu}{\lambda_i}$ so that (12) becomes (19):

$$t^{*}_{T1i} = - \frac{\alpha \sum_i U^i_G F^{1i}_{T1i}}{\lambda_i} \quad (22)$$

Finally, to transform (11) to (18) the social planner normalizes each individual's adjusted net income by $\frac{\mu}{\lambda_i}$. In determining each tax rate, the social planner evaluates both t^{*}_{X1i} and t^{*}_{T1i} at the solution's optimal values. This implies that, in a world with perfect information, the social planner would assign a unique tax to each individual. Thus, there would be no uniform gas tax, but instead one tailored to an individual's "adjusted" marginal utility. In reality, "smart" gas-pumps would be required to identify each (type of) individual and change the price at the pump accordingly.

Model and specification

Because social planners (i.e., regulators) do not have perfect information, we move beyond normative tax analysis to a positive analysis – estimation of a uniform seasonal gas tax. To determine the effect that an at-the-pump gas tax would have on vehicle use in Cache County, we establish an empirical relationship between *Trip_Count* and *GPrice* (i.e., estimate a "gas-price regression") using a methodology somewhat similar to that of the initial $PM_{2.5}$ regression. Equation (23) shows the regression model chosen to explain this relationship, where C is a constant term, $\boldsymbol{\beta_n}$ is the vector of coefficients to be estimated, $\boldsymbol{X_t}$ is the matrix of the explanatory variables, in this case *GPrice, Temp, and Recession*, and ε_t is a mean-zero, constant variance error term,[15]

$$Trip\ Count_t = C + \boldsymbol{\beta_n X_t} + \varepsilon_t \quad (23)$$

[15] As with the $PM_{2.5}$ regressions, we ran several alternative specifications for (23).

Analysis of the *Trip_Count* variable indicates that it exhibits seasonality.[16] In other words, Cache County residents maintain consistent and predictable driving patterns depending on the day of the week (i.e. there is a strong correlation between trips taken on any given Monday and the Monday preceding, between trips taken on any given Tuesday and the Tuesday preceding, etc.). Therefore, this apparent seasonal trend in *Trip_Count* must be controlled for if the marginal effects associated with the various explanatory variables in (23) are to be accurately estimated.[17] To accomplish this, we test a multiplicative seasonal ARIMA model (SARIMA), which is specified with the shorthand notation (#p, #d, #q) x $(\#P, \#D, \#Q)_{\#s}$, where "the dependent variable and any independent variables are lag-#s seasonally differenced #D times, and 1 through #P seasonal lags of autoregressive terms and 1 through #Q seasonal lags of moving-average terms are included in the model" (STATA 2013a). Appendix A illustrates the seasonality of *Trip_Count* and shows how the effects of the seasonal trend are mitigated through multiplicative SARIMA modeling. Similar to the $PM_{2.5}$ regression, the multiplicative SARIMA model used for the gas price regressions also corrects for first-order serial correlation.

To more accurately capture the potential effects that large increases in gas prices over relatively short periods of time might have on vehicle usage in Cache County, we limit our data to only observations in which there is a $1.00 or greater increase in gas

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[16] In time-series data, seasonality is a regular pattern of changes that repeats over *S* time periods (Pennsylvania State University, 2014).

[17] Although explicit control for seasonality in *PM25* (equation (1)) was unnecessary, we note that in our initial $PM_{2.5}$ regression (represented by equation (6)) moving average processes "eliminate the repetitive seasonal component" (Giles, 2014). In the subsequent IV $PM_{2.5}$ regression equation, we use a HAC weighting matrix to correct for autocorrelation, the main source of which is seasonality (Yafee, 2014).

prices over a four-month interval.[18] This simulates a "high price variability environment," and enables us to predict the potential impact of a relatively aggressive gas tax that empirical results from previous resource demand studies suggest would likely be necessary, all while preserving degrees of freedom for econometric analysis.

Numerous prior studies have found the household price elasticity of demand for gasoline to be relatively inelastic. As an example, Dahl and Sterner (1991) estimate a short- to intermediate-run price elasticity between -0.22 to -0.31 based on a meta-analysis of 97 estimates on data prior to 1989. Similarly, Espey's (1998) meta-analysis of 277 prior estimates between 1929 and 1993 yield mean short-run and long-run elasticities of -0.26 and -0.58, respectively. These results align closely to those obtained from our gas-price regressions, detailed in the following section.[19]

Empirical Results

$PM_{2.5}$ Regression Analysis

Results from both the initial ARIMA and IV $PM_{2.5}$ regressions are presented in Table 2. These results show that *Trip_Count* is strongly correlated with $PM_{2.5}$ concentrations for the average winter-inversion season in Cache County. The functional form of our regression model allows us to interpret *Trip_Count*'s effect on *PM2.5* as an elasticity measure, since both variables are (natural) logged. We start by examining the ARIMA (1,0,0) specification, labeled Model 1 in Table 2. The coefficient estimate for *Trip_Count* in this model indicates that, ignoring endogeneity for the time being, a one-

[18] A four-month interval was necessary in order to obtain a large enough subsample for econometric estimation.

[19] We also conducted a literature review of prior estimates for household-level price elasticities of demand for resources such as water and electricity (see Olmstead et al. (2007) and Espey (1997) for meta-analyses of water demand literature, and Branch (1993) for a meta-analysis of electricity demand literature). Similar to the estimates of gas price elasticities, these studies show household demand for resources to be generally price-inelastic.

percent increase in *Trip_Count* leads to an approximately 0.89 percent increase, on average, in $PM_{2.5}$ concentrations for Cache County during the average winter-inversion season. This implies that taking 100% of vehicles off the road in the valley during the winter months would lead, on average, to an 89% reduction in $PM_{2.5}$ concentrations. This result affirms evidence presented by the UDEQ that vehicle emissions, particularly VOC's, play a key role in the formation of $PM_{2.5}$ (UDEQ 2014b). Utilizing a moving-average process in the initial $PM_{2.5}$ regression yields an even stronger correlation between *Trip_Count* and *PM2.5*. Model 2 in Table 2 shows that, with an ARIMA (1,0,3) specification, there is a virtually one-to-one relationship between these two variables, suggesting that removing all vehicles from the valley's streets during the typical winter-inversion season would eliminate $PM_{2.5}$ concentrations altogether.

Both the ARIMA (1,0,0) and ARIMA (1,0,3) specifications produce the expected relationships between *PM2.5* and the various weather variables included in the models. For example, because inversions are primarily a winter-time occurrence, we expect increases in temperature to bring about reductions in $PM_{2.5}$ concentrations. This expectation is supported by the results in Table 2 showing both a statistically significant and inverse relationship between *Temp* and *PM2.5*. While *Wind* is statistically insignificant, much of wind's effect on $PM_{2.5}$ concentrations is captured by the interaction term $HumWind$.[20] Slight breezes stimulate the evaporation of water, thus leading to increases in humidity. Therefore, as expected, $HumWind$ exhibits a negative

[20] A $(Wind)^2$ term was also included in the model, but was found to be statistically insignificant.

relationship with *PM2.5*.[21] Overall, Model 2 fits the data best, as demonstrated by a larger, or less negative, log-likelihood value compared with Model 1.

