Optimal Investment to Control "Red Air Day" Episodes: Lessons from Northern Utah, USA[ǂ]

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Abstract: We address the issue of optimal investment in "preventative capital" to mitigate episodic, mobile-source air pollution events by calibrating an endogenous-risk model with parameter estimates obtained from a unique dataset related to "red air day" episodes occurring during the winter months in Northern Utah. Our analysis demonstrates that, under a wide range of circumstances, the optimal steady-state level of preventative capital stock – raised through the issuance of a municipal "clean air bond" that provides foundational funding for more aggressive mitigation efforts – can meet the standard for PM2.5 concentrations with positive social net benefits. We estimate benefit-cost ratios ranging between 3.1:1 and 11.3:1, depending upon the assumed trip-count elasticity with respect to preventative capital stock. These ratios are clustered in the lower end of the range estimated for the 1990 Clean Air Act Amendments in general.

Keywords: preventative capital; endogenous risk; $PM_{2.5}$ concentrations; episodic air pollution
JEL Classifications: D62, Q53, Q58

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1. Introduction

Although much is now known about the human health and environmental impacts associated with elevated air pollution concentrations during episodic outbreaks – both in general physiological terms and via copious dose-response studies conducted worldwide – relatively little research has been directed toward possible market-based economic policies that might effectively mitigate the costs associated with these outbreaks.[1] These costs are huge. An estimated 6.5 million pre-mature deaths occurred worldwide in 2012 due to elevated air pollution concentrations. Moreover, 90 percent of the world's population is currently estimated to reside in locations where air pollution levels exceed the World Health Organization's (WHO's) ambient standards (WHO, 2017).[2] The annual mortality rate in the US alone due to elevated air pollution concentrations is estimated to be 200,000, of which over a quarter of the premature deaths are attributable to vehicle emissions (Caiazzo et al., 2013).

The current paper applies Berry et al.'s (2015) endogenous-risk, disease-outbreak framework to determine the optimal level of investment in "preventative capital" necessary to control mobile-source, episodic air pollution occurring during the winter months in our study area, Northern Utah.[3] Northern Utah has been identified by the American Lung Association (ALA) as

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[1] Pope et al. (2002) provide detailed estimates of the human health costs associated with elevated $PM_{2.5}$ concentrations; estimates that corroborated by Utah Department of Environmental Quality (UDEQ) (2016b). See Liu et al. (2014) and Zanobetti and Schwartz (2009) (and references therein) for examples of dose-response studies. Morbidity and mortality estimates for US populations have since been compiled in the US Environmental Protection Agency's (EPA's) Environmental Benefits Mapping and Analysis Program (BenMAP) (EPA, 2016a), which is used in this study to estimate health damages incurred by Northern Utah residents during episodic outbreaks.

[2] Roughly half of the 6.5 million deaths are in turn attributable to elevated $PM_{2.5}$ concentrations, the specific pollutant considered in this study (Apte et al., 2015).

[3] The application of Berry et al.'s (2015) framework to the problem of mobile-source episodic air pollution is a natural modeling extension given the measurable interplay between exogenous and endogenous risk factors associated with recurring "outbreaks" of elevated pollution events, which in turn induce similarly measurable impacts on human health. Recently, Moscardini and Caplan's (2017) seasonal gas tax study and Cropper et al.'s (2014) piloted permit program have investigated specific market-based solutions to the prolific problem of mobile-source, episodic air pollution. Moscardini and Caplan (2017) find that, on average, a one-percent decrease in county-level trip count results in a 0.75 percent reduction in $PM_{2.5}$ concentrations, all else equal. Further, a one-percent increase in gas price is correlated with a 0.31 percent reduction in vehicle trips. The authors estimate substantial seasonal social net benefits associated with this reduction. Cropper et al. (2014) also investigate the use of a market-

persistently experiencing some of the nation's worst short-term particulate matter (PM) pollution problems (ALA, 2017), specifically PM measuring less than 2.5 microns in size ($PM_{2.5}$). In this paper we estimate the preventative capital stock (in dollar value terms) necessary to optimally mitigate "red air day" episodes that occur during a typical winter inversion season. A red air day occurs whenever the region's $PM_{2.5}$ concentration level averaged over a 24-hour period exceeds 35 $\mu g/m^3$, the National Ambient Air Quality Standard (NAAQS) for $PM_{2.5}$ concentrations. An "episode" is a cluster of consecutive red air days of variable length occurring intermittently throughout the winter months, primarily during temperature inversions, when a band of higher-altitude warm air sits atop lower-altitude colder air.

Because the risk of a red air day episode occurring in Northern Utah is driven almost exclusively by the process of automobile emissions interacting with a particular set of wintertime weather variables, the preventative capital stock envisioned in this paper consists of cumulative investment in infrastructure that can be used to facilitate a relatively pronounced reduction in regionwide use of fossil-fuel powered vehicles. The capital stock would be raised through the issuance of, say, a general-obligation municipal "clean air" bond, the par value of which would equal the optimal capital stock determined via numerical analysis such as ours.

To be precise, by "preventative capital stock" we mean cumulative investment in (1) physical infrastructure, such as enhancement and expansion of public transportation systems, aggressive subsidization of the purchase of zero-emission vehicles (EVs) and installation of EV charging stations, covering the fixed costs associated with enlargement of the county's administrative

based policy to control episodic air pollution attributable to vehicle emissions, in their case ground-level ozone concentrations in Washington, DC. According to the authors' estimates, their proposed permit scheme would remove one million vehicles from the road during high-ozone days, resulting in a corresponding reduction in NO_x emissions of 30 tons per day and generating an estimated $111 million annually in government revenue, even in the face of non-compliance.

structure in order to support subsequent implementation of an alternative market-based incentive such as a seasonal gas tax (à la Moscardini and Caplan, 2017), and installation of a county-wide camera system to support the implementation of a vehicle permitting program on red air days, as well as (2) social infrastructure, such as more persuasive advertising campaigns encouraging vehicle owners to become less reliant on their vehicles in the first place. Any investment of this nature – fixed investment that serves to reduce the ex ante probability of a red air day episode occurring during any given winter season – would therefore qualify as preventative capital in our sense of the term.[4]

Berry et al. (2017) develop a model to assess the potential role of restoration (in addition to prevention) in the control of large-scale, non-native species invasion. The authors conclude that investments in prevention may not be optimal in cases with very low probabilities of invasion or extremely ineffective prevention. In their numerical simulations of Emerald Ash Borer invasions in Colorado, US, they find no instances where the threshold for investing in preventative measures is not crossed, i.e., it is always optimal to invest in prevention and to do so relatively heavily. As discussed in Sections 4.1 and 4.2, estimates of our study area's "background risk" (of a red air day episode occurring at any given time during any given winter season) coupled with an endogenously determined hazard function that increases with region-wide vehicle trips suggests that Northern Utah clearly faces a substantial overall risk associated with episodic red air day occurrences. Further, as shown in Section 5 investment in preventative capital returns relatively large social net benefits over a range of effectiveness levels, suggesting that prevention

[4] Hence, prevention in our case means preemptively restraining $PM_{2.5}$ concentrations below the NAAQS during the winter season. By comparison, prevention in Berry et al.'s (2015) model refers to the preemption of a possible disease outbreak. It may therefore be more accurate to refer to the type of capital stock we have in mind as "precautionary", as in Polasky et al. (2011), rather than "preventative" per se. Lastly, we reiterate that our focus in this paper is on estimating the optimal stock of capital – a capital stock which can then be used to fund a variety of programs aimed at mitigating mobile-source pollution – not on which particular program might subsequently be implemented. Program-by-program assessment is beyond the scope of this study.

is indeed quite effective. Thus, our focus in this paper on optimal investment in preventative capital is warranted, especially when considering the earlier work of Cropper et al. (2014) and Moscardini and Caplan (2017), which focus exclusively on the restorative, market-based policies of permits and seasonal gas taxes, respectively (see footnote 5 for details about these two studies).[5]

Our calibration exercise incorporates parameter estimates derived from a unique compilation of Northern Utah data for the period 2002 – 2012. This exercise entails econometric estimation of the steady-state levels of background risk and red-air-day hazard rates associated with daily, winter, vehicle trip counts and relevant weather variables. We estimate that Northern Utah's optimal, steady-state preventative capital stock ranges from \$4 to \$14 million depending upon the assumed vehicle trip count elasticity with respect to the capital stock (with corresponding amortized annual values ranging from \$330,000 to \$1.13 million per year, respectively). Introduction of the trip count elasticity measure is a key innovation in our study, borne of necessity. It is the measure we use to link investment in preventative capital directly with reductions in the source of air pollution in our study area – emissions-producing vehicles. As explained in more detail in Section 4.3, we calibrate the elasticity measure based on the available literature.

[5] The regime-shift literature, which proposes somewhat more complex models to control problems such as climate change, invasive species spread, overfished fisheries, etc., similarly distinguishes between investments in preventative and restorative (or adaptive) capital (Polasky et al., 2011; Crepin et al., 2012; Ren and Polasky, 2014). However, regime shifts are fundamentally different than episodes, since the former involves either a change in system dynamics or stock collapse with either no return or long-delayed return to the initial regime (i.e., hysteresis), while the latter does not. The "substantial reorganization in system structure, functions and feedbacks that often occurs abruptly and persists over time" as a result of regime shift (Crepin et al., 2012, page 15) is absent in the episodic problem. Interestingly though, Polasky et al. (2011) show that optimal management is preventative in the presence of an endogenous regime shift with changed system dynamics, where "endogenous" in this case refers to the hazard function being conditioned on choice of resource stock.

