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ABSTRACT

Defensive Investments and the Demand for Air Quality: Evidence from the NO_x Budget Program and Ozone Reductions[1]

Demand for air quality depends on health impacts and defensive investments that improve health, but little research assesses the empirical importance of defenses. We study an important cap-and-trade market, which dramatically reduced NO_x emissions, a key ingredient in ozone formation. A rich quasi-experiment reveals that it decreased summertime ozone, pharmaceutical expenditures, and mortality rates. Reductions in pharmaceutical purchases and mortality are each valued at $900 million annually, suggesting that defensive investments are a substantial portion of willingness-to-pay. We cautiously conclude that ozone reductions are the primary channel for these effects, implying that ozone's costs are larger than previously understood.

JEL Classification: H4, I1, Q4, Q5, D1

Keywords: willingness to pay for air quality, cap and trade, ozone, pharmaceuticals, mortality, compensatory behavior, human health

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I. Introduction

Theoretical models make clear that willingness to pay for wellbeing in a variety of contexts is a function of factors that enter the utility function directly (e.g., the probability of mortality, school quality, local crime rates, etc.) <u>and</u> the costly investments that help to determine these factors. For example in the canonical models of health production, individuals trade off the damages from exposure to harms with investments or costly actions to protect themselves from these harms (Grossman 1972). To be concrete, homeowners install burglar alarms, companies hire private security guards, infants are vaccinated, builders install thick windows in noisy areas, and people take medications to protect themselves from respiratory problems. All of these actions are costly and displace consumption of utility-generating goods. Indeed, it is widely believed that these actions constitute a significant portion of the costs of harms, as the marginal utility of their purchase should be equalized with the marginal utility of avoiding the harm itself.

However, the empirical literature has largely focused on the incidence of the harm (e.g., health outcomes) as a measure of the full welfare consequences, leaving unanswered the empirical importance of the compensatory behavior and the completeness of the welfare measure (e.g., Chay and Greenstone 2003a and 2003b; Currie and Neidell 2005). Indeed, depending on prices and preferences, a harm may have substantial welfare consequences but an exclusive focus on its incidence could lead to a significant understatement of willingness to pay.

This paper develops a measure of willingness to pay for air quality improvements that accounts for <u>both</u> defensive expenditures and the direct health impacts. As a measure of defensive behavior, we investigate whether pharmaceutical or medication usage responds to changes in air quality. This is likely to be an especially important measure of defensive expenditures, because, for example, the annual cost of prescription medications for asthma is reported to exceed the monetized value of <u>any</u> other component of asthma's social cost, including mortality, emergency department admissions, or lost productivity (Weiss and Sullivan 2001). The analysis also provides new evidence on how air quality affects mortality and hospital admissions, which allows us to measure the share of health costs of air pollution due to defenses.

The empirical exercise is based on a quasi-experiment that exploits the variation in space and time of the introduction of an emissions market for nitrogen oxides (NO_x). The NO_x Budget Trading Program (NBP) operated a cap-and-trade system for over 2,500 electricity generating units and industrial boilers in the Eastern and Midwestern U.S. between 2003 and 2008. Because this market had the goal of decreasing ozone pollution, which reaches high levels in summer, the market operated only between May 1 and September 30. Importantly, NO_x is a primary ingredient in the complex function that produces ozone air pollution and thus the NBP provides quasi-experimental variation in air pollution at the seasonal level, much longer than daily and monthly shocks analyzed in prior research; in this respect, it is more similar to the variation that would be induced by a change in ozone regulation.

Figure 1 shows the dramatic effect of this market on NO_x emissions in the states participating in the NBP.[2] In 2002, daily NO_x emissions were fairly flat throughout the calendar year, with a peak in summer. In 2005, emissions were also flat between January and April. But in May, 2005, when the market's cap began to apply, NO_x emissions dropped by 35 percent, practically overnight. Emissions remained lower throughout summer 2005 and then returned to their original level in October, when the cap stopped applying. Emissions dropped in May, 2005 because many power plants began operating abatement technologies that substantially decreased their NO_x emissions. The geographic, annual, and seasonal variation in the NBP's introduction

[2] Unless otherwise noted, our data on NO_x emissions refer to emissions from power plants covered by our data (i.e., in the Acid Rain program).

provides the basis for a simple research design. Specifically, we use a triple-difference estimator that compares pollution, defensive expenditures and health outcomes in the NBP participating and non-participating states, before versus after 2003, and summer versus winter.[3]