Table 2 PM2.5 Regression Analysis[ab]

Explanatory Variable	Model 1 AR(1,0,0)	Model 2 ARIMA(1,0,3)	Model 3 IV
Constant	-8.669*	-9.736*	-7.475***
	(2.635)	(2.676)	(3.837)
Trip_Count	0.893*	0.999*	0.751**
	(0.252)	(0.256)	(0.365)
Temp	-0.009*	-0.01*	-0.023*
	(0.003)	(0.003)	(0.005)
Precip	-0.845*	-0.863*	-1.190*
	(0.178)	(0.176)	(0.359)
Humid	0.031*	0.031*	0.040*
	(0.004)	(0.004)	(0.004)
Wind	0.049	0.053	–
	(0.045)	(0.045)	
HumWind	-0.002*	-0.002*	-0.002*
	(0.001)	(0.001)	(0.001)
AR(1)	0.731*	0.926*	–
	(0.025)	(0.027)	
MA(1)	–	-0.211*	–
		(0.053)	
MA(2)	–	-0.234*	–
		(0.049)	
MA(3)	–	-0.129*	–
		(0.047)	
Number of Observations	646	646	646
Log Likelihood	-489.25	-481.45	–
R^2	–	–	0.55

* = significant at 1% level, ** = significant at 5% level, *** = significant at the 10% level

[a]Dependent variable is *PM2.5*.

[b]Standard errors in parenthesis, IV model reports HAC standard errors.

[21] Models tested without *HumWind* yielded comparable results. In these models, *Wind* exhibited a negative relationship with *PM2.5* and was statistically significant at the 1% level.

While the results of the initial $PM_{2.5}$ regressions are promising, they do not take into account the potential endogeneity of *Trip_Count*. The existence of endogeneity can be uncovered using a Hausman test, detailed results for which are shown in Appendix B. In fact, even with multiple lag lengths of gas price, endogeneity remains a robust problem in our system of regression equations (shocks in gas prices are felt largely by *Trip_Count* in our $PM_{2.5}$ regressions). Table 3 contains the results of Hausman tests conducted for two-, four-, six-, eight-, ten-, and twelve-week lagged gas prices. The significance of the χ^2 statistic indicates the existence of endogeneity, meaning that the residuals of *Trip_Count* from the gas-price regressions are statistically significant in the $PM_{2.5}$ regressions.

Table 3 Hausman Tests for Endogeneity of *Trip_Count* in *PM2.5*

Lagged gas price (weeks)	χ^2
2	2.37**
4	3.47*
6	2.59**
8	3.24*
10	2.89*
12	5.02*

* = significant at 1% level, ** = significant at 5% level

To correct for endogeneity, we test an IV model, with *Trip_Count* the instrumented variable and *Temp, Humid, HumWind, Precip*, and dummy variables for each week-day[22] the instruments (note that we have excluded *Wind* from the model because of its statistical insignificance). First order serial-correlation is corrected with a

[22] We also tested an IV model using two lags of *Trip_Count* as instruments, following Wadsworth (2006). This model yielded comparable results.

HAC matrix following the Newey-West method (STATA 2013b). Model 3 in Table 2 shows that, when corrected for endogeneity, the relationship between *Trip_Count* and *PM2.5* in our IV $PM_{2.5}$ regression is still negative and statistically significant. We find that a one percent increase in *Trip_Count* in Cache County during the winter months leads to an approximately 0.75 percent increase in $PM_{2.5}$ concentrations. In other words, removing all vehicles from the streets in the valley during the wintertime will, on average, drop total $PM_{2.5}$ concentrations by roughly 75 percent. Moreover, we continue to achieve the expected relationships between *PM2.5* and the inversion-inducing weather variables. An adjusted R^2 value of 0.55 indicates that 55% of the variation in *PM2.5* is explained by the model.

Gas-Price Regression Analysis

Because we are interested solely in the effects that dramatic gas price changes might have on vehicle usage in Cache County (simulating the likely gas tax rates that would be necessary to curtail vehicle trips taken in the valley during winter inversions), recall that we have limited observations in our dataset to only those where gas-price increases are greater than or equal to $1.00 per gallon over four-month intervals. This time interval was not chosen arbitrarily, but rather out of statistical necessity. Shorter time differentials were too restrictive in terms of limiting the number of usable observations, which made estimating the effect of gas prices on *Trip_Count* untenable. To explain the variation in *Trip_Count* caused by *GPrice*, we estimate three different models, each with the same multiplicative SARIMA (1/7,0,0) x $(0,1,0)_7$ specification but reflecting slightly higher gas price increases over four-month intervals.[23] Models 1, 2, and 3 in Table 4 show that more significant gas-price increases lead to fewer trips taken in the valley, as evidenced by an increasingly negative *GPrice* coefficient (an increasing elasticity).

Table 4 Gas-Price Regression Analysis[abcd]

Explanatory Variable	Model 1 Gas Price △$1.00	Model 2 Gas Price △$1.05	Model 3 Gas Price △$1.09
Constant	-0.005	-0.001	-0.010
	(0.005)	(0.006)	(0.008)
GPrice	-0.276***	-0.312**	-0.352***
	(0.151)	(0.152)	(0.192)
Temp	0.002**	0.002**	0.003***
	(0.001)	(0.001)	(0.001)
AR(1)	0.582*	0.550*	0.443*
	(0.082)	(0.090)	(0.117)
AR(7)	-0.405*	-0.436*	0.504*
	(0.070)	(0.080)	(0.100)
Number of Observations	93	78	64
Wald χ^2	932.81	818.22	312.83
Log likelihood	145.69	116.62	88.60

* = significant at 1% level, ** = significant at 5% level, *** = significant at 10% level
[a]Dependent variable is *Trip_Count*.
[b]Standard errors in parenthesis.
[c]*Recession* dropped due to collinearity.
[d]All variables are lag-7 seasonally differenced.