The lowest trip-count elasticity assumed for this study (which is associated with an optimal preventative capital stock of $4 million) results in a concomitant 13 percent decrease in the region's vehicle trip count. The study's largest elasticity (associated with an optimal preventative capital stock of $14 million) corresponds to a 93 percent reduction in trip count. As expected, annual benefits associated with the concomitant decreases in $PM_{2.5}$ concentrations track the reductions quite closely. Social net benefits (which are positive in all 10 scenarios considered in this study) increase monotonically with trip count elasticity, indicating that the more responsive is vehicle trip count to investment in preventative capital, the larger the social net benefit. The corresponding benefit-cost ratios increase from 3.1:1 at the lowest trip count elasticity to 11.3:1 at the highest. These ratios are clustered in the lower end of the EPA's (2011) estimated range for the 1990 Clean Air Act Amendments of between 3:1 and 90:1.[6]

This paper therefore demonstrates that, under a wide range of circumstances, the optimal, steady-state level of preventative capital stock necessary to fund more aggressive mitigation efforts can meet the NAAQS with positive social net benefits. In the process of reaching this conclusion, we empirically estimate a series of models that not only measure the marginal impact of vehicle travel in the county, but also the impacts of a host of weather variables that are unique in explaining the red air day phenomenon. The methodologies and empirical approaches developed in this paper are applicable to any region of the world where the control of mobile-source pollution is of public policy concern, more so where the pollutant is episodic in nature, as it is in several Latin American, Asian, and European cities (c.f., Gallego 2013a and 2013b; Ajanovic 2016), than where it occurs more regularly throughout the year, as in Beijing, China

[6] It is important to point out that these ratios do not account for any potential co-benefits associated with the control of other air pollutant concentrations in Northern Utah to which mobile sources contribute, such as summertime ground level ozone (UDEQ, 2019; UDH, 2019). Estimating the extent of these co-benefits is beyond the scope of this particular study.

(see Cao et al., 2014 and Chen et al., 2013). Although the ultimate goal of our research is to numerically estimate the social net benefit of optimal investment in preventative capital, some researchers may be particularly interested in the various econometric components of the analysis, in particular regressions establishing linkages between air pollution concentrations, on the one hand, and vehicle usage and key weather variables on the other.

As mentioned above, the problem of episodic air pollution is pervasive worldwide. WHO (2017) identifies mobile-source emissions as major contributors, particularly in several of the world's larger cities. By isolating the marginal impact of mobile-source emissions on episodic air pollution outbreaks in our study area, and by estimating the social net benefits associated with public investments to mitigate these impacts, our analysis therefore contributes to an on-going empirical assessment of what has become a widespread environmental problem driven by the necessity of transportation.

The next section provides details about the study area's red air day problem as well as the health consequences associated with elevated $PM_{2.5}$ concentrations in general. Section 3 discusses the data used in the empirical analyses underlying our subsequent calibration and numerical simulation exercises. Section 4 presents our econometric results, and Section 5 discusses our numerical results for optimal investment in, and the social net benefits associated with, preventative capital. Due to space constraints, and because we closely follow the endogenous risk framework developed in Berry et al. (2015), we eschew presenting the full theory underlying our numerical results. Interested readers are instead referred to Berry et al. (2015) for those details. Section 6 summarizes our empirical and numerical results.

2. The Red Air Day Problem

Elevated particulate matter ($PM_{2.5}$) concentrations have been a persistent, episodic pollution problem in Northern Utah's Cache County for the past several years (Figure 1 shows the county's location in the northern region of the state highlighted yellow. The red highlighted area is the state's fastest growing region, the Wasatch Front).[7] As shown in Figure 2, which depicts the annual distributions of $PM_{2.5}$ concentrations in the region during the 2002 – 2007 period (the period 2008 – 2012 depicts similar annual distributions), concentrations frequently spike above the NAAQS of 35 $\mu g/m^3$ averaged over any 24-hour period (horizontal red line) during the winter months (primarily December – February). The figure also reveals the variability in spikes from year to year. For instance, during the 2002, 2004, and 2005 inversion seasons spikes occurred more frequently, reaching markedly higher levels than those experienced in the 2003, 2006, and 2007 inversion seasons.

[INSERT FIGURES 1 AND 2 HERE]

Table 1 provides both the frequencies and relative frequencies of winter days in which $PM_{2.5}$ concentrations exceeded the NAAQS for each year in our dataset. Commensurate with Figure 2, there is pronounced variability across years – during some years Cache County residents experienced a relatively large number of "red air days", while during others the frequency was lower. Figure 3 shows the distribution of monthly average $PM_{2.5}$ concentrations in Cache County for the years of our study, 2002 – 2012. Together, the two figures illustrate the episodic and seasonal nature of the region's red air day problem.

[INSERT TABLE 1 AND FIGURE 3 HERE]

[7] Logan is Northern Utah's largest city. In 2009, Logan's population consisted of 46,000 people residing in 16,000 households (U.S. Census Bureau, 2016). The population of Northern Utah is roughly 150,000. See Moscardini and Caplan (2017) for a detailed explanation of Northern Utah's winter inversion phenomenon.

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. In addition, short-term exposure is 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 (EPA, 2016b; Dockery et. al, 1993; Pope et. al, 1995; Pope, 1989).[8]

The primary sources of $PM_{2.5}$ concentrations in Northern Utah are vehicle exhaust, agricultural and industrial activities, and wood burning, the most pronounced of which is attributed to the former. The UDEQ has therefore concluded that reducing emissions associated with motor vehicle use offers the best near-term approach to reducing the region's $PM_{2.5}$ concentrations during winter inversions (UDEQ, 2016a). In an effort to reduce vehicle emissions, county officials recently adopted a mandatory vehicle emissions testing program (VETP) – the efficacy of which has been hotly debated, primarily due to exemptions for diesel trucks (Anderson, 2013). To date, the VETP has been the sole mandatory initiative enacted by the state of Utah to control the region's red air day problem. Given Cache County's persistent

[8] Utah residents concur that air quality is an insistent social concern. According to Envision Utah (2014 and 2013), Utah residents believe that mitigation of poor air quality should be the state's second highest priority, tied with funding of public education and only slightly behind management of water resources. Survey results indicate that, inter alia, over 60 percent of respondents believe air quality negatively impacts their lives, over 90 percent believe good air quality is integral in maintaining good health, and almost 80 percent believe air quality has worsened in the Greater Wasatch and Northern Utah regions over the past 20 years. Further, residents identify changes in how they transport themselves (i.e., changes in the extent to which they contribute mobile-source emissions), e.g., telecommuting, ridesharing, use of public transportation, reduced idling and unnecessary driving, as being the most beneficial approaches to improving air quality. Roughly 65 percent of respondents report that they would likely reduce the use of their vehicles if a tax increased the per-gallon price of gasoline by $1.00; 32 percent indicating that they would be very likely to do so (Envision Utah, 2013 and 2014).

non-attainment status for $PM_{2.5}$ concentrations, the preponderant health impacts associated with equally persistent red air day episodes, and the relatively low expected efficacy of the county's VETP, the need to devise serious-minded polices to control these episodes is urgent.

3. Data

The data used in the empirical analyses presented in Section 4 are compiled from several different sources. Each variable in the dataset consists of a daily time step for the years 2002 – 2012.[9] Since the problem addressed in this study occurs seasonally each year (from December – February) we restrict the dataset to these months. $PM_{2.5}$ concentrations are recorded hourly for Cache County by the Utah Division of Air Quality (UDAQ) at EPA station code 490050004 located in downtown Logan (UDEQ 2016c).

The weather variables – consisting of temperature gradient, wind speed, humidity, snow depth and snowfall level – were obtained from the Weather Underground and the Utah Climate Center (Weather Underground, 2016; Utah Climate Center, 2016). Lastly, vehicle trip count data was obtained from Utah Department of Transportation (UDOT, 2014). The Automatic Traffic Recorder (ATR) stations for the trip count data in Cache County are #303, #363, and #510. Figure 4 identifies the specific locations of the various stations in Cache County.

[INSERT FIGURE 4 HERE]

The summary statistics for and specific definitions of the variables used in our ensuing regression analyses are presented in Table 2. As indicated, the average daily $PM_{2.5}$ concentration in Cache County during the winter months each year is 19.5 μg/m³ (recall that the hourly averaged NAAQS is 35 μg/m³ for any given day of the year). Average daily trip count (*TC*) is 40,538 (the natural log of this value is 10.61), whereas the average for the threshold indicator

[9] $PM_{2.5}$ concentrations, vehicle trip counts, and the weather variables used in this study are reported by their various sources on an hourly basis. For the analyses we have created daily averages from the hourly data.

variable $\overline{PM}_{2.5}$ is 0.15 (meaning that on average roughly 15 percent of the sampled days are red air days in any given winter season).[10] The weather variables *WIND, TEMP, HUMIDITY*, *SNOWFALL*, and *SNOWDEPTH* measure the average daily wind speed, temperature gradient, humidity level, snowfall level, and snow depth occurring in Cache County during our study period. Weather variables are included as controls for relevant weather conditions determining $PM_{2.5}$ concentrations. *TEMP* is of particular importance. It is measured as the difference in temperatures between the region's high point (Mount Logan peak) and the valley's floor, i.e., a vertical temperature gradient. As discussed in Gillies et al. (2010) and Wang et al. (2015), a positive (or inverted) temperature gradient, where the air is colder near ground level and warmer at higher altitudes, is a key determinant of winter inversion conditions, in effect a necessary condition along with *SNOWDEPTH* and *SNOWFALL* for determining persistence of the region's wintertime red air day episodes.