The empirical analysis produces several key results. First, the reductions in NO_x emissions decreased mean ozone concentrations by roughly 6% and reduced the number of summer days with high ozone levels (i.e., more than 65 ppm) by about 23%, or a third of a standard deviation. Second, these improvements in air quality produced substantial medium run benefits. Drug expenditures decreased by about 1.9% or roughly $900 million annually. Notably, these savings exceed an upper bound estimate of the market's abatement costs. Third, the summertime mortality rate declined by approximately 0.5%, corresponding to 2,200 fewer premature deaths per summer, mainly among individuals 75 and older. The application of age-adjusted estimates of the value of a statistical life implies this reduced mortality is valued at about $900 million annually. The mortality estimates are less precise than the medication estimates, and the results must be interpreted accordingly. Fourth, there appears to have been little systematic evidence of an effect of the NBP on hospitalization charges.

Finally and importantly, it may be appropriate to conclude the reductions in ozone concentrations are the primary channel for these improvements in health. For example, we find no association between the NBP and health conditions that are plausibly unrelated to air quality. Additionally, we find that the NBP did not affect ambient concentrations of carbon monoxide and sulfur dioxide. However, there is mixed evidence about whether it reduced airborne particulate matter so we cautiously utilize the NBP as an instrumental variable for ozone

[3] "Winter" in this paper refers to the combined months of January-April and October-December. Because NO_x abatement technologies have substantial operating costs (Fowlie 2010), units begin operating them around May 1 and stop around September 30. Part of the operating cost comes from the "heat rate penalty" of selective catalytic reduction—the fact that they require a small amount of electricity to operate.

concentrations. The estimates imply that a 10% decline in an 8-hour measure of ozone which the EPA regulates leads to a 3.3% reduction in spending on drugs. Analogously, a 10% decline in the number of days with high ozone concentrations – above 65 ppb – reduces drug spending by 4.7%. Additionally, we find that a 1 ppb increase in ozone pollution leads to 2.6 additional summertime deaths per 100,000 people or an elasticity of mortality with respect to ozone of 0.31. The analogous elasticity for the days greater than 65 ppb measure of ozone is 0.06.

In addition to providing new evidence on the empirical importance of defensive expenditures, this paper makes several contributions.[4] First, we are unaware of other studies that demonstrate the impact of an emissions market on ambient pollution and human health with real world data. Most evaluations of emissions markets combine engineering models of emissions abatement, chemistry models of pollution transport, and epidemiological dose-response models (e.g., Muller and Mendelsohn 2009). The limitations of this approach are underlined by our failure to find consistent evidence of an impact of the NBP market on particulates air pollution, which the models (and the EPA) projected as the primary channel for any health benefits.

Second, the results may be useful for contentious current academic and policy debates about ambient ozone pollution. National Ambient Air Quality Standards for ozone have changed repeatedly since the Clean Air Act—more than for any other pollutant except particulates.[5] In 2010, President Obama announced that the EPA would tighten ambient ozone standards. The EPA then missed four deadlines to decide on an ozone standard, and in September 2011 announced that it would wait to implement new standards. This announcement was followed by

[4] An emerging empirical literature aims to measure behavioral responses. Including defenses, to health-reducing environmental factors (Barreca et al. 2012; Deschênes and Greenstone 2011; Neidell 2009; Graff-Zivin and Neidell 2009; Graff-Zivin, Neidell, and Schlenker 2011). An older theoretical literature analyzes defenses and willingness to pay (Courant and Porter 1981; Bartik 1988). A small epidemiological literature, largely using samples of under 100 asthma patients, shows that asthmatics increase medication use on polluted days (Menichini and Mudu 2010).
[5] The original 1971 1-hour ozone standard of 0.08 ppm increased to 0.12 ppm in 1979. An 8-hour standard of 0.08 ppm was proposed in 1997 then litigated until the Supreme Court supported its legality in 2001. This 8-hour standard came into force in 2004. In 2008, the Bush Administration proposed a new 8-hour standard of 0.075.

litigation by environmental groups and widespread public debate about the importance of additional ozone regulation. These ozone standards are so contentious partly because there is substantial uncertainty about how ozone affects health (NRC 2008; Bell et al. 2004; Currie and Neidell 2005; Jerrett et al. 2009; Neidell 2009; Moretti and Neidell 2011; Lleras-Muney 2010).