In our gas-price regression models, *GPrice* can be interpreted in a fashion similar to *Trip_Count* in our $PM_{2.5}$ regressions (note that *Trip_Count* is now the dependent

[23] Seasonal ARIMA (1/7,0,0) x $(0,1,0)_7$ is used to account for the weekly (7-day) trend in *Trip_Count*. This specification applies the lag-7 seasonal difference operator to the dependent and independent variables, which removes the seasonal trend. Note that only lags 1 and 7 of the non-seasonal autoregressive terms of the structural model's disturbance are included. This accounts for additive seasonal effects and corrects for autocorrelation (STATA, 2013).

variable). Model 1 in Table 4 indicates that, on average, in what we have labeled a "high-price-variability environment" where price increases (e.g., brought about by aggressive tax rates) are no less than $1.00 per gallon, a one-percent increase in per-gallon gas price leads to an approximately 0.28 percent decrease in *Trip_Count*. Another way to conceptualize this result is that a doubling of the average gas price in Cache County would decrease *Trip_Count* by roughly 28 percent.[24]

As Table 4 indicates, larger increases in gas price cause greater declines in *Trip_Count*. For example, Model 3 in Table 4 shows that, based on the sub-sample of our data where price increases are no less than $1.09 per gallon, doubling gas prices in Cache County leads to an approximately 35 percent decrease in *Trip_Count*. Our results therefore provide some evidence to suggest that valley residents' driving habits may indeed be at least as sensitive in a high-price-variability environment as estimates from the previous literature would suggest. Coupled with our results from the $PM_{2.5}$ regression analysis of the previous section, these findings indicate that a gas tax may be an effective control mechanism for elevated $PM_{2.5}$ concentrations during the winter inversion season in Cache County.

[24] The average 2012 gas price in Cache County was $3.49 per gallon (GasBuddy 2013). Therefore, doubling gas price effectively satisfies the lower-bound condition placed on our regression analyses, where price increases brought about by a seasonal tax are greater than or equal to $1.00.

BENEFIT-COST ANALYSIS: CONTROLLING $PM_{2.5}$ CONCENTRATIONS

In order to subject the concept of a seasonal gas tax to benefit-cost analysis, we first approximate the benefits associated with the tax using a variety of different approaches, including (1) analyzing local health-care estimates provided by Utah State Representative Ed Redd (mentioned previously in The Problem and Proposed Solution), (2) utilizing the EPA's COBRA simulation software, and (3) compiling results from the clean-air willingness-to-pay (WTP) literature. Next, we estimate the gross, net, and adjustment costs, as well as deadweight loss, associated with a large-enough gas tax to bring about necessary reductions in wintertime $PM_{2.5}$ concentrations in Cache County, using both the elasticity estimates obtained from the regression analyses of the previous sections, as well as estimates of the number of registered vehicles and miles driven in Cache County from the Utah State Tax Commission and the Utah Department of Transportation.[25]

Estimating the Benefits of Control

Approaches

Traditionally, economists have relied on hedonic techniques for estimating the value of improved air quality (Smith & Huang 1995). Over 40 years ago, Ridker and Henning (1967) suggested that "property value differences as a result of variations in air pollution with location could be used to estimate the benefits from policies intended to reduce that pollution" (Smith & Huang 1995). Unfortunately, the studies on household's marginal WTP (MWTP) for clean air have yielded vastly disparate results.[26]

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[25] The methodology for the cost analysis is explained in detail in the following sections.
[26] See Smith & Huang (1995) for a meta-analysis of MWTP for clean air estimates.

Smith and Huang (1995) conducted an early meta-analysis of 37 air pollution studies that accounts for 86 separate estimates of household MWTP for clean air[27] between 1982-1984. Like similar studies, MWTP estimates were calculated as the change in the asset value of property. Smith and Huang's (1995) hedonic meta-analysis estimated a statistical average of these MWTP values under specific circumstances across several U.S. cities, and reported a mean MWTP of approximately $110 per household (in 1992 dollars) for each unit reduction in air pollution (Smith & Huang 1995).

The Clean Air Act, passed in 1963 and amended for the first time in 1970,[28] provided an exciting opportunity to evaluate MTWP for clean air. Chay and Greenstone's (2005) study on MWTP "exploits the structure of the Clean Air Act Amendments (CAAs) to provide new evidence on the capitalization of air quality into housing values" (Chay & Greenstone 2005). In their study, Chay and Greenstone (2005) use "nonattainment status as an instrumental variable for changes in total suspended particles (TSPs) in first-differenced equations for the 1970-80 change in county-level housing prices" (Chay & Greenstone 2005). Their estimate of household MWTP for a one unit reduction in TSPs, approximately $22 (in 1982-84 dollars), is much lower than the statistical average derived from Smith and Huang's (1995) earlier hedonic meta-analysis. However, the authors find that "nonattainment status is uncorrelated with virtually all other observable determinants of change in housing prices, including economic shocks" (Chay & Greenstone 2005). Therefore, their model is far less sensitive to specification than those prior.

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[27] It is important to note that this analysis explored reductions in particulate matter measuring 10 micrometers or less (PM_{10}), not $PM_{2.5}$. Most of this literature focuses either on PM_{10}concentrations or total suspended particles (TSPs).

[28] The 1970 amendment required federal and state regulations for both stationary and mobile pollution sources.

While studies using conventional hedonic techniques for estimating the value of clean air are prolific, most “rely on the assumption that households move freely among locations” (Bayer et al. 2009). Instead, a study by Bayer et al. (2009) shows that “when moving is costly, the variation in housing prices and wages across locations may no longer reflect the value of differences in local amenities,” such as air quality (Bayer et al. 2009). Therefore, the authors develop an alternative discreet-choice approach that directly models household location decision (Bayer et al. 2009). In this model, air quality is instrumented using the “contribution of distant sources to local pollution” (Bayer et al. 2009). Their study finds that, when migration is accounted for, the median household’s MWTP for a one-unit reduction in PM_{10} concentrations ranges from $149 to $182 (in constant 1982-84 dollars) (Bayer et al. 2009). The authors compare this result to that yielded when a conventional hedonic technique is used to model the same data. They estimate that, with a traditional hedonic model, MTWP for a one-unit reduction in PM_{10}concentrations is approximately $55 (in constant 1982-84 dollars) (Bayer et al. 2009). Because this estimate is roughly three times less than that which accounts for mobility costs, the authors stress the importance of considering migration and instrumenting for local air pollution (Bayer et al. 2009).

Because the aforementioned studies measure the benefits of reducing either PM_{10} concentrations or TSPs (broader measures of air pollution compared to $PM_{2.5}$ concentrations alone), we consider them to be upper-bound estimates of the benefits of reducing $PM_{2.5}$ concentrations in Cache County. In order to approximate lower-bound estimates (i.e., estimates that consider the medical benefits of reduced $PM_{2.5}$ concentrations only), we include two additional approaches that act as “comparables” with the MWTP studies. First, we use the data collected in 2004 by Utah State Representative Ed Redd, which indicate that the annual medical cost of elevated $PM_{2.5}$ concentrations in Cache County exceeds $23 million per winter-inversion season, as shown in Table 5. For the purposes of our analysis, we assume that if $PM_{2.5}$ concentrations are reduced by half - on average during a given winter-inversion season - then so would Redd's estimate of roughly $23.9 million.