[INSERT TABLE 2 HERE]

According to UDEQ (2018), a snow-covered valley floor reflects rather than absorbs heat from the sun, preventing normal mixing of warm and cold air and exacerbating the accumulation of $PM_{2.5}$ concentrations in the atmosphere. The deeper the snow depth the more heat is absorbed and the greater the positive effect on concentrations. Snowfall is coincident with lower air pressure, which in turn negatively affects $PM_{2.5}$ concentrations, all else equal. Calm winds reduce

[10] Specifically, 40,538 is the average daily trip count across our entire dataset based on the ATRs reporting the largest trip counts per day. We chose the largest reported daily trip count rather than the average across all ATRs because even the former measure is likely an underestimate of daily trips taken in the valley. This is due to the fact no one ATR is capable of recording all daily trips taken in the county. We were precluded from adding daily trips across all ATRs because of potential double-counting errors. It is important to bear in mind that even though our measure of daily trip counts is thus an underestimate in absolute terms, the measure exhibits no bias in relative terms across days. This fact is crucial for our analysis since it is the variability in trip count across days that we are interested in measuring in order to estimate trip count's marginal effect on the variability in daily $PM_{2.5}$ concentrations.

the mixing of warm and cold air and can also negatively affect concentrations, while higher levels of relative humidity are associated with higher concentration levels.

4. Empirical Analyses

In this section we present the empirical models used to derive the key parameter estimates for our subsequent numerical analysis in Section 5. We first estimate a Probit model using a subset of the variables contained in Table 1 in order to derive a mean estimate of the region's steady-state level of background risk, R^{ss}, where background risk in this case means the average probability of a red air day occurring irrespective of countywide vehicle trips taken. We then derive an estimate of the region's episodic hazard function $\Psi(N(t), R(t))$ for any day t, where $N(t)$ and $R(t)$ represent day t's preventative capital stock and background risk levels, respectively. As shown in Section 4, estimates of R^{ss} and $\Psi(N(t), R(t))$ are crucial for our subsequent numerical simulations of the optimal steady-state preventative capital stock, N^{ss}, and corresponding investment in preventative capital, z^{ss}.[11]

4.1. Probit Analysis

Empirically, we can represent R^{ss} as the average probability of a red air day occurring in the region during the winter months. We proxy for background risk with the probability of a red air day occurring rather than merely the probable occurrence of a temperature inversion because our data suggests that roughly 30 percent of red air days are not coincident with an inversion. Following Greene (2018, Section 17.3) and Long and Freese (2014, Section 5.1), we estimate the

[11] We have chosen not to jointly estimate an underlying structural model linking determination of the region's steady-state background risk with its hazard function for two reasons. First, our underlying theoretical framework portrays background risk as an exogenous process. Thus, as in Berry et al. (2015), this risk factor is assumed to affect the hazard function exogenously, rather than as a joint determinant per se. Second, the probit and survival models estimated in this section are 'un-nested', in the sense that the categorical variable being determined in the former equation (whether or not a red air day has occurred) is not an endogenously determined explanatory variable in the latter equation (which itself determines the number of days until a red air day episode commences). As a result, any error correlation across these two equations potentially affects the efficiency of each equations' estimated coefficients not their accuracy.

marginal effect of covariate $x_i(t) \in \boldsymbol{X}(t), i = 1, \dots I$, on the probability of the occurrence of a red air day during the winter inversion season as,

$$\frac{\partial\left(Pr\left(\overline{PM}_{2.5} = 1 \middle| \boldsymbol{X}(t)\right)\right)}{\partial x_i(t)} = \phi'(\boldsymbol{X}(t)\beta)\beta_i, \tag{1}$$

where variable $\overline{PM}_{2.5}$ is as defined in Table 2, matrix $\boldsymbol{X}(t)$ contains daily observations on the model's covariates (a subset of the variables defined in Table 2), β is the corresponding vector of parameters to be estimated from the data, and $\phi'(\boldsymbol{X}(t)\beta)$ is thus the marginal probability density function evaluated at a given value of $x_i(t)$ (Greene, 2018, Section 17.3). R^{ss} is computed as the average of the predicted probability across observations. The estimated coefficients and associated marginal effects for our preferred specification of the model are presented in Table 3.[12]

[INSERT TABLE 3 HERE]

We begin by noting that the marginal effect of *TEMP* on dependent variable $\overline{PM}_{2.5}$ is of the expected sign (positive) and statistically significant at the one percent level. The higher the temperature gradient between Logan Peak and the valley floor, the higher the probability of a red air day occurring, all else equal, which conforms with Gillies et al. (2010) and Wang et al. (2015). The marginal effects for $LagPM_{2.5}$, *SNOWDEPTH*, and *HUMIDITY* are each also of the expected signs (positive) and statistically significant, while the coefficient for *SNOWFALL* is expectedly negative in sign and likewise statistically significant. Variable $LagPM_{2.5}$ is included in our model to account for any lagged effects of previous $PM_{2.5}$ concentrations from the

[12] We ran a host of other specifications for this model, including different sets of explanatory variables. We also tested for causal effects (endogeneity) associated with the *TEMP*, *HUMIDITY*, and *HUMWIND* weather variables, even though we know of no theory to suggest that $PM_{2.5}$ concentrations partially determine these weather conditions. Results for these specifications were qualitatively similar to those reported in Table 3, particularly with respect to the estimation of R^{ss}, which is the key value being estimated in these regressions. Results for these models are available from the authors upon request. We used STATA version 14.1 for our regression analyses.

previous day that have accumulated in the atmosphere. Accounting for short-term cumulative effects follows the approach used by Moscardini and Caplan (2017) in their $PM_{2.5}$ regression model.[13] The sign for *HUMWIND* is also expectedly negative but statistically insignificant.[14]

Most importantly for our purposes the model estimates that the average probability of a red air day occurring in the region during the winter inversion season as 16%. As mentioned above, the average probability measure is calculated as an average across daily predicted probabilities and serves as our estimate of steady-state background risk, R^{ss}. The pseudo R^2 and McFadden's R^2 values for this regression are both 60%, which is slightly above McFadden's Adjusted R^2 value, and the Wald χ^2 test for at least one statistically significant coefficient in the model is significant at the 1% level. The model correctly predicts the positive outcomes of red air days 86% of the time, and negative outcomes (i.e., non-red air days) 94% of the time. The sample size for this analysis is 601.

4.2. Survival Analysis

Letting $G(\boldsymbol{X}(t))$ represent the probability of an episodic outbreak on any given day, where in this case $\boldsymbol{X}(t)$ is potentially a different vector of covariates from Table 2 than those used to estimate the probit model in Section 4.2, the corresponding survival function is written as $S\big(\boldsymbol{X}(t)\big) = 1 - G\big(\boldsymbol{X}(t)\big)$, and the hazard function $\Psi(\cdot)$ solves for the probability of an episodic outbreak given

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[13] We also ran the model in Table 3 without *LagPM*$_{2.5}$ as a regressor in order to assess the impact on the remaining regressors' coefficient estimates (as a test of *LagPM*$_{2.5}$'s potential endogeneity) and standard errors (as a test of potential serial autocorrelation). The results were qualitatively very similar. Further, the estimate for R^{ss} was 15.8 percent, also very similar to the 16 percent estimate from the model including *LagPM*$_{2.5}$. Lastly, we do not consider *TC* as an omitted variable from this model because it is uncorrelated with the remaining variables. As we discuss in Section 4.2, *TC* can instead be instrumented with either a weekday dummy or a series of day-of-the-week dummies.

[14] Slight breezes stimulate the evaporation of water, leading to increases in humidity. Thus, we expected *HUMWIND* to exhibit a negative relationship with *PM2.5*. *WIND* was included in an earlier specification and found to be statistically insignificant.

its non-occurrence prior to any given day.[15] Following Berry et al. (2015) and Barbier (2013), we ultimately estimate a hazard function defined in general as,

$$\Psi\big(\boldsymbol{X}(t), R(t)\big) = -\frac{R(t)d\ln\big(S\big(\boldsymbol{X}(t)\big)\big)}{S\big(\boldsymbol{X}(t)\big)}, \tag{2}$$

where $R(t)$ again represents exogenous background risk.

Conditioning $\Psi\big(\boldsymbol{X}(t), R(t)\big)$ on $N(t)$ post-estimation requires that a functional relationship be assumed between $TC(t)$ (which is a member of $\boldsymbol{X}(t)$) and $N(t)$**.** For this study we assume a constant-elasticity formulation,

$$\ln\big(TC(t)\big) = A - c\ln\big(N(t)\big), \tag{3}$$

where $c \in [0.1,1]$ represents the (absolute value) of trip-count elasticity with respect to preventative capital stock, constant A is calibrated from equation (3) assuming median trip count for the region and initial capital stock $N(t = 0)$ = $1 million.[16] The conditioning occurs post-estimation because data on trip counts, rather than on preventative capital stock, is available for Cache County. Although a set of arbitrary relationships are therefore assumed to exist between $N(t)$ and $TC(t)$ for this study, we do find some empirical evidence to suggest that our chosen set includes those gleaned from relevant expense studies (APTA, 2014; Litman, 2011 and 2017;

[15] Because multiple red air day episodes typically occur in Northern Utah during the inversion season, we consider each episode as a special case and format the data accordingly (which is discussed in more detail below). Hence, the wording "given no such outbreak has occurred prior to day t" should, in a more technical sense, read "given no such outbreak has occurred prior to day t *since the previous episode*". The episodes must be independently distributed in order to warrant such a statement, which in our case is evidenced by the statistically significant role that the weather variables (which are themselves exogenously determined) play in determining the start and finish of any given episode, as well as the episode's duration and intensity. Hence, in our case survival is tracked between successive episodes during a given inversion season. As an example of what we mean by "successive episodes", suppose the first episode in a given inversion season does not begin until day 20 and then lasts until day 23. Then the period during which no outbreak has occurred for the first episode (i.e., the first episode's survival period) is days 1 to 19. If the second episode then begins on day 31, the associated survival period for the second episode is then days 24 to 30.