Third, the analysis relies on a new source of identification and is conducted with the most comprehensive data file ever compiled on emissions, pollution concentrations, defensive expenditures, and mortality rates. We show that the NBP provides rich quasi-experimental variation in ambient ozone concentrations over seasonal periods of five months, which reduced ozone exposure of over 135 million individuals. Our results are therefore more informative about the possible impacts of new ozone regulation than is the existing literature, which focuses on short-run (daily or weekly) ozone variation and on specific states or groups of cities. In addition, due to medium-run variation leveraged in the statistical models, concerns about "harvesting" or temporal displacement of the drug expenditures and mortality are less relevant than is the case in much of the previous literature that focuses on daily or weekly health outcomes.

The rest of this paper is organized as follows. Section II reviews the main aspects of ozone formation and provides details on the NO_x Budget Trading Program. Section III presents a simple economic model of defensive investments in response to exposure to pollutants. Section IV describes the various data sources and the construction of the analysis sample. Section V discusses the econometric models used in the study. Section VI reports the results and Section VII uses the results to conduct a cost-benefit analysis of the NBP and develop a measure of willingness to pay for ozone reductions. Section VIII concludes.

II. Ozone and the Emissions Market

A. Ozone

The Clean Air Act was designed to control ambient levels of ozone and five other pollutants that harm health. Ozone differs from the other pollutants in three important ways. First, polluters do not emit ozone directly. Instead, ozone forms through a complex nonlinear function combining two chemicals precursors – nitrogen oxides (NO_x) and volatile organic compounds (VOCs) – with sunlight and heat. The market we study operates only in summer because winter ozone levels in the Eastern U.S. are low, and ozone spikes to high peaks on hot and sunny days.

Second, the health consequences of ozone are believed to occur from short-term exposure to high levels. Ozone regulation has targeted these peak exposures, rather than focusing on mean ozone levels. For example, the National Ambient Air Quality Standards for ozone primarily reflect the highest few readings of the year. Hence, this market is most likely to affect health if it truncates the right tail of the ozone distribution. Research has found negative effects of ozone on cardiovascular and particularly respiratory health (Lippman 2009).

Third, when this market began, national ozone levels had changed relatively little since the Clean Air Act first regulated ozone in 1970. By contrast, concentrations of all five other "criteria" pollutants decreased substantially between 1973 and 2002 (USEPA 2008). During this period, the EPA imposed numerous regulations to decrease VOC and NO_x emissions. This muted effect of existing ozone regulations set the stage for an emissions market as a new approach.

B. The NO_x Budget Trading Program

The NO_x Budget Trading Program (NBP) grew out of the Ozone Transport Commission (OTC), an organization of Northeast States formed in the 1990s. OTC studies found that ozone levels the Northeast U.S. had high ozone partly because prevailing winds transported NO_x from the industrial Midwest to the Northeast, where it produced ozone in the Northeast (OTC 1998). The OTC led to a version of the NO_x Budget Program (NBP) that operated in 1999-2002 and produced small declines in summer NO_x emissions.[6] The OTC then created a more stringent version of the NBP which began in 2003 and operated until 2008.[7] The market included 2,500 electricity generating units and industrial boilers, though the 700 coal-fired electricity generating units in the market accounted for 95 percent of all NO_x emissions in the market (USEPA 2009b).

The market was implemented partially in 2003 and fully in 2004. The 2003-2008 emissions market originally aimed to cover the eight Northeast states plus Washington DC (which were the focus of the OTC), plus 11 additional Eastern states. Litigation in the Midwest, however, delayed implementation in the 8 additional states until May 31, 2004.[8] Appendix Figure 1 shows the division of states by NBP participation status in the subsequent analysis.

Accordingly, the EPA allocated about 150,000 tons of NO_x allowances in 2003, 650,000 tons in 2004, and about 550,000 tons in each of the years 2005-2008. Many firms banked allowances: In each year of the market, about 250,000 tons of allowances were saved unused for subsequent years (USEPA 2009a).[9] Before the NBP began, about half of NO_x emissions in the