Table 5 Annual Public Health Cost of $PM_{2.5}$ in Cache County[ab]

Incident	Frequency	Cost/incident	Total cost
Deaths	3	$7.9 million*	$23,700,000
Hospitalizations	5	$18,000	$90,000
ER Visits	109	$26,000	$26,000
Asthma Attacks	344	$20	$7,000
Follow-up Visits	200	$65	$13,000
Extra Prescriptions	300	$80	$24,000
Sick Days	400	$160	$64,000
		Grand Total:	$23,924,000

[a]From winter 2004: 2003 as cost basis.
[b]Data: Ed Redd, M.D., Bear River Department of Health.
*EPA life value > age 70

Second, we estimate Cache County's potential public health savings using the EPA's Co-Benefits Risk Assessment (COBRA) Screening Model. According to the EPA, COBRA is "a screening tool that provides preliminary estimates of the impact of air pollution emission changes on ambient particulate matter air pollution concentrations, translates this into health effect impacts, and then monetizes these impacts" (EPA 2012). COBRA is programmed using predicted emissions estimates[29] for the year 2017, and uses

[29] COBRA Emissions Estimates include those for $PM_{2.5}$, NOx, SO2, NH3, and VOCs.

these estimates as a base, or control, scenario. Users can then "create their own scenarios by specifying increases or reductions to the emissions estimates for the analysis year" (2017) (EPA 2012). COBRA then calculates changes in $PM_{2.5}$ concentrations between the control and user-supplied scenario: a source receptor (S-R) matrix "translates the air pollution emission changes into changes in ambient $PM_{2.5}$" (EPA 2012).

Next, using a multitude of health impact functions, COBRA transforms ambient $PM_{2.5}$ changes into incidences of human health impacts (EPA 2012). Appendix C provides a summary of the epidemiological studies in COBRA used to estimate health impacts of $PM_{2.5}$ concentrations (EPA 2012). Lastly, COBRA assigns a monetary value to these health impacts. Note that, according to the EPA, COBRA's approach is "consistent with EPA Regulatory Impact Analyses," and "reflects the current state of the science regarding the relationship between particulate matter and adverse human health" (EPA 2012).

To conduct our simulation analysis, COBRA allows us to select the State of Utah and Cache County specifically. COBRA further enables us to select the category to which our proposed policy would apply. In our case, because we are considering a seasonal gas tax, we choose what COBRA calls the "Highway Vehicles" category, which encompasses the tiers of light-duty gas vehicles and motorcycles, light-duty gas trucks, heavy duty gas trucks, and diesels. Next, COBRA requests that we input emissions reduction estimates (in tons) that we predict will be realized through the gas tax, including reductions in $PM_{2.5}$ concentrations, as well as SO2, NOx, NH3, and VOC emissions.

Table 6 Mobile Source Emissions Inventories for Cache County[a]

Pollutant	Mobile Source Inventory per Inversion Season (2010-2011)*	Emissions Reductions from Proposed Gas Tax	COBRA Estimated Mobile Source Inventory (2017)
$PM_{2.5}$	58.7	28.8	45.1
SO2	2.6	1.3	9.6
NOx	532.5	260.9	1113.2
VOC	316.7	155.2	500.5
NH3**	80.3	20.1	26.7

[a] Emissions are in tons
*Source: UDEQ (2014c)
**NH3 data from 2002.

Table 6 shows mobile source emissions estimates by pollutant in Cache County for the 2010 - 2011 inversion season. Furthermore, it indicates the emissions reductions that we project our proposed seasonal gas tax will achieve (we discuss these calculations below). Finally, COBRA's 2017 mobile source emissions estimates for Cache County are shown. Note that in some cases, they are higher than current emission conditions, perhaps to account for future population growth. COBRA provides high- and low-bound estimates of public health savings for each simulation.

Total Benefit Projections

To estimate the total benefits of control, we must first approximate the required reduction of wintertime $PM_{2.5}$ concentrations in Cache County necessary to comply with EPA standards (recall that the 24-hour standard for $PM_{2.5}$ concentrations is less than or equal to 35 μg/m³). To accomplish this, all instances in our dataset where $PM_{2.5}$ concentrations exceeded this standard are isolated and averaged. The result reveals that the mean $PM_{2.5}$ concentration level during a wintertime inversion is approximately 56 μg/m³. Therefore, should Cache County residents desire clean air (air that complies with

EPA regulations), it will be necessary to reduce $PM_{2.5}$ concentrations, on average, by about 21 μg/m³ during the winter-inversion season, which translates to an approximately 38 percent reduction overall. The elasticity estimate obtained from our IV $PM_{2.5}$ regression (Table 2, Model 3), indicates that in order to obtain a 38 percent reduction in $PM_{2.5}$ concentrations, a 51 percent reduction in *Trip_Count* is required.[30]

Based on the estimates of household MWTP presented previously, we can derive a rough estimate of the total benefits associated with reductions in $PM_{2.5}$ concentrations using MWTP estimates from the existing literature. To do so, we multiply the estimate of MWTP given in each study by 21 (the amount that $PM_{2.5}$ concentrations must be reduced, on average, in Cache County in order to achieve compliance with EPA standards). This product provides our best approximation of the total benefit per household of achieving the necessary reductions in $PM_{2.5}$ concentrations during an average winter-inversion season. To estimate the total benefit for Cache County as a whole, we multiply the benefit per household by the total number of households in the valley (35,234 in 2012) (Census Bureau 2014). Table 7 shows the results of these calculations for each MWTP study, and indicates that Cache County may potentially realize an approximate total benefit of between $16 million and $136 million per winter-inversion season (recall that we consider this range to be an interval of upper-bound estimates).[31]

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[30] From our IV $PM_{2.5}$ regression, we estimate that a 100% decrease in *Trip_Count* will lead to, on average, a 75% reduction in $PM_{2.5}$. Therefore, we solve the ratio ($\frac{100}{75} = \frac{x}{38}$) for x, where 38 represents the desired 38% decrease in $PM_{2.5}$ concentrations and x represents the percent reduction in *Trip_Count* necessary to achieve this goal. Solving for x equals (approximately) 51%.

[31] The studies discussed in the previous section estimate the MWTP for clean air based on either PM_{10} or TSPs. Therefore, we most likely overestimate the benefit that would be realized from reducing $PM_{2.5}$ only.

Table 7 Estimates of the Benefits of Controlling an Average Winter Inversion Season

Approach	Estimated MWTP*	Total Benefit
Smith and Huang (1995)	$110	$81,390,540
Chay and Greenstone (2005)	$22	$16,278,108
Bayer et al. (2009)		
Conventional Hedonic	$55.20	$40,843,253
Migration and IV		
Low-bound	$149	$110,247,186
High-bound	$185	$136,884,090
Ed Redd, (R-Utah) (2004)	–	$9,091,120
COBRA**		
Low-bound	–	$479,403
High-bound	–	$1,086,075
Mean	104.24	$48,710,972
Median	110	$28,560,681
Standard Deviation	(66.57)	(54,082,938)

*We assume that the estimated annual MWTP values from the literature are not affected by the fact that the winter inversions in Cache County occur solely during a three-four month window, i.e., are episodic. By their very nature, elevated $PM_{2.5}$ concentrations are episodic in any location, with episode lengths varying across locations.
**COBRA uses a 3% discount rate for future benefits.