[16] As we discuss in Section 4.3, we find some empirical evidence to support our presumed range for elasticity measure c. The range of trip-count elasticities adopted for this study represent a range of possible behavioral responses of drivers to different scales of investment in preventative capital. As we also discuss at greater length in Section 4.3, since $N(t = 0)$ is per force a best-guess estimate provided by a county executive officer for this analysis, we sensitize the analysis to alternative values, $N(t = 0) \in [\$500{,}000, \$1 \text{ million}]$.

Pratt and Evans, 2004). We explain the functional relationship between $N(t)$ and $TC(t)$ in greater detail in Section 4.3.[17]

We test several standard parametric models for the ensuing survival analysis – exponential, Weibull, and Gompertz, as well as the semi-parametric Cox model. The Weibull hazard function (defined specifically as $\Psi\big(\boldsymbol{X}(t), R(t)\big) = R(t)pt^{p-1}\exp(\boldsymbol{X}(t)'\boldsymbol{\beta})$, where parameter p represents the function's shape parameter and all other terms are as previously defined (Cleves et al., 2010, Section 3.1)) performed best in fitting our data.[18]

The occurrence of a series of daily $PM_{2.5}$ concentrations above the NAAQS threshold 35 μg/m³ level in the region is considered an event in this study. For this analysis, a count-data variable must also be specified (Cleves et. al, 2010, Section 3.1); ours is defined as follows. After the first episodic outbreak, for example in December, we begin the count within a window during which $PM_{2.5}$ concentrations steadily increase, consecutively day-after-day, until the next episode occurs, i.e., our count-data variable is the number of steadily increasing days between red air day episodes. Similar counts are then taken between succeeding episodes.[19]

The survival analysis results are presented in Table 4 for two versions of the Weibull model. In Weibull 1, potential endogeneity in *TC* is controlled with a weekday dummy variable for Monday – Friday as in Moscardini and Caplan (2017) (note that for expository convenience time

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[17] Notationally speaking, the post-estimation version of $\Psi\big(\boldsymbol{X}(t), R(t)\big)$ is perhaps best written as $\Psi\Big(\boldsymbol{X}(t), R(t); f\big(N(t)\big)\Big)$, where $f\big(N(t)\big)$, which represents the functional relationship between $N(t)$ and $TC(t)$, is decreasing in $N(t)$.

[18] The Weibull hazard function exhibits the appealing property of increasing hazard over time for $p > 1$.

[19] It is important to note that the intervening periods between red air day episodes and the lengths of the episodes themselves each occur independently both within and between years. This is due to the fact that weather conditions, which are necessary for the emergence of the episodes, are exogenously determined. We also considered an alternative specification of the count-data variable, whereby the number of consecutive inversion days (i.e., days in which the Logan-peak temperature exceeds the valley floor temperature (*TEMP* > 0)) were counted between episodes. However, this approach unfortunately whittled our sample size down to a mere 21 observations. Results based on this count-variable specification are qualitatively similar to those presented in Table 4 and are available from the authors upon request.

designator t is henceforth dropped). In Weibull 2 the endogeneity is controlled with daily dummy variables for Monday through Friday. For both models we conducted standard Durbin-Wu-Hausman tests to establish the presence of potential endogeneity in the relationship between $PM_{2.5}$ and *TC* (Davidson and MacKinnon, 1993). The theoretical basis for *TC*'s endogeneity is premised on what is essentially routinized transportation behavior of the average household, i.e., trips for the most part are informally pre-scheduled for different days of the week, and fewer trips are taken valley-wide during weekends. Predicted trips subsequently used as regressors in each model are denoted as TC^*.

[INSERT TABLE 4 HERE]

The coefficients for TC^* in both models are positive, indicating that on average an increase in the region's vehicle trip count increases the hazard rate of a red air day occurring. These effects are statistically insignificant, however, most likely due to the relatively small sample sizes of the regressions and relative coarseness of the trip count variable used in each model.[20] The coefficients for *TEMP*, *SNOWDEPTH*, and *SNOWFALL* are each of the expected signs and statistically significant. The positive effect of *ln_p* in each model signifies that the hazard of a red air day occurring is monotonically increasing over the course of any given winter season in Northern Utah.

Comparing the AIC and BIC statistics across the two models, we base the ensuing numerical analysis of optimal investment in preventative capital on the Weibull 1 model, where the two statistics are lowest (Cleves et al., 2010, Section 3.1). In the numerical analysis, each of the

[20] *TC* is "coarse" in the sense that it serves as a proxy for vehicle-use decisions that are inherently made at the household level and yet is aggregated at the county level (recall that it is calculated as the total number of vehicle trips per day made in the region). In contrast, each weather variable is a non-aggregated, relatively precise scientific measurement of a meteorological occurrence.

covariates included in the Weibull 1 model are evaluated at their mean values, except for *TC*, which, as we now explain in Section 3.3 is expressed as a constant-elasticity function of N.

4.3. Vehicle Trip Count and Preventative Capital Stock

The assumed functional relationship between vehicle trip count *TC* and the value of preventative capital stock *N* on any given day is, as previously mentioned in Section 4.2, represented by equation (3). Three previous studies of investments in public transportation provide comparable estimates of the implicit relationship between vehicle usage and investment in preventative capital stock. APTA (2014) consider aggregate savings in vehicle operating and fuel costs (associated with reduced vehicle usage) in response to expanded capital investment in mass transport. In one scenario (the "Doubling Ridership Scenario") where ridership increases by 3.53 percent per year, the associated elasticity (these authors' own calculation) is 0.56. Under a "High Growth Scenario" where ridership increases by 4.67 percent per year the elasticity falls to 0.48. Similarly, Litman's (2011) assessment of the Transport for London's investment in a video camera network to manage congestion in Central London suggests an elasticity of roughly 0.2. Litman (2017) reports an average elasticity of transit use with respect to transit service frequency of 0.5, and elasticities with respect to service expansion ranging between 0.6 and 1. Taken together, these findings suggest that our chosen range for parameter $c \in [0.1,1]$ encompasses what empirical evidence is available.

We calibrate (3) such that the (A,c) combinations are based upon our data for TC and a rudimentary assumption about the current level of N in Cache County. Specifically, to generate values for parameter A for each assumed value of c we use the median number of daily vehicle trips per day in the region from our dataset, $TC(t = 0) = 40{,}538$. For $N(t = 0)$, we assume the region's current capital stock devoted to prevention of red air day episodes presently stands at $1 million, reflecting what we estimate is the cumulative, present value of both the human capital (e.g., any city employee time directed toward promoting preventative activities city wide) and physical capital (infrastructure investments, including additional buses added to the county's fleet that are used specifically during the inversion season to increase ridership, etc.) that Cache County authorities had invested during the study period to prevent the occurrence of red air day episodes.[21] Using (5), we obtain the resulting (A,c) combinations presented in Table 5.

[INSERT TABLE 5 HERE]

5. Estimates of the Optimal Preventative Capital Stock

We begin this section by completing the calibration of the theoretical model developed in Berry et al. (2015). Toward this end, values are assigned to parameters δ (constant rate of capital depreciation), r (discount rate), B (annual value of Northern Utah's GDP), and J (present value of ex post net benefits given a red air day episode has occurred) reflecting current conditions in Northern Utah, and the functional form for the background-risk motion equation, $\sigma(R)$, is chosen (Table 6 compiles the full set of calibrated values and functions used in our subsequent numerical analysis). We then solve the model numerically for the associated optimal steady-state levels of z and N. Lastly, we numerically derive the time path of z for the case of increasing background risk over time.[22]

[INSERT TABLE 6 HERE]

[21] The value $N(t=0)$ = \$1 million represents Cache County Executive M. Lynn Lemon's best estimate, provided through personal communication on June 14, 2016. We have also run separate simulations assuming $N(t=0) = \$500{,}000$, which was Mr. Lemon's lower-bound estimate provided at the time. Results based on this assumption are contained in Appendix Table A.1. Note the current preventative capital stock described here is notably different than the types of preventative capital we described in Section 1. This is because the preventative capital described in Section 1 represents what might best be described as investments in what are now considered to be "outside-the-box" technologies and information campaigns that heretofore have been deemed infeasible given current funding levels.

[22] We use Matlab version R2016b (9.1.0.441655) 64-bit for our numerical analyses.

As indicated in Table 6, we assume that exogenous background risk follows a probit function. As mentioned in Section 4.2, Weibull Model 1 performs best in estimating hazard function $\Psi(N, R)$, which is parameterized with the corresponding coefficients provided in Table 4. The value for B is the Census Bureau's (2016) most recent estimate of Cache County's annual GDP; GDP being the best aggregate estimate of county-wide benefits at stake during red air day episodes. As shown in Table 6, the value for J is then calculated as B net of average seasonal environmental damages (D) in perpetuity, which according to the values reported for B and D equates to \$77.6 billion. The estimate for D of \$63 million is calculated using the Environmental Benefits Mapping and Analysis Program (BenMAP) (EPA, 2016a). This benefit is based on the assumption that, on average, a reduction of 40 percent in $PM_{2.5}$ concentration is required to attain the NAAQS of no greater than 35 μg/m³ per day during the inversion season in Northern Utah (Moscardini and Caplan, 2017).[23] Thus, following Berry et al. (2015), our measure of J captures the present discounted stream of social net benefits into perpetuity that remains after an outbreak has occurred (relative to no outbreak having occurred). This reflects the on-going health costs incurred into the future that are associated with any given red air day episode.