[6] This market also goes under the name NO_x SIP Call. This smaller market also operated in May-September, although as Figure 1 illustrates, it did not produce large differences in summer and winter NO_x emissions.
[7] 2007 is the last year of the MarketScan dataset available for this analysis, so that is the last year of data for the analysis. In 2009, the Clean Air Interstate Rule (CAIR) replaced this market. In 2010, the EPA proposed a Transport Rule which would combine this NO_x market with a market for SO_2 emissions. In July 2011, the EPA replaced this proposal with the Cross-State Air Pollution Rule, which regulates power plant emissions in 27 states with the goal of decreasing ambient ozone and particulate levels.
[8] In 2003, the emissions cap applied to Connecticut, Delaware, Maryland, Massachusetts, New Jersey, New York, Pennsylvania, Rhode Island, and Washington DC. In 2004, it also began applying to Alabama, Illinois, Indiana, Kentucky, Michigan, North Carolina, Ohio, South Carolina, Tennessee, Virginia, and West Virginia. Missouri entered the market in 2007. Georgia was initially slated to enter the market in 2007 but the EPA eventually chose to exclude Georgia.
[9] In 2002, summertime emissions from sources participating in this market totaled approximately 1 million tons, with a significant downward pre-trend that had similar magnitude in both the East and West (Figure 2). Compared to the level of NO_x emissions in 2002, the final cap of 550,000 tons would have decreased emissions by 45%. As discussion of our results later in the paper shows, however, accounting for the pre-trend and the fact that emitters banked allowances across years shows that the causal impact of the market was to decrease emissions by only 35-39 percent.

Eastern US came from electricity generation and industry—the rest were from mobile and other sources. About a fourth of NO_x emissions in the East came from these stationary sources following the establishment of the NBP (USEPA 2005).

Each state received a set of permits and chose how to distribute those permits to affected sources. Once permits were distributed, affected sources could buy and sell them through open markets. A single emissions cap affected the entire market region, though firms could bank allowances for any future year.[10] At the end of each market season, each source had to give the EPA one allowance for each ton of NO_x emitted.[11] Seventy percent of units complied by using emissions controls (e.g., low NO_x burners or selective catalytic reduction), and the remainder complied exclusively by holding emissions permits (USEPA 2009b).

The mean resulting permit price in the emissions market was $2,080 per ton of NO_x. This reflects the marginal abatement cost of the last unit of NO_x abated. In the results below, we use it to develop an upper bound on the aggregate abatement cost associated with the NBP market.

III. Model of Willingness-to-Pay

We build upon the canonical Becker-Grossman health production function to highlight the role of defensive investments in the measurement of willingness-to-pay for clean air (Becker 1965; Grossman 1972). This model shows that accurate measurement of willingness-to-pay requires knowledge of both how pollution affects health outcomes such as mortality and how it affects defensive investments that maintain health but otherwise generate no utility, such as medications.

[10] Unused allowances from the NBP could be transferred to the CAIR ozone season program.
[11] In most years, fewer than 5 units of the 2,500 in the market (i.e., less than two-tenths of a percent) had insufficient allowances to cover their emissions.

Assume the sick days *s(d)* which a person suffers depends on the dose *d* of pollution she is exposed to. The ingested dose *d(c,a)* depends on the ambient concentration *c* of the pollutant and on the defensive behavior *a*. Substituting provides the following health production function:

(1) $s = s(c,a)$

People gain utility from consumption of a general good *X* (whose price is normalized to 1), leisure *f*, and health. Budgets are constrained by non-labor income *I*, the wage rate p_w, available time *T*, and the price p_a of defensive investments: $max_{X,f,a}u(X,f,s)$ *s.t.* $I + p_w(T - f - s) \geq X + p_a a$.

Assuming an interior solution to the maximization problem, we can rearrange the total derivative of the health production function (1) to give the following expression for the partial effect of ambient pollution on sick days:[12]

(2) $$\frac{\partial s}{\partial c} = \frac{ds}{dc} - \left(\frac{\partial s}{\partial a}\frac{\partial a*}{\partial c}\right)$$

This expression is useful because it underscores that the partial derivative of sick days with respect to pollution is equal to the sum of the total derivative and the product of the partial derivative of sick days with respect to defensive behavior (assumed to have a negative sign) and the partial derivative of defensive behavior with respect to pollution (assumed to have a positive sign). In general, complete data on defensive behavior is unavailable, so most empirical investigations of pollution on health (see, e.g., Chay and Greenstone 2003a and 2003b) reveal $\frac{ds}{dc}$, rather than $\frac{\partial s}{\partial a}$. As equation (5) demonstrates, the total derivative is an underestimate of the

[12] If all patients were at corner solutions – if some patients purchased no medications and others would purchase the maximum available dosage even with moderate changes in air quality – then this emissions market might not induce changes in medication purchases. But for asthma medications at least, stronger dosages generally have higher costs, and more powerful medications also typically have higher costs.

desired partial derivative. Indeed, it is possible that virtually all of the response to a change in pollution comes through changes in defensive behavior and that there is little impact on health outcomes; in this case, an exclusive focus on the total derivative would lead to a substantial understatement of the health effect of pollution. The full impact therefore requires either estimation of $\frac{\partial s}{\partial a}$, which is almost always infeasible, or of $\frac{ds}{dc}$ and $\frac{\partial a*}{\partial c}$.