As shown in Table 7, we estimate that the total public health savings from reducing $PM_{2.5}$ concentrations by 38 percent in Cache County to be approximately $9 million based on Dr. Redd's data. COBRA simulations yield lower estimates,[32] as we estimate that, on average, valley residents may realize an approximately $1 million dollar benefit from a 38 percent reduction in $PM_{2.5}$ concentrations during the winter-inversion season. Because both the data provided by State Representative Redd and the simulations estimated by COBRA account only for public health impacts, we consider them to be lower-bound estimates. In all, the average across our upper- and lower- bound benefit

[32] To estimate using COBRA, we reduce each pollutant found in the mobile source emissions inventory for Cache County per season (Table 6) by 51% (we require a 51% reduction in *Trip_Count* to realize a 38% reduction in $PM_{2.5}$ concentrations). Once done, these values (in tons) are used as inputs to COBRA for purposes of simulation.

estimates is approximately $48.7 million per typical winter-inversion season. However, due to the relatively large standard deviation associated with this mean estimate, we use the median benefit estimate of $28.5 million per winter-inversion season to compare with the gross, net, adjustment, and deadweight loss costs of a seasonal gas tax in Cache County, presented below.

Estimating the Costs of Control

In this section we estimate the various costs involved with the imposition of a gas tax necessary to reduce $PM_{2.5}$ concentrations by an average of 38 percent. Recall that this reduction is necessary for Cache Country to meet the national EPA standard for $PM_{2.5}$ concentrations during a typical winter-inversion season, which, as our regression results indicate, requires a concomitant 51 percent decrease in *Trip_Count*.

Gross cost serves as our estimate of the upper bound on costs incurred by the household as a result of the gas tax, where it is assumed that (1) the costs associated with the adjustments households make in response to the tax (i.e., the costs associated with making fewer trips by vehicle) are just equal to the extra tax burden they would have encountered had they not made the adjustments (in sum, rather than just on the margin), and (2) that none of the tax revenue obtained by the regulator is returned to the households in any way. With net cost, it is assumed that the adjustment costs are zero (i.e., there are essentially no costs associated with a household's adjustments made in response to the gas tax), but, similar to gross cost, no tax revenue is returned to the households. The difference between gross and net costs therefore represents our (upper-bound) estimate of the adjustment costs associated with the tax. If we further assume that tax revenues are returned in full to the households in some lump-sum fashion (e.g., through subsidies for green energy, transportation, etc.), our adjustment cost estimate reflects the sole economic cost of the gas tax incurred by the households.

Additionally, we provide our best estimate of the social deadweight loss, or excess burden, associated with the seasonal gas tax we recommend. Based on a meta-analysis of existing literature regarding the excess burden of taxation, Conover (2010) finds the deadweight loss associated with an excise tax to be, on average, 32 cents per dollar of tax revenue. Because this estimate assumes a full transfer of tax revenue and zero adjustment costs, we consider it to be a lower-bound estimate of the cost associated with the imposition of a seasonal gas tax in Cache County.

To begin, our question is: at what level should the gas tax be set? For our answer, we use the average over our gas-price elasticities (approximately -0.31) to determine the amount that gas prices must increase to decrease *Trip_Count* by 51 percent, which we find to be roughly 165 percent.[33] From our dataset, we calculate that the average 2012 gas price in Cache County was $3.49 per gallon. Thus, in 2012, our seasonal gas tax would need to be set at, on average, $5.76 per gallon in order to induce the requisite 51 percent reduction in *Trip_Count*. Therefore, in 2012, Cache County residents would have needed to pay approximately $9.25 per gallon during the winter-inversion season in order to attain the target reduction in $PM_{2.5}$ concentrations of 38 percent, on average, if the tax were the sole policy instrument used to achieve the targeted reduction.[34]

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[33] The average across all elasticities from our gas-price regressions is -0.31. In other words, a 100% increase in gas prices leads to, on average, a 31% reduction in *Trip_Count*. Therefore, we solve the ratio ($\frac{100}{31} = \frac{x}{51}$) for x, where 51 represents the desired 51% decrease in *Trip_Count* and x represents the percent reduction in gas prices necessary to achieve this goal. Solving for x equals approximately 165%.

[34] Given the size of the tax needed to induce the requisite reductions in vehicle trips, two potential social dilemmas present themselves. First, gas prices for Cache County residents would also have to rise outside of the valley in order to prevent residents from "driving across the border" for cheaper prices. Second,

While the tax we propose may perhaps seem outlandish at first glance, it is not necessarily unreasonable when compared to the fuel excise duties imposed by several European countries on a regular, non-seasonal basis. Between 1980 and 2012, the average tax on fuel – adjusted to a dollar-per-gallon basis – in the Netherlands was $3.61 (corrected for inflation to 2005 prices), which was then added on top of a 21 percent value added tax (VAT) to determine the final fuel price (EEA 2013). Average gas taxes for larger European nations such as Italy and the United Kingdom between the same years were $3.52 and $3.26, respectively, again adjusted to a dollar-per-gallon basis and corrected for inflation to 2005 prices (EEA 2013).

To estimate the gross cost to Cache County households of the seasonal gas tax, we begin by dividing the number of registered passenger vehicles by the total annual vehicle miles traveled (both values for Cache County in 2012) to obtain an estimate for the annual miles traveled per vehicle in Cache County, which we calculate to be 11,244.[35] Separately, we divide the number of registered vehicles in the county by the number of households in 2012 to determine the number of vehicles per household, which we find to be 2.21. The product of this value and our previous estimate of the annual miles traveled per vehicle yields an estimate for the number of miles traveled annually per Cache County household. This figure, multiplied by 0.25 (the percent of the year that Cache County witnesses inversions), yields an approximation of the average number of miles traveled per Cache County household per winter-inversion season, roughly 6,212 miles.

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some form of control would need to be put in place to prevent Cache County residents from hoarding gasoline during the non-winter-inversion season for use during the inversion season.

[35] Data from the Utah State Tax Commission (2012) indicate that there were 77,932 registered passenger vehicles in Cache County in 2012. The Utah Department of Transportation (2012) estimated that the annual vehicle miles traveled for vehicles registered in Cache County was 876,333,868 in 2012.