To determine the optimal steady-state preventative capital stock, we follow Berry et al. (2015) in utilizing the theoretical model's two steady-state equations,[24]

$$\dot{N} = z - \delta N = 0 \tag{4}$$

$$\sigma(R) = R(1 - \frac{R}{R^{ss}}) = 0. \tag{5}$$

[23] In other words, we assume an initial red air day $PM_{2.5}$ concentration level of 50 μg/m³, which is roughly equal to the mean estimate of the concentration level that occurs in our sample strictly on red air days, i.e., given that the concentration level is no less than 35 μg/m³ per day to begin with. BenMAP requires input of an initial $PM_{2.5}$ concentration level in order to generate benefits associated with the reduction in damages from that level. For detailed information on the BenMAP facility visit https://www.epa.gov/benmap.
[24] Note that equations (23) and (24) in Berry et al. (2015) are used to derive the expression for N^{ss} used in our simulations.

Equation (4) indicates that the capital stock reaches its steady state when the investment level z equates with the value of depreciated capital and equation (5) updates the exogenous background risk, R , according to a standard logistic function, where in the steady state R equals its steady value, R^{SS}. Results for steady-state capital stock, N^{ss}, given the different (A,c) combinations presented in Table 5, along with corresponding optimal, steady-state vehicle trip counts (derived directly from equation (3), and henceforth denoted as TC^{ss}), are presented in Table 7.

[INSERT TABLE 7 HERE]

From Table 7 we see that the value of Cache County's optimal, steady-state preventative capital stock ranges from roughly \$4 to \$14 million depending upon the (A,c) combination. The corresponding amortized annual values ranges from \$330,000 to \$1.13 million per year.[25] In column 5, a social deadweight loss (DWL) is applied to the annual investments in preventative capital, reflecting both the region-wide social cost associated with raising revenue through the issuance of a county bond and the inefficiency calculated in Moscardini and Caplan (2017) corresponding to induced reductions in vehicle trips. To account for the DWL associated with the issuance of a preventative-capital bond, we use the lower-bound DWL estimate of 20 percent (per dollar of revenue raised) reported in Campbell and Brown (2003). Campbell and Brown's (2003) estimate is in turn relatively conservative when compared with earlier DWL estimates reported in Findlay and Jones (1982), Freebairn (1995), Feldstein (1999), and Bates (2001).

To account for the DWL associated with reduced vehicle trips we first obtained a national estimate of the annual cost of vehicle ownership and operation, which for 2017 is estimated to be roughly \$9,000 (AAA, 2017). We then utilize the Bureau of Labor Statistic's (BLS's) CPI Inflation Calculator to obtain corresponding values for each of the years represented in our

[25] A 5 percent interest rate and 20-year loan term period are assumed for the amortization exercise.

dataset, resulting in a mean estimate of the annual benefit of owning and operating a vehicle in our study area, during our study period, of $7,504 (BLS, 2018). Next, we obtained the Utah State Tax Commission estimates of the number of passenger vehicles registered in our study area for each of the years represented in our dataset, resulting in a mean value of 50,288 (USTC, 2018). Multiplying these two values together results in our mean estimate of the aggregate annual benefit of vehicle travel in our study area of $377,389,090.

To convert this aggregate benefit value into a corresponding measure of benefit per vehicle trip, we calculate the aggregate number of vehicle trips taken annually in our study area. From our dataset we are able to calculate the average number of trips taken per day of the week (Sunday-Saturday), which are then each multiplied by 52 days. Summing these day-of-the-week averages results in an annual average of 16,359,044 vehicle trips, which, when divided into our mean estimate of the aggregate annual value of vehicle trips results in an estimated benefit-per-trip of $23.07. This value is used to represent the DWL per reduced vehicle trip.

It is interesting to note that although the county's optimal steady-state vehicle trip count decreases monotonically from a mean of just over 40,000 to approximately 35,000 and 3,000 trips per day as trip-count elasticity c rises from 0.1 to one, respectively, the corresponding values of optimal steady-state preventative capital stock exhibit a non-monotonic relationship with the elasticity.[26] The value rises from approximately $4 million with an elasticity of 0.1 to just over $14 million for an elasticity of 0.8, and then declines to just under $14 million at an elasticity of one. This divergent relationship between optimal trip count TC^{ss} and preventative capital stock N^{ss} is impelled, on the one hand, by the constant trip-count elasticity assumption

[26] This non-monotonic relationship between trip count elasticity and optimal investment in preventative capital contrasts with Berry et al.'s (2017) finding of a monotonically decreasing effect of prevention effectiveness on optimal investment.

(which drives the monotonic decrease in TC^{ss}) and on the other by the diminishing (negative) effect of N on hazard function $\Psi(N,R)$ (which drives the non-monotonic pattern in N^{ss}).[27]

The corresponding mean percentage changes in $PM_{2.5}$ concentration due to decreases in vehicle trip counts are calculated via Monte Carlo simulation using the ARMAX(1,0,0) and ARMAX (1,0,9) versions of Moscardini and Caplan's (2017) $PM_{2.5}$ regression equations.[28] The results in Appendix Table A.2 depict a positive relationship between reductions in vehicle trip counts and reductions in $PM_{2.5}$ concentrations for both the ARMAX(1,0,0) and ARMAX(1,0,9) models, denoted Models 1 and 2, respectively. The effects of weather variables *TEMP*, *SNOWFALL*, and *SNOWDEPTH* on $PM_{2.5}$ concentrations are likewise as anticipated. The AIC and BIC statistics indicate that Model 1 fits the data best, hence we use the Monte Carlo results from this model to estimate the percentage changes in $PM_{2.5}$ concentrations associated with decreases in vehicle trip counts.

Recall the overall median trip count level for Cache County in our sample is roughly 40,000 trips per day. Hence, as shown in Table 7, at the lowest trip-count elasticity assumed for this study an optimal preventative capital stock of approximately $4 million results in a concomitant 13 percent decrease in the county's vehicle trip count (from 40,538 to 34,924 trips). At the largest elasticity assumed in this study, an optimized $14 million capital stock corresponds to a roughly 93 percent reduction in trip count. Obviously a trip count this low would have to be obtained with a large percent of zero-emission vehicles included in the region's fleet, a finding is not unlike the California Public Utility Commission's recent estimation that seven million

[27] The specific curvature conditions assumed for $\Psi\big(N(t),R(t)\big)$ are provided in Section 2.
[28] The percentage change in $PM_{2.5}$ concentration is calculated as the mean of the sampling distribution of 10,000 sample means, where each sample consists of 90 observations (representing the length of the three-month winter inversion season) randomly drawn from respective normal distributions for each variable used in the ARMAX(1,0,0) equation, where the mean of the variable's distribution is the variable's sample mean.

electric vehicles will need to be on the road in order for the state to meet its 2030 greenhouse gas reduction goals (Walton, 2018).

Annual benefits associated with the concomitant decreases in $PM_{2.5}$ concentrations are calculated using BenMAP (EPA, 2016a). As anticipated, these benefits track the reductions in $PM_{2.5}$ concentrations. Social net benefits are then calculated as the respective differences between annual benefits and the annual amortized values of the steady-state preventative capital stocks adjusted for deadweight loss. It is interesting to note that social net benefits increase monotonically with trip count elasticity, indicating that the more responsive is trip count to investment in preventative capital, the larger the social net benefit.[29] Corresponding benefit-cost ratios increase from 3.1:1 to 11.3:1.

Two aspects of our trip-count results bear mention. First, the data upon which key functions in the numerical model are based, in particular the hazard function, implicitly link the region's $PM_{2.5}$ concentrations to the composition of the region's vehicle fleet during the period 2002 – 2012 in terms of vehicle models, ages, fuel-efficiencies, and emission-control technologies, etc. Thus, the optimal daily trip-count reductions derived here do not necessarily mean that trips themselves must decrease to those levels in today's terms. Rather, vehicle trips that produce emissions consistent with the fleet's composition during that time period (i.e., emissions-equivalent trips) must be reduced. Obviously, as more tier-three and zero-emission vehicles are included in the region's fleet over time, the magnitude of the reductions in vehicle trips necessary to meet the NAAQS threshold for $PM_{2.5}$ concentrations (i.e., the associated emissions-equivalent trips) will naturally decrease (Moscardini and Caplan, 2017).

[29] Social net benefit begins to diminish at $c = 7.5$.

Second, it is interesting to note that Moscardini and Caplan (2017) estimate a required reduction to roughly 15,000 daily vehicle trips in order for Cache County to be in compliance with the NAAQS of 35 μg/m³ for an average inversion-season day. This threshold is closest to the optimal daily trip count level of 15,140 that we estimate for a trip-count elasticity of 0.4 (Table 7). Thus, Moscardini and Caplan's (2017) threshold estimate falls well within the range of optimal trip counts that we have estimated for this study.[30]

Figure 5 presents a phase diagram corresponding to steady-state equations (6) (blue line) and (7) (grey line) for the case of $c = 0.1$ and the parameter values and functional forms contained in Table 6. The steady-state equilibrium for this case occurs at the intersection of the two lines, corresponding to $N^{ss} = \$4.1$ million (from Table 7) and $R^{ss} = 16$ percent (from Table 3). The system's two eigenvalues (0.16 and -0.24), indicate a saddle-path equilibrium, depicted by the teal-colored arrowed line in the figure.