To express the marginal willingness to pay for clean air w_c in dollars, we manipulate the previous expressions to obtain the following decomposition:

$$(3) \qquad w_c = \left(p_w \frac{ds}{dc} \right) + \left(p_a \frac{\partial a^*}{\partial c} \right) - \left(\frac{\partial u / \partial s}{\lambda} \frac{ds}{dc} \right)$$

Expression (3) shows that the marginal willingness to pay for clean air includes three terms.[13] The first is the effect of pollution on productive work time, valued at the wage rate. The third is the disutility of sickness, valued in dollars. This third component includes mortality. The second is the cost of defensive investments, valued at their market price. This second component is the aspect of willingness-to-pay that existing research has not measured. It is important to note that medications are not a complete measure of defensive investments against air pollution. However, given that medications cost more than mortality, emergency visits, or any other components of asthma's social costs (Weiss and Sullivan 2001), they represent an important component of defensive investments. The paper's primary empirical goal is to develop a measure of marginal willingness to pay that is based on $\frac{ds}{dc}$ and $\frac{\partial a*}{\partial c}$.

[13] A similar framework can derive explicit expressions for medical expenses (Harrington and Portney 1987). As we show below, the NBP led to marginal reductions in mean ozone concentrations but non-marginal reductions in the number of high concentration ozone days. An alternative approach would be to consider the model of Bartik (1988) to value non-marginal changes. Both the model outlined here and Bartik's model, highlight the tradeoff between costly defensive actions and health.

This neoclassical model assumes that markets are competitive, but the setting analyzed here has two important deviations from this benchmark: markups and moral hazard. Branded medications generally have low marginal cost and high markups that reflect intellectual property rights. Hence, it is natural to question whether changes in medication purchases amount to a transfer from consumers to drug firms, and not a social cost. In the short-run, this is indeed the case. However, pharmaceutical firms must invest socially valuable resources to develop medications that treat conditions exacerbated by air pollution. With lower levels of air pollution, fewer resources would be spent to develop these medications. Thus over the long run, there is a social benefit (see Finkelstein (2004) for a similar induced innovation process.

The second important deviation is that price exceeds the marginal cost to the consumer, by 80-90 percent in our data, because consumers with insurance generally pay a copayment or deductible for medications. Although we use data on the transacted price for medications (which is more accurate than the published or wholesale price), it remains likely that private willingness-to-pay for medications is smaller than the medication prices we analyze. However even with health insurance and moral hazard, the defensive component of social willingness-to-pay for clean air is measured by the market price of medications taken in response to air pollution.[14]

IV. Data

This analysis has compiled an unprecedented set of data files to assess the impacts of the NO_x Budget Program. Although market-based instruments are viewed as among the most important contributions of economics to environmental policy, to the best of our knowledge this study

[14] Suppose in the extreme that consumers have infinitesimally small private value for medications and purchase them in response to air pollution primarily because copayments are zero. If markups are zero and so the marginal cost of medications equals the purchase price, then each medication purchase caused by air pollution represents a case where pollution has used up socially valuable resources, with value equal to the medication's price.

represents the first time any analysis has linked ex post health measurements directly to emissions and air quality measures in order to evaluate an emissions market. The analysis excludes Alaska, Hawaii, and states adjacent to the NBP participating states, which have ambiguous treatment status given the potential of pollution to cross state borders.[15]

Medications. We use confidential data on medication and hospital admissions from MarketScan. MarketScan contracts with large employers to obtain all insurance-related records for their employees and their dependents including children, who may be especially susceptible to air pollution's effects. The data report the purchase county, date, the medication's National Drug Code (NDC), and the money paid from consumer and insurer to the medication provider.

We use data from all persons in the 16 covered firms which appear in all years, 2001-2007, of MarketScan, which is the largest panel the data allow us to obtain with these firms. This extract includes over 22 million person-season year observations, and over 100 million separate medication purchases.[16] Because the distribution of persons across counties is skewed, we report all values as rates per 1,000 people, and use generalized least squares (GLS) weights equal to the square root of the relevant MarketScan population. Because the other datasets become available in 1997 but medication data become available in 2001, for non-medication results we report parameter estimates both with data for the period 1997-2007 and for the period 2001-2007.