The Utah Department of Transportation (2012) estimates that the average Utah vehicle achieves a fuel efficiency of 24.06 miles per gallon (MPG). Hence, dividing the miles traveled per Cache County household per season by UDOT's estimate of average MPG enables us to approximate the total gallons of gas used by the average Cache County household per inversion season, which we calculate to be 258.19. Finally, we multiply this value by our proposed per-gallon tax ($5.76) and then again by the number of households in Cache County to estimate the gross cost of a 2012 seasonal gas tax to Cache County residents: approximately $52.4 million per season.

To calculate the net cost associated with the gas tax we simply reduce the gross cost by a factor of 0.51, representing the estimated reduction in vehicle trips induced by the requisite gas tax of $5.76 per gallon. This results in a net cost of approximately $25.7 million per winter-inversion season in Cache County. The difference between gross and net costs, which represents our estimate of the costs faced by Cache County households in adjusting to the tax by reducing vehicle trips, is therefore approximately $26.7 million per inversion season. Finally, recall that there is excess burden associated with taxation; in particular, we use Conover's (2010) estimate that 32 percent of tax revenues associated with an excise tax result in deadweight loss. Therefore, to calculate the excess burden imposed on society associated with our seasonal gas tax, we multiply net cost by 32 percent, thus obtaining a deadweight loss estimate of $8.2 million.

Table 8 Estimates of Social Net Benefit by Cost Measure

Cost Measure	Cost (millions)	Social Net Benefit (millions)
Gross	$52.4	($23.9)
Net	$25.7	$2.8
Adjustment	$26.7	$1.8
Deadweight Loss	$8.2	$20.3

Again, neither the gross nor net costs of the seasonal gas tax assume that any gas-tax revenue is rebated to Cache County residents (e.g., in the form of subsidies for green energy and/or community reinvestment). On the other hand, the adjustment cost assumes no leakage in tax revenues due to government inefficiency, and that 100 percent of these revenues are transferred back to taxpayers. Alternatively, our deadweight loss estimate assumes no adjustment cost and a full transfer of tax revenues. In examining our estimated costs – gross, net, adjustment, and deadweight loss – and comparing those costs with the median benefit of reduced $PM_{2.5}$ concentrations in Cache County, it becomes apparent that the tax passes a cost-benefit analysis based on gross costs only if an effective rebate system is in place. In all, approximately 45 percent of the gross cost of the tax (about $23.9 million) would need to be refunded to Cache County residents in order for the policy to prove beneficial when weighed against gross costs.[36] Cost-benefit analysis based upon net cost requires no tax rebate, while adjustment cost and deadweight loss assume a full tax revenue transfer. Table 8 compares each cost measure to the corresponding estimated social net benefit for Cache County. We approximate social net

[36] We estimate the median benefit of clean air in Cache County to be approximately $28.5 million, while the gross cost of the tax to be approximately $52.4 million. Reducing gross cost by approximately 45 percent equates the cost to the benefit. Hence, about $23.9 million would need to be refunded to taxpayers annually.

benefit by subtracting each respective cost from $28.5 million, our estimation of the median benefit of reduced $PM_{2.5}$ concentrations in the valley.

Sensitivity Analysis: Accounting for Future Technology

While a seasonally-imposed gas tax in excess of five dollars per-gallon may lead some to despair, there is good reason to be optimistic about the future. The EPA's Tier 3 Vehicle Emission and Fuel Standards Program will set new vehicle emission standards and lower the sulfur content of gasoline beginning in 2017 (EPA 2014b). The expected result is dramatically reduced mobile-source emissions from that point forward, with particularly large reductions in nitrogen oxides (NOx) and VOCs, the precursor emissions of $PM_{2.5}$ concentrations (Redd 2014). According to Redd (2014), approximately five Tier 3 vehicles collectively emit as much as a single Tier 2 vehicle, and approximately 30 Tier 3 vehicles collectively emit as much as a single Tier 1 vehicle. Thus, the adoption of this technology over time portends rather pronounced emissions reductions in Cache County.

Figure D1 presented in Appendix D shows that, while controlling for future population growth in the valley, Tier 3 technology is expected to drastically reduce both NOx and VOC emissions versus Tier 2 (Redd 2014). Hence, it is quite possible that in the coming years, it may no longer be necessary to reduce *Trip_Count* (via a seasonal gas tax) by the full 51 percent to achieve $PM_{2.5}$ concentrations that comply, on average, with EPA standards. This implies that the cost of a per-gallon gas tax in Cache County could effectively be decreased each successive season in response to the progressive adoption of Tier 3 technology. Additionally, higher gas prices have been shown to have an effect on vehicle fleet composition. Li et al. (2009) estimated that "a ten percent increase in gasoline prices will generate a 0.22 percent increase in fleet fuel economy in the short run (one year), and a 2.04 percent increase in the long run (after the current vehicle stock is replaced)." Because our proposed gas tax is seasonal, its effect on fuel economy in Cache County may not be as dramatic. However, there will likely be a "spillover" effect that incentivizes the more rapid adoption of Tier 3 technology, thus leading to larger emissions reductions that are realized faster than those depicted in Figure D1.

Table 9 Sensitivity Analysis

Reduction in *Trip_Count* (%)	Required Seasonal Gas Tax (per gallon)
45	$5.06
40	$4.50
35	$3.94
30	$3.39
25	$2.83
20	$2.27
15	$1.68
10	$1.12

Table 9 shows that with each five-percent reduction in *Trip_Count* equivalent (brought about via the steady adoption of Tier 3 technology over time), there is a reduction of about $0.56, on average, in the required cost of a per-gallon seasonal gas tax (again using the average gas price in 2012 as a base) needed to obtain the EPA $PM_{2.5}$ standard.[37]

[37]According to Redd (2014), Tier 3 vehicle prices are expected to rise by roughly $135 per new car, and the EPA estimates that Tier 3 fuel will add an additional penny to the per-gallon cost of gasoline at the pump.

CONCLUSION

Elevated winter-time $PM_{2.5}$ concentrations have been a persistent problem in Cache County, Utah for several years, and the predicament remains almost wholly unsolved today. While some preventative measures are in place to aid in reducing harmful $PM_{2.5}$ precursor emissions, more can be done to improve air quality in the valley, particularly during winter months. Using time-series, instrumented-variable regression analysis, we show that reducing vehicle trips in Cache County by one percent during the inversion season will, on average, lead to an approximately 0.75 percent reduction in average $PM_{2.5}$ concentrations.

Furthermore, through multiplicative seasonal ARIMA modeling, we find that Cache County residents' driving habits in a "high price volatility environment" (which mimics the imposition of an aggressive gas tax) are indeed as elastic as conventional estimates of resource-use elasticities typically suggest. Specifically, we find that a one-percent increase in gas prices leads to an approximately 0.31 percent reduction in vehicle trips. These results lean in favor of an argument for a seasonal tax on gasoline. Should the tax be appropriately set – which we find would be approximately $5.00 more per-gallon than the current per-gallon price of about $3.50 – we estimate that Cache County would witness a dramatic reduction in vehicle use, thus decreasing health costs through concomitant decreases in $PM_{2.5}$ concentrations during the typical winter-inversion season. Furthermore, we predict that the benefits of cleaner wintertime air would outweigh the costs associated with such a tax, particularly in tandem with a system that effectively transfers tax revenues back to Cache County residents.