[INSERT FIGURE 5 HERE]

Lastly, as in Berry et al. (2015) we can appeal to the law-of-motion equation for $\sigma(.)$ from Table 6 to explore the dynamics of increasing background risk over time and its effects on the optimal investment z in preventative capital. Letting initial background risk be relatively close to zero (at the end of period 0), in particular $R(t = 0) = 0.005$, and using $\sigma(.)$ to update R over time, background risk (at the end of) period 1 is given by $R(1) = R(0) + \sigma(0)$, where $\sigma(0) = R(0)(1 - \frac{R(0)}{0.16})$, and similarly for $R(2)$, $R(3)$ and so on. The corresponding z values can then be calculated for given N^{ss} using (3) (we set $N^{ss} = \$4.1$ million for the analysis, which equals the

[30] It is important to point out that the reduction in vehicle trips necessary to attain the NAAQS for $PM_{2.5}$ concentrations in this model, as well as in Moscardini and Caplan (2017) are not necessarily socially optimal from a purely normative perspective. We estimate the socially optimal vehicle trip count and corresponding $PM_{2.5}$ concentration level for Northern Utah in a separate study, Acharya and Caplan (2018b).

N^{ss} value calculated from the simulation for $c = 0.1$), resulting in Figure 6 (y-axis is in billion $). As indicated, investment for the initial period, $z(0)$, equals approximately $3.8 million. The investment level for the next period is $z(1) = \$\ 0.5$ million, at which point the value of the preventative capital stock equals N^{ss}. Thus, for the remaining periods $z = \delta N^{ss} = 0.05 \cdot \$4.1$ million = $205,000 per period. Background risk continues increasing until reaching R^{ss} at the end of the eighth period.

[INSERT FIGURE 6 HERE]

6. Summary

This paper provides empirical estimates of the optimal investment in preventative capital to control episodic, wintertime, elevated $PM_{2.5}$ concentrations in Northern Utah, a region recently identified by the American Lung Association (ALA) as experiencing one of the nation's worst short-term particulate pollution problems (ALA, 2017). The problem in this region is emblematic of similar problems faced throughout the world. Indeed, roughly 90 percent of the world's population is currently estimated to reside in locations where air pollution levels exceed the World Health Organization's (WHO's) ambient standards, with annual mortality rates attributed to these elevated pollution levels of over six million people (WHO, 2017).

For our study area we have estimated an average background probability of a red-air day occurring during the winter inversion season of 16%. We also estimate a positive relationship between the aggregate number of vehicle trips taken in the region and the hazard rate associated with exceeding the NAAQS $PM_{2.5}$ concentration threshold of 35 μg/m³ on an average winter day. Theoretically expected correlations between exceeding the threshold, on the one hand, and a host of unique weather variables on the other, are also established.

The value of Northern Utah's optimal, steady-state preventative capital stock is estimated to range from $4 to $14 million depending upon the assumed vehicle trip count elasticity with respect to investment in preventative capital (with corresponding amortized annual values ranging from $330,000 to $1.13 million per year, respectively). Further, we find that although the region's optimal vehicle trip count decreases monotonically from approximately 35,000 trips per day to just under 3,000 (emission-equivalent trips) as trip-count elasticity rises, the corresponding optimal preventative capital stock exhibits a non-monotonic relationship with the elasticity. The value rises from just over $4 million with an elasticity of 0.1 to just over $14 million for an elasticity of 0.8.

At the lowest trip-count elasticity assumed for this study the optimal preventative capital stock of approximately $4 million results in a concomitant 13 percent decrease in the region's vehicle trip count. At the study's largest elasticity an optimized $14 million capital stock corresponds to a 93 percent reduction in trip count. As expected, annual benefits associated with the concomitant decreases in $PM_{2.5}$ concentrations track the reductions quite closely. Social net benefits (which are positive for each scenario considered in this study) increase monotonically with trip count elasticity, indicating that the more responsive is vehicle trip count to investment in preventative capital, the larger the social net benefit. Corresponding benefit-cost ratios increase from 3.1:1 at the lowest trip count elasticity to 11.3:1 at the highest. These ratios are clustered at the lower end of the EPA's (2011) estimated range for the 1990 Clean Air Act Amendments of between 3:1 and 90:1.

Acharya and Caplan (2018a) replicate this study's analysis for Utah's fast-growing, densely populated Wasatch Front region. The analysis for the Wasatch Front is complicated by the need to control for multiple county-level fixed effects in our estimation of background risk, hazard rate, and, ultimately, optimal steady-state investment in preventative capital. These types of replications in other regions of the world where episodic air pollution problems occur is one obvious avenue for future research, particularly where the type(s) of preventative capital and the scale of investment are relatively novel and large, respectively. It would be interesting to learn whether social net benefits are routinely positive under different circumstances than those considered in this study. Concomitant with replicating our approach across different study areas, it would be of interest to account for any potential co-benefits associated with the control of other air pollutant concentrations to which mobile sources contribute. For example, Northern Utah also suffers from elevated ground level ozone concentrations during the summer months (UDEQ, 2019; UDH, 2019). To what extent do preventative investments in the control of winter time red air day episodes provide spillovers for the control of ground level ozone during the summer months? Surely to the extent that they do, the social net benefit associated with the issuance of a clean air bond would increase.

Of course to firm up the estimates of optimal investment, study locations need to measure the impact on vehicle usage of varying levels of preventative capital stock over time, preferably at the household level. It would be useful to measure household-level behavioral responses to these investments from the perspective of more accurately calibrating the endogenous-risk numerical model we have used to derive the social net benefit estimates, as well as from the perspective of simply learning the extent to which the investments induce both short- and longer-term changes in vehicle usage at the household level.

Extending our analysis to account for the possible temporal impacts of climate change on local weather variables such as snowfall, snow depth, humidity, temperature, and wind (i.e., weather variables already serving as controls in our regression framework), is another logical direction that future research can take. For example, Lin et al. (2017), Chang et al. (2016), and Schroeder et al. (2017) estimate the impacts of climate variables on drought conditions in California, tropical cyclone activity, and predicted precipitation across the US, respectively. To the extent that the impacts of these climate drivers on local weather variables can similarly be estimated, our regression framework will ultimately permit us to project the effects of these impacts onto $PM_{2.5}$ concentrations, and thereby predict the attendant impacts of vehicle trip counts on the occurrence of red air days in the presence of climate change.

Finally, the regulatory implications associated with issuing a municipal clean air bond to raise revenue for what might currently be considered “outside-the-box”, and therefore risky investment in preventative capital, bears mention. To begin, it is important to acknowledge that the justification for issuing a municipal bond to control mobile-source air pollution is similar to a community’s premise for funding the fixed expenses associated with other major public goods, such as new schools, wastewater treatment facility upgrades, and preservation of open space. The required expenditures for these types of public goods are relatively large, and other funding mechanisms such as charging user fees are wrought with either high implementation barriers (e.g., how exactly to levy a seasonal gas tax in the case of Moscardini and Caplan, 2017), or fairness concerns (i.e., ensuring that a new tax is not regressive). Because they avoid these two potential bottlenecks in raising the revenue necessary to expeditiously solve a local air quality problem, we believe municipal clean air bonds at least deserve a closer look by policy makers and regulators when it comes to seriously considering how to improve local air quality conditions, especially in regions of the country that are persistently in violation of the NAAQS.

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Table 1. Frequency of winter days in which $PM_{2.5}$ concentrations exceed 35 μg/m³.

Year	Number of Winter Days Above 35 μg/m³	Percent of Winter Days Above 35 μg/m³[a]
2002[b]	50	98
2003	11	13
2004	35	39
2005	28	31
2006	6	7
2007	11	13
2008	20	25
2009	23	28
2010	25	33
2011	11	13
2012	5	6
Median[c]	20 (13.73)	25 (25.81)

[a]Percentages are based number of winter days for which data is not missing. The average number of non-missing winter days per year is 82.
[b]$PM_{2.5}$ concentrations were recorded on only 51 winter days in 2002.
[c]Standard deviations are reported in parentheses.

Source: Moscardini and Caplan (2017).

Table 2. Variable definitions and summary statistics.[a]

Variable	Description	Mean (SD)
TC^b	Log of daily trip count (# of vehicle trips).	10.61 (0.36)
$PM_{2.5}$	Daily $PM_{2.5}$ concentration ($\mu g/m^3$).	19.56 (19.39)
$\overline{PM}_{2.5}$	=1 if daily $PM_{2.5}$ concentration is above 35 $\mu g/m^3$, 0 otherwise.	0.15 (0.36)
TEMP	Temperature gradient between Logan Peak and valley floor (^{0}F).	-7.30 (10.24)
WIND	Daily wind speed (miles/hour).	3.03 (2.67)
HUMIDITY	Daily humidity level (%).	82.67 (8.78)
SNOWFALL	Daily snowfall level (mm).	14.45 (37.54)
HUMWIND	HUMIDITY x WIND.	243.74 (203.89)
SNOWDEPTH	Daily snow depth (mm).	127.26 (115.87)

a Standard deviations are in parentheses. The sample size (of the variable with the largest number of observations) is 752.

[b] *TC* is the log of maximum daily trip count as measured across the three ATR stations located in Cache County that consistently reported counts during our study period.