Medications, unlike hospital visits or death counts, are not linked to a single International Classification of Disease (ICD) code. In the subsequent analysis, we follow the convention in the pollution-health literature and treat respiratory and cardiovascular related episodes as most likely to be affected by air pollution. We define an NDC as respiratory if it satisfies any of three

[15] The excluded states from the main analysis sample are: Alaska, Georgia, Hawaii, Iowa, Maine, Mississippi, Missouri, New Hampshire, Vermont, and Wisconsin. In the Appendix, we show that the estimates are similar with other sample selection rules.
[16] The appendix reports estimates from a balanced panel of about 600,000 persons in these firms. For confidentiality reasons MarketScan does not identify the 16 firms, but the firms do cover most sectors of the U.S. economy.

criteria: (1) if it is listed in the Third Treatment Guidelines for Asthma (NHLBI 2007); (2) in a recent New England Journal of Medicine guide to asthma treatment (Fanta 2009); or (3) in the standard industry publication for medication characteristics (PDR 2006) as indicated for asthma, emphysema, bronchitis, or chronic obstructive pulmonary disorder. We identify cardiovascular and gastrointestinal medications by their corresponding therapeutic groups in Red Book (PDR 2006).[17] The latter category is unlikely to be affected by air pollution and is used as a placebo test for the validity of the respiratory-cardiovascular results.

This broad approach to identifying respiratory and cardiovascular drugs is the most appropriate we can discern. Nonetheless, because doctors prescribe medications to treat conditions for which the medications are not indicated, some of these medications were probably prescribed for non-respiratory and non-cardiovascular conditions. Moreover, it is also likely that medications prescribed for respiratory and cardiovascular conditions are not in this list.

Hospitalizations. We count hospital admission costs as including all inpatient episodes plus all emergency outpatient episodes. We follow procedures in the MarketScan guide (Thompson Healthcare 2007, p. 59) to extract emergency department admissions from outpatient claims files. We define a hospital visit as respiratory or cardiovascular or external if the ICD9 diagnosis code applies to these categories. When a hospital visit has several associated procedures each with its own ICD9 code, we take the mode procedure. Our measure of hospital costs includes all charges from the hospital to the insurer and patient.

Mortality. To measure mortality, we use restricted-access data on the universe of deaths in the 1997-2007 period. These Multiple Cause of Death files (MCOD) come from the National

[17] Red Book has no category for respiratory medications. The therapeutic groups we extract are Antineoplastic Agents; Cardiovascular Agents; and Gastrointestinal Drugs. Medication purchase rates are skewed and few county-season values equal zero, so the main tables report medication regressions in logs, with values of zero excluded from the regressions. Appendix Tables 1-3 show alternative specifications for medications and other response variables.

Center for Health Statistics (NCHS) and were accessed through an agreement between NCHS and the Census Research Data Centers. These files contain information on the county, cause of death, demographics, and date of each fatality.

Pollution Emissions. To measure pollution emissions, we extract daily totals of unit-level NO_x, SO_2, and CO_2 emissions for all states from the EPA's Clean Air Markets Division.[18] The NO_x emissions are the quantities for which firms must hold emissions permits in this cap-and-trade market, so they are the most accurate measure available. In 2008, ninety-seven percent of emissions came from units with continuous emissions monitoring systems, which have little measurement error. Units which are part of the Acid Rain Program must report NO_x emissions throughout the year, while units in the NBP must report NO_x emissions only in the May 1 – September 30 period. Because we compare summer versus winter, estimates in the paper use only data from Acid Rain Units. However, in the examined period, units in the NBP and not in the Acid Rain Program represent a tiny share of NO_x emissions.

Ambient Pollution. We use a few criteria to select ambient pollution monitoring data from the EPA's detailed Air Quality System. Many EPA monitors operate for limited timespans and may change reporting frequency in response to pollution (Henderson 1996). The main analysis uses a fairly strenuous selection rule of limiting to monitors which have valid readings for at least 47 weeks in all years 1997-2007. Appendix Table 1 shows that we obtain similar results with a weaker monitor selection rule. For ozone, we focus on a concentration measure the EPA regulates: for each day, we calculate an "8-hour value" as the maximum rolling 8-hour mean

[18] Electricity generating units did not report high-frequency measurement of mercury, particulate matter, toxics, or other emissions in this time period. Other data sources for emissions of these other pollutants have inadequate data to use in this research design.

within the day.[19] Finally, we calculate the number of days on which this 8-hour value was equal to or greater than 65 ppb, which is an indicator of high-ozone days.