Further investigation into the logistical practicalities of implementing a seasonal gas tax is needed, as there would need to be strong cooperation between the communities and municipalities surrounding Cache County to prevent tax evasion. Moreover, detailed plans would need to be generated on how best to (equitably) refund tax revenue back to Cache County residents, perhaps through community reinvestment, education, or even subsidies for public transportation. Finally, as Tier 3 vehicles become integrated into the valley's fleet over the next several decades, the statistical relationship between vehicle emissions and $PM_{2.5}$ concentrations must be reevaluated on a regular basis, as the per-gallon cost of a seasonal gas tax in Cache County may be allowed to progressively decrease, all while maintaining comparable outcomes over time.

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APPENDICES

Appendix A: Seasonal Trend and Variable Transformation

To illustrate its seasonality, we examine a graph of *Trip_Count*'s autocorrelations, shown below in Figure B1.

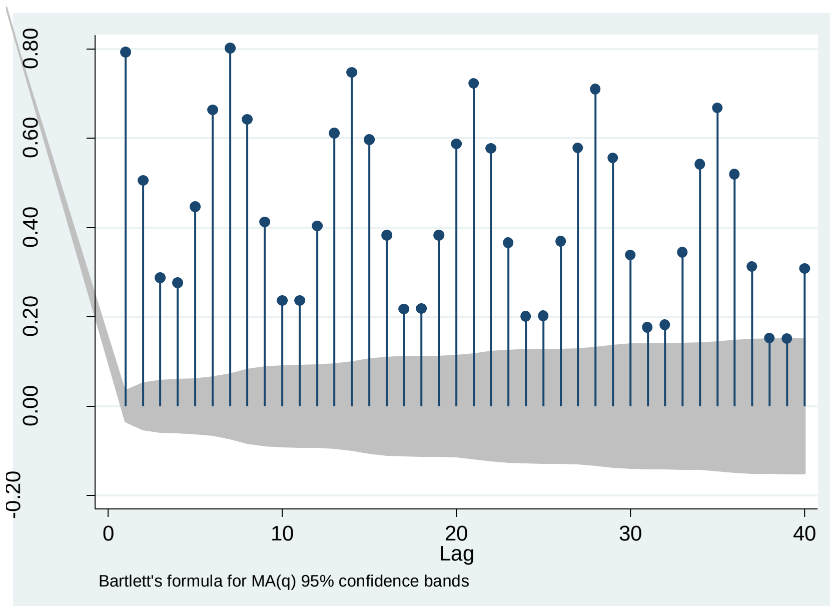

Fig. A1 Autocorrelations of *Trip_Count*

Note the seasonal (weekly) trend *S*, where *S* repeats every 7^{th} observation. To mitigate the adverse effects that this trend may have on our gas price regressions, we lag-7 seasonally difference *Trip_Count* (along with all other explanatory variables) to remove the trend (STATA 2013b). Figure B2 shows the transformation of *Trip_Count* after seasonal adjustment, shown now as *S7Trip_Count*:

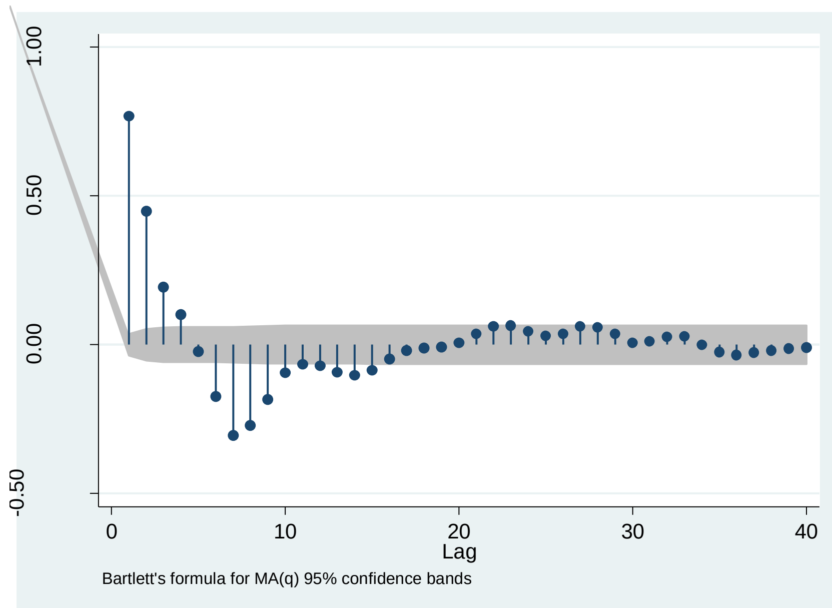

Fig. A2 Autocorrelations of S7*Trip_Count*

Comparing figure B2 to figure B1, we conclude that seasonal-differencing has mitigated the potential effect of the seasonal trend in confounding *GPrice*'s marginal effect on *Trip_Count*. Recall that we also use autoregressive processes at lags 1 and 7 in our multiplicative SARIMA models to correct for potential autocorrelation.

Appendix B: Hausman Test with 12-week Lagged Gas Price

We begin by estimating a simple gas price regression with *Trip_Count* as the dependent variable. The explanatory variables include 12-week lagged gas prices (*Gprice12*), *Temp*, and *Recession*. The results of this regression are shown in Table A1. Note that in this instance, the relationship between between *GPrice12* and *Trip_Count* is positive but insignificant. Similar to the gas-price regressions used for empirical analysis, our gas-price regression used for the Hausman test is structured to a multiplicative SARMA (1/7,0,0)x(0,1,0,)$_7$ specification to control for the seasonal trend in *Trip_Count* and first-order serial correlation.

Table B1 Gas-Price Regression with 12-Week Lagged Gas Price[abc]

Explanatory Variable	Result
Constant	-0.002
	(0.002)
GPrice12	0.014
	(0.017)
Temp	0.001*
	(0.001)
Recession	0.002
	(0.020)
AR(1)	0.746*
	(0.009)
AR(7)	-0.197*
	(0.012)
Number of Observations	1783
Log likelihood	3314.19

* = significant at 1% level
[a]Dependent variable is *Trip_Count*
[b]Standard errors in parentheses.
[c]All variables are lag-7 seasonally differenced

Next, we collect the residuals of the above regression and include them as an explanatory variable, (*Trip_Count_Resid*), to our initial $PM_{2.5}$ regression. We use an ARIMA (1,0,3) specification to correct for first-order serial correlation and seasonality. The results are shown in Table A2. Note the statistical significance of *Trip_Count_Resid*, indicating endogeneity.