Table 3. Probit regression results.[a]

Variable		Coefficients (SE)	Marginal Effects (SE)
$LagPM_{2.5}$		0.047***	0.004***
		(0.008)	(0.001)
TEMP		0.057***	0.005***
		(0.012)	(0.001)
HUMIDITY		0.035*	0.003*
		(0.02)	(0.002)
HUMWIND		-0.001	-0.0001
		(0.001)	(0.0001)
SNOWFALL		-0.01*	-0.001*
		(0.006)	(0.001)
SNOWDEPTH		0.003***	0.0003***
		(0.001)	(0.0001)
R^{ss}		16%	
Log pseudolikelihood		-105.36	
χ2 (Wald)		136.57***	
Pseudo R^2		0.60	
Number of observations		601[b]	
Ω_1=	Predictedredairday=1 Observedredairday=1	0.86	
Ω_2=	Predictedredairday=0 Observedredairday=0	0.94	
	McFadden's R^2	0.60	
	McFadden's Adj. R^2	0.58	

[a] Dependent variable is $\overline{PM}_{2.5}$ from Table 2. Robust standard errors are in parentheses.
[b] 124 observations were dropped from this regression due to missing values for *SNOWDEPTH*.
***, ** and * indicate significance at 1, 5 and 10% levels, respectively.

Table 4. Survival regression results.[a]

Variable	Coefficients (S.E.)	
	Weibull 1	**Weibull 2**
*TC**	0.476 (0.663)	0.151 (0.628)
TEMP	0.081*** (0.013)	0.080*** (0.013)
SNOWDEPTH	0.004*** (0.001)	0.004*** (0.001)
SNOWFALL	-0.01*** (0.004)	-0.01*** (0.004)
AIC	116.821	117.288
BIC	132.331	132.797
ln_*p*	1.003 (0.077)	1.003 (0.077)
Number of observations	98	98

[a] Robust standard errors are in parentheses, *TC** is predicted trips,
and ln_*p* is natural log of the Weibull shape parameter (see Section 4.2).
***, ** and * indicate statistical significance at 1, 5 and 10% levels, respectively.

Table 5. (A, c) combinations used in the numerical analysis.

c	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
A	9.91	9.22	8.53	7.84	7.15	6.46	5.77	5.08	4.39	3.69

Table 6. Parameter values and functional forms for the numerical analysis.

Parameter/ Function	**Value/Function Form**	**Source**
R^{SS}	16%	Probit analysis (Section 3.1)
σ	$R(1 - \frac{R}{R^{\mathrm{ss}}})$	Berry et al. (2015)
$\Psi(N, R)$	$R\mathrm{p}t^{p-1}\ exp(\boldsymbol{\beta X'})$	Survival analysis (Section 3.2)
δ	0.05	Berry et al. (2015)
r	0.03	Berry et al. (2015)
B	\$ 2.39 billion	U. S. Census Bureau (2014)
D	\$63 million	BenMAP (EPA, 2016)
J	\$ 77.6 billion	$= \frac{B - D}{r}$
TC	$= exp(A - c \log(N))$	Arbitrary

Table 7. Estimated N^{ss} values (million \$), associated TC^{ss} (daily county-level vehicle trips), and social net benefit (million \$).

c	A	N^{ss}	Annual N^{ss}	Annual N^{ss} + DWL	TC^{ss}	% Change in PM2.5	Annual Benefit	Social Net Benefit	Benefit/Cost Ratio
0.1	9.91	4.1	0.33	0.52	34,924	1.0	1.6	1.08	3.08
0.2	9.22	7.4	0.59	1.014	26,950	2.7	4.2	3.19	4.14
0.3	8.53	9.8	0.79	1.408	20,278	4.5	7	5.59	4.97
0.4	7.84	11.5	0.92	1.682	15,140	6.4	10	8.32	5.95
0.5	7.15	12.7	1.02	1.891	11,285	8.2	13	11.11	6.87
0.6	6.46	13.5	1.08	2.029	8,437	10.0	16	13.97	7.89
0.7	5.77	13.9	1.12	2.125	6,372	11.7	18	15.88	8.47
0.8	5.08	14.1	1.13	2.172	4,842	13.4	21	18.83	9.67
0.9	4.39	14.1	1.13	2.198	3,716	14.9	23	20.80	10.46
1	3.69	13.9	1.12	2.205	2,893	16.3	25	22.80	11.34

Figure 1. Cache County (highlighted yellow) and Wasatch Front (highlighted red).

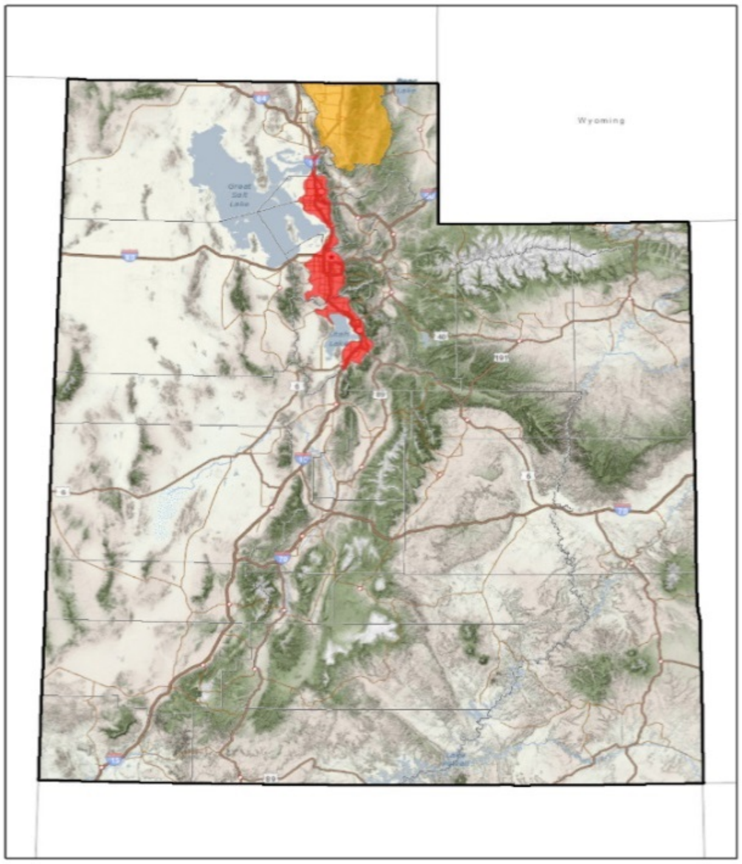
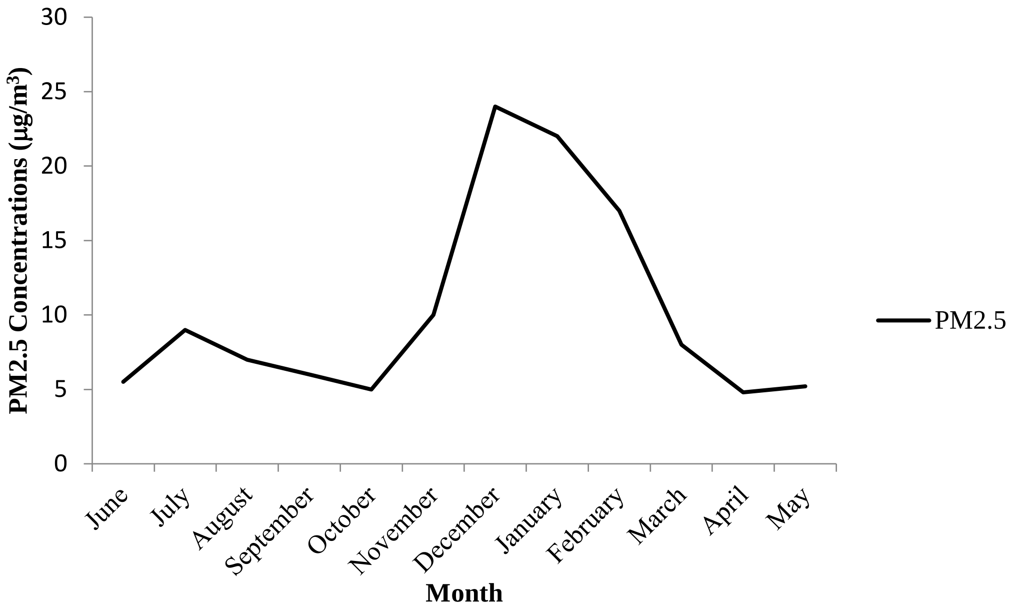


Figure 2. Annual $PM_{2.5}$ concentrations in Cache Valley, Utah, 2002 – 2007.