Weather. We also compiled weather data from records of the National Climate Data Center Summary of the Day files (File TD-3200). The key control variables for our analysis are the daily maximum and minimum temperature, total daily precipitation, and dew point temperature. To ensure the accuracy of the weather readings, we construct our weather variables for a given year from the readings of all weather stations that report valid readings for every day in that year. The acceptable station-level data is then aggregated at the county level by taking an inverse-distance weighted average of all the valid measurements from stations that are located within a 200 km radius of each county's centroid, where the weights are the inverse of their squared distance to the centroid so that more distant stations are given less weight. This results in complete weather by county-day files that we can link with the other files in our analysis.

Data Summary. Table 1 shows that emissions, weather, and mortality data are available for all 2,539 counties in our sample. Medication and hospitalization data are available for 95 percent of these counties, which had a population of 261 million in 2004. Ambient ozone data are only available for 168 counties, but these counties are heavily populated and their 2004 population was 97 million. Data on particulates less than 2.5 micrometers ($PM_{2.5}$) are available in 298 counties (population 144 million) and data on particulates less than 10 micrometers (PM_{10}) are available for 39 counties (population of 26 million).

The summary statistics in Table 1 also provide a benchmark to measure the economic importance of medications and the emissions market. In summer, ozone averages 48 ppb. The

[19] Mean ozone is calculated between midnight and 8 am, 1 am and 9 am, etc. The maximum of these values in a given day is defined as the "8-hour value" for that day. For each pollutant, we calculate ambient levels in each monitor-day, then the unweighted average across monitors in each county-day, and finally aggregate up to county-season. All regressions are GLS based on the square root of the total number of underlying pollution readings.

2010 proposed EPA air quality standard stipulated that a county could have no more than 3 days over a total of three years which exceed 60-70 ppb. Table 1 shows that during the sample period, 24 days every summer exceed 65 ppb in the typical county. On average during this time, the average person spent $339 per summer on medications, and about $500 on hospital admissions.

The summary statistics also show why the observational associations between ozone and health may reflect unobserved variables. Columns (4) through (10) of Table 1 divide all counties with ozone data into two sets—one set with mean summer ozone above the national median ("high ozone"), and another with mean summer ozone below the national median ("low ozone"). Row 1 shows that counties with high NO_x emissions are slightly *underrepresented* in the high-ozone counties, which reflects the reality that NO_x primarily creates ozone in counties other than where it is emitted. All ambient pollutant measures except carbon monoxide have significantly higher levels in the high-ozone counties. Temperature, precipitation, and dew point temperature have lower levels in high-ozone counties.[20] The finding that so many of these observed county characteristics covary with ozone suggests that an observational association of ozone with health is likely to reflect the contributions of other unobserved variables and may explain the instability of the estimated health-ozone relationship that has plagued the previous literature. It is apparent that the estimation of the causal effect of ozone on health and defensive expenditures requires a research design that isolates variation in ozone that is independent of potential confounders.

V. Econometric Model

We use a differences-in-differences-in-differences (DDD) estimator to isolate the causal effects of the emissions market on pollution and health, and use an instrumental variables approach to

[20] The cross-sectional comparison of temperatures between high- and low-ozone counties partly reflects the high ozone levels in the relatively cold Northeast.

measure the "structural" effect of ozone on health. The DDD estimator exploits three sources of temporal and geographical variation in the emission and health data. First, we compare the years before and after the NBP's operation. Eight states plus Washington DC initiated this market in 2003, while 11 other states joined in 2004. This market did not operate before 2003. Second, twenty states participated in the NBP while twenty-two other states did not participate and were not adjacent to a NBP state (see Appendix Figure 1). Third, the NBP market only operated during the summer, so we compare summer versus winter.[21]

Specifically, we estimate the following model:

$$(7)\qquad Y_{cst} = \gamma_1 1(NBP\ \ Operating)_{cst} + W_{cst}^{'}\beta + \mu_{ct} + \eta_{st} + \nu_{cs} + \varepsilon_{cst}$$