Table B2 Hausman Test of *Trip_Count* for Endogeneity[ab]

Explanatory Variable	Result
Constant	-4.064
	(3.419)
Trip_Count	0.405
	(0.334)
Temp	-0.005
	(0.004)
Precip	-1.263*
	(0.309)
Humid	0.034*
	(0.006)
Wind	0.068
	(0.072)
HumWind	-0.002*
	(0.001)
Trip_Count_Resid	1.364*
	(0.609)
AR(1)	0.943*
	(0.033)
MA(1)	-0.377*
	(0.066)
MA(2)	-0.259*
	(0.075
MA(3)	-0.076
	(0.068)
Number of Observations	380
Log Likelihood	-282.004
χ^2	3832.21

* = significant at 1% level
[a]Dependent variable is *PM2.5*.
[b]Standard errors in parentheses.

Appendix C: Epidemiological Studies Used in COBRA

Table C1 Epidemiological Studies Used to Estimate Adverse Health Impacts of PM2.5[a]

Endpoint	Author	Age
Mortality, All Cause	Krewski et al. (2009)	30-99
Mortality, All Cause	Laden et al. (2006)	25-99
Mortality, All Cause	Woodruff et al. (1997)	Infant
Acute Myocardial Infarction, Nonfatal	Peters et al. (2001)	18-99
Acute Myocardial Infarction, Nonfatal	Pope et al. (2006)	18-99
Acute Myocardial Infarction, Nonfatal	Sullivan et al. (2005)	18-99
Acute Myocardial Infarction, Nonfatal	Zanobetti and Schwartz (2006)	18-99
Acute Myocardial Infarction, Nonfatal	Zanobetti et al. (2009)	18-99
HA, All Cardiovascular (less Myocardial Infarctions)	Bell et al. (2008)	65-99
HA, All Cardiovascular (less Myocardial Infarctions)	Moolgavkar (2000)	18-64
HA, All Cardiovascular (less Myocardial Infarctions)	Peng et al. (2008)	65-99
HA, All Cardiovascular (less Myocardial Infarctions)	Peng et al. (2009)	65-99
HA, All Cardiovascular (less Myocardial Infarctions)	Zanobetti et al. (2009)	65-99
HA, All Respiratory	Zanobetti et al. (2009)	65-99
HA, Asthma	Babin et al. (2007)	0-18
HA, Asthma	Sheppard (2003)	0-18
HA, Chronic Lung Disease	Moolgavkar (2000a)	18-64
Emergency Room Visits, Asthma	Mar et al. (2010)	0-99
Emergency Room Visits, Asthma	Slaughter et al. (2005)	0-99
Acute Bronchitis	Dockery et al. (1996)	8-12
Asthma Exacerbation, Cough	Mar et al. (2004)	6-18
Asthma Exacerbation, Cough	Ostro et al. (2001)	6-18
Asthma Exacerbation, Shortness of Breath	Mar et al. (2004)	6-18
Asthma Exacerbation, Shortness of Breath	Ostro et al. (2001)	6-18
Asthma Exacerbation, Wheeze	Ostro et al. (2001)	6-18
Minor Restricted Activity Days	Ostro and Rothschild (1989)	18-64
Lower Respiratory Symptoms	Schwartz and Neas (2000)	7-14
Upper Respiratory Symptoms	Pope et al. (1991)	9-11
Work Loss Days	Ostro (1987)	18-64

[a]Source: COBRA Users Manual, 2012

Appendix D: Tier 2 versus Tier 3 Technology

The arrival of Tier 3 technology in 2017 is estimated to provide drastic reductions of mobile-source emissions, particularly NOx and VOCs. Figure D1 shows that, while controlling for future population growth (represented by yearly increases in daily vehicle miles traveled), the per-day emissions (in tons) of these pollutants will significantly decrease in Cache County compared to Tier 2 technology (Redd 2014).

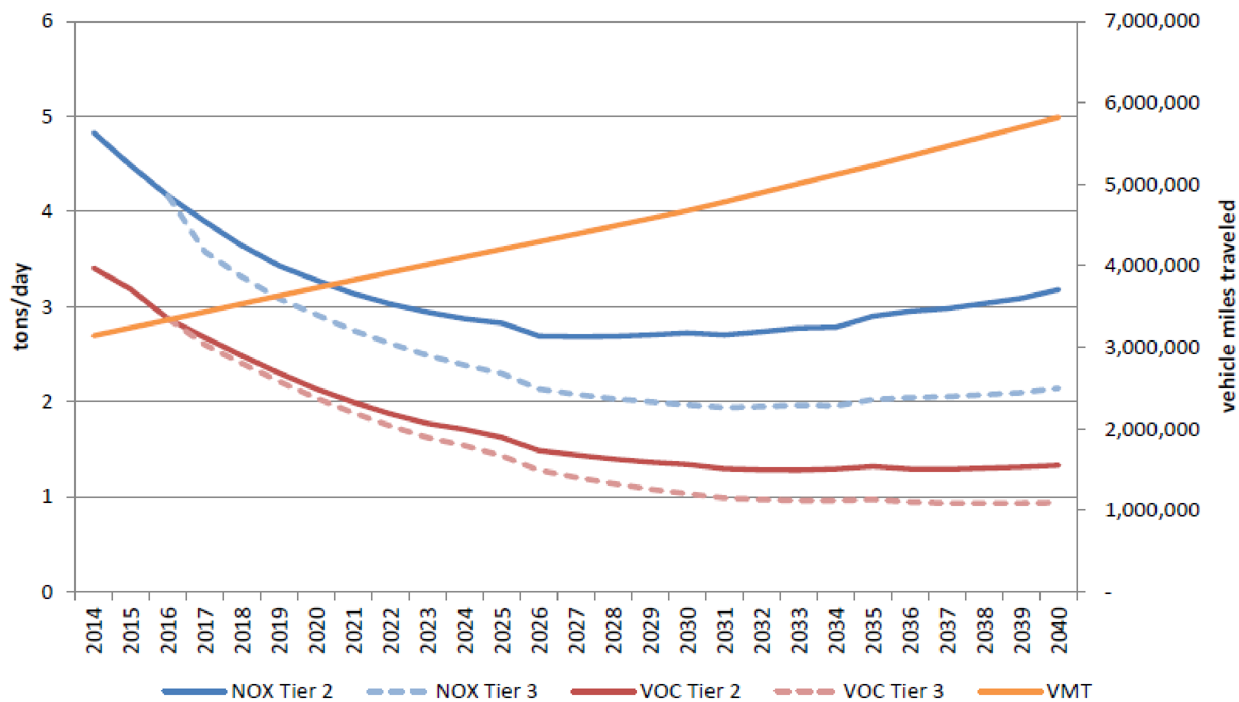

Fig. D1 Estimates of emissions reductions from Tier 3 technology for Cache County