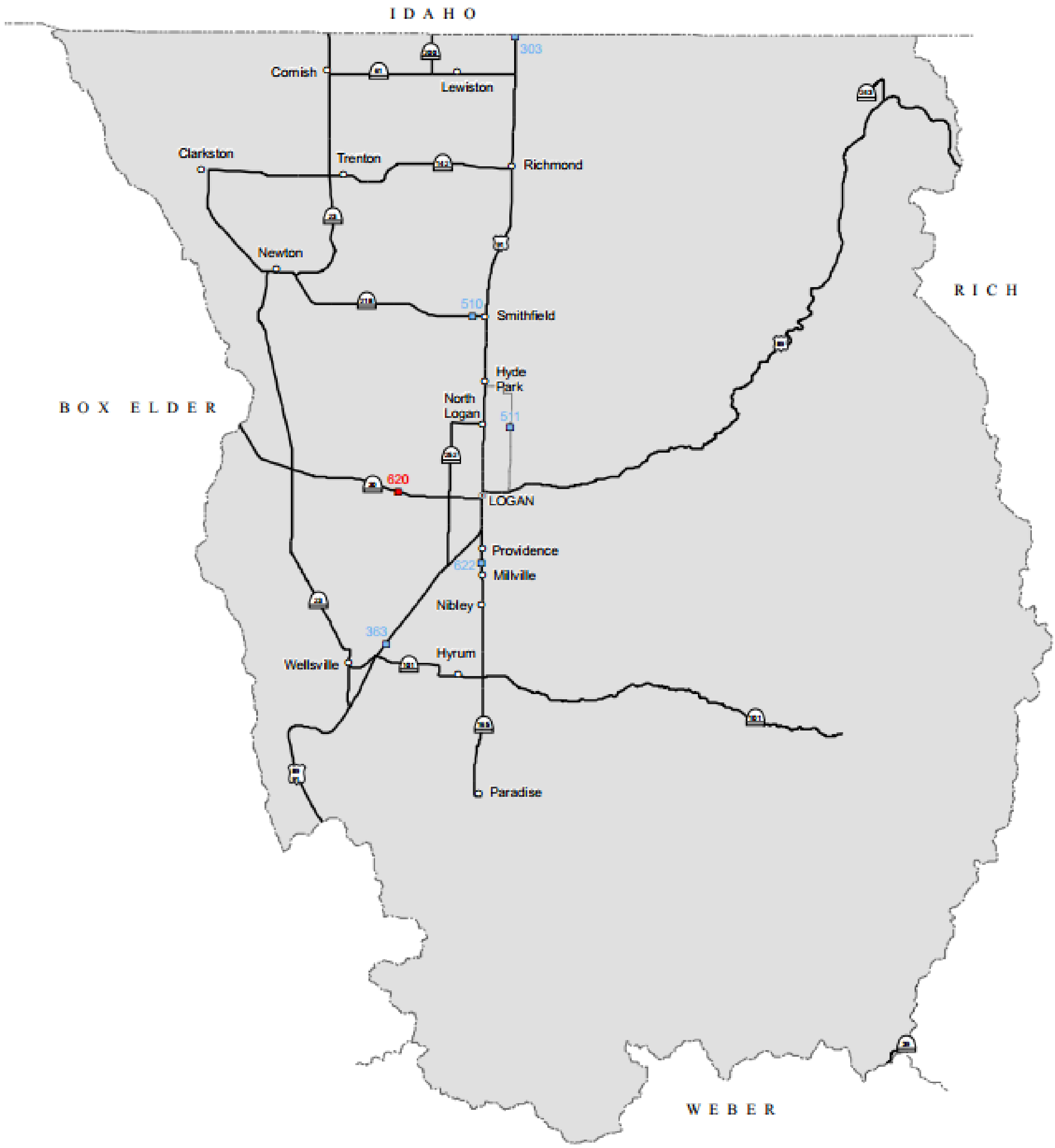
Source: Moscardini and Caplan (2017).

Figure 3. Monthly average PM 2.5 concentrations for 2002 – 2012.



Source: Moscardini and Caplan (2017).

Figure 4. Automatic Traffic Recorder (ATR) station locations in Cache County, Utah.



Source: Moscardini and Caplan (2017).

Figure 5. Phase diagram for a steady-state equilibrium.

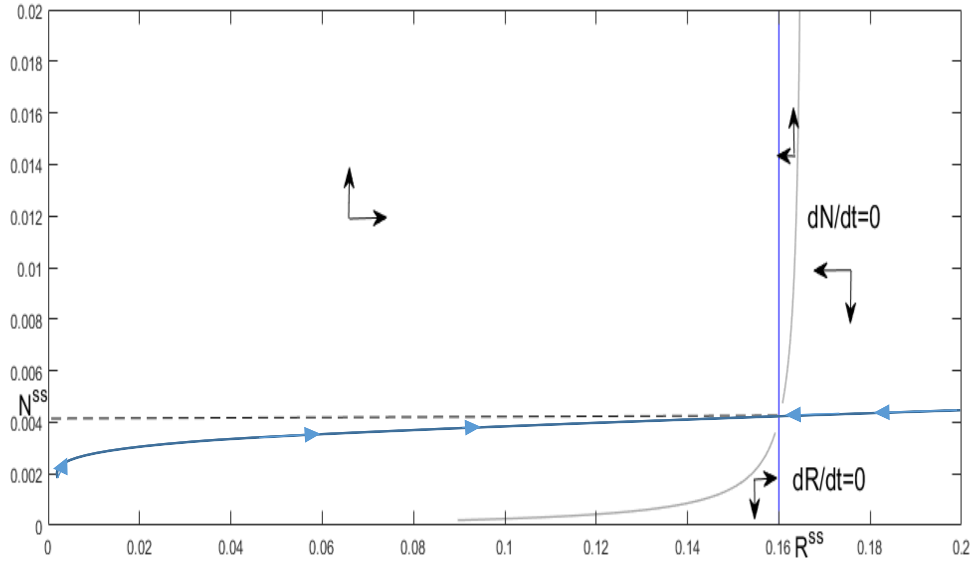


Figure 6. Time paths of z and R assuming increasing background risk over time.

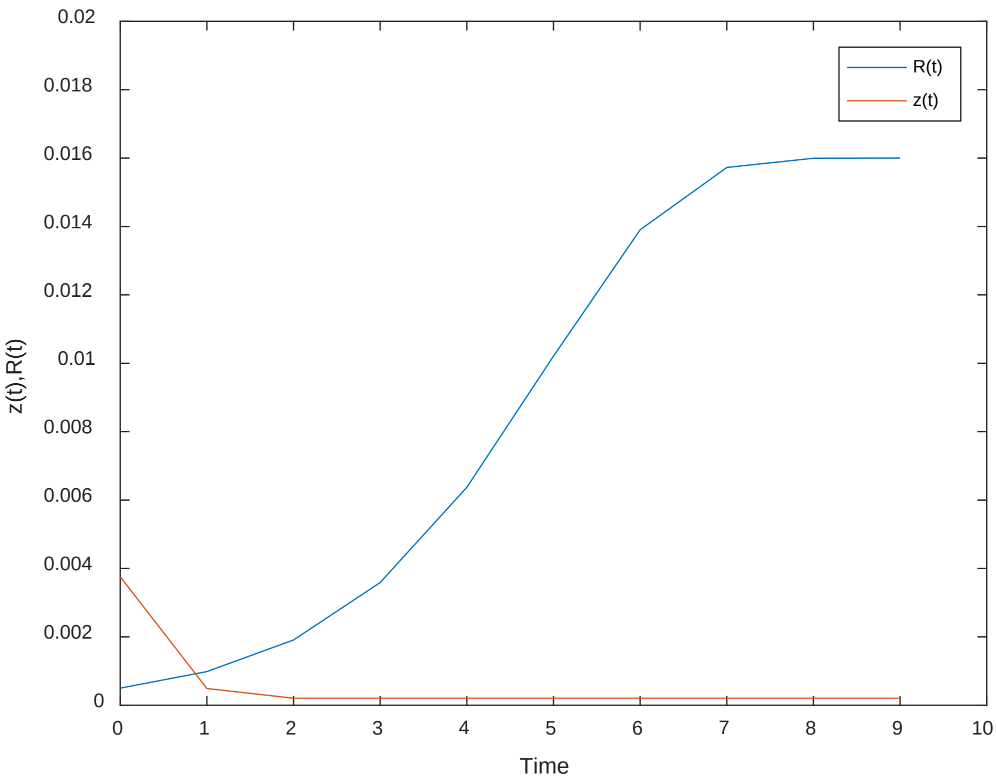


Table A.1. Simulation results for the case of $N(t = 0) = \$500{,}000$.*

c	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
A	9.84	9.08	8.32	7.56	6.80	6.04	5.28	4.52	3.76	3.00
N^{ss}	4	7	9	10	11	12	12	12	12	11
TC^{ss}	32,666	23,723	16,841	11,945	8,497	6,066	4,399	3,229	2,392	1,795

*As c increases the corresponding preventative capital stocks associated with $N_0 = \$500{,}000$ are everywhere lower than that associated with $N_0 = \$1{,}000{,}000$. The lower N^{ss} values associated with $N_0 = \$500{,}000$ case are driven by the lower corresponding A values for each c.

Table A.2. Regression results for Monte Carlo Simulation.[a]

Variable	Coefficients (S.E.)	
	Model 1	**Model 2**
TC	0.17** (0.08)	0.23** (0.1)
TEMP	0.04*** (0.004)	0.05*** (0.004)
SNOWDEPTH	0.002*** (0.001)	0.002*** (0.001)
SNOWFALL	-0.004*** (0.001)	-0.004*** (0.001)
Log likelihood	-406.94	-401.59
$\chi 2$ (Wald)	503.47***	12,981.88***
AIC	827.877	833.18
BIC	857.295	896.22
AR(1)	0.603*** (0.034)	0.98*** (0.028)
MA(1)		0.983 (1.36)
MA(2)		-0.87 (2.62)
MA(3)		-3.01 (5.89)
MA(4)		1.37 (9.0)
MA(5)		11.58 (--)
MA(6)		-4.69 (5.74)
MA(7)		0.27 (6.34)
MA(8)		-2.28 (7.95)
MA(9)		-3.30 (3.37)
Number of observations	494	494

[a] Robust standard errors in parentheses.
***, ** and * indicate significance at 1, 5 and 10% levels, respectively.