Here, *c* references county, *s* indicates season, and year is denoted by *t*. The year is divided into two seasons, summer and winter: Summer matches the NBP's operation period of May 1-September 30. The outcome variables, Y_{cst}, are pollution emissions, ambient pollution concentrations, medication costs, hospitalization costs, and mortality rates. Because the NBP market started partway in 2003, we define Post=0.5 in 2003 and Post=1.0 in 2004 through 2007. All regressions limit the sample to a balanced panel of county-season-years.[22]

Ozone formation is a complex function of ambient NO_x, ambient volatile organic compounds and temperature. Since there is a nonlinear relationship between health and temperature, it is important to adjust for weather flexibly. The matrix of weather controls, W_{cst},

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[21] The abrupt beginning and end of the market on May 1 and October 1 makes a daily regression discontinuity estimator seem appealing. However, because ozone in the Eastern US mainly reaches high levels in July and August, the market is likely to have small effects on ambient pollution on April 30 or October 1. Although emitted pollution changed sharply around these dates (Figure 1), we detect no change in mean daily ambient pollution in small windows around these dates.

[22] We explored statistical models that separately estimate effects of the market on pollution and health outcomes in each month of summer. These specifications did not have statistical power to distinguish effects in different months of summer, and hence we focus on results that treat summer as homogenous. Modeling the market's impact on summer overall, rather than month-by-month, also produces medium-term estimates of the market's impact. This makes the results less susceptible to the concern that changes in air quality cause short-term displacement of mortality or medication purchases without changing their medium- or long-run values.

includes measures of precipitation, temperature, and dew point temperature (a measure of humidity). For temperature and humidity, we calculate 20 quantiles of the overall daily distribution.[23] For each county-season-year observation in the data, we then calculate the share of days that fall into each of the 20 quantiles.

To operationalize the DDD estimator, the specification includes all three sets of two-way fixed effects. The vector μ_{ct} is a complete set of county by year fixed effects, which account for all factors common to a county within a year (e.g., local economic activity and the quality of local health care providers). The season-by-year fixed effects, η_{st}, control for all factors common to a season and year: for example, they would adjust for the development of a new drug to treat asthma that was sold in NBP and non-NBP states. Finally, the county-by-season fixed effects, ν_{cs}, allow for permanent differences in outcomes across county-by seasons.

The parameter of interest is $\gamma_{1,}$ associated with the variable $1(NBP\ Operating)_{cst}$. This variable takes the value of 0.5 for all NBP states in 2003, when the market was operating in 9 of the 20 states, and a value of 1 in 2004 and all subsequent years in these states. The 2003 value is assigned to all NBP states, rather than just states which entered the market in 2003, because NO_x and ozone travel far and emissions reductions in one NBP state affected ambient ozone in other NBP states. After adjustment for the fixed effects, γ_1 captures the variation in outcomes specific to NBP states, relative to non-NBP states, in years when the NBP operated, relative to before its initiation, and in the summer, relative to the winter. Importantly, this only leaves variation in the outcomes at the level at which the market operated. We also report variants on equation (7) that change the level of county, year, and season controls, and the detail of weather controls.

[23] The lower quantiles of the precipitation distribution all equal zero, so for simplicity we specify the precipitation control as the mean level of precipitation in each county-year-summer.

Given the potential for temporal and spatial autocorrelation, we use a few approaches for inference. Pollution and health data are available for each county. States decided whether to enter the market, but the market only affected pollution in summer. As a result, we report standard errors that allow clustering at the state*season level in the main tables. The appendix reports standard errors that allow for arbitrary autocorrelation within counties, states, state-years, and county-seasons; but in general the conclusions are unaffected by these alternative assumptions about the variance-covariance matrix.

Although the tables focus on the triple-difference parameter γ_1 from equation (7), separate measures of the market's effect in each year provide additional useful information. Hence, for most outcomes, we also report the parameters $\alpha_{1997}\ldots\ \alpha_{2007}$ from the following model:

$$(8) \qquad Y_{cst} = \sum_{t=1997}^{2007} \alpha_t 1(NBP\ State\ and\ Summer)_{cs} + W_{cst}^{'}\beta + \mu_{ct} + \eta_{st} + \upsilon_{cs} + \varepsilon_{cst}\ ,$$

where *1(NBP State and Summer)*$_{cs}$=1 for all summer observations from NBP states, regardless of the year. We plot the α_t's in event-study style figures to provide visual evidence on the validity of the conclusions from the estimation of equation (7).[24] Importantly, the event study style graphs provide an opportunity to assess whether there were pre-NPB trends in outcomes that were specific to NBP States after nonparametric adjustment for all county by year, season by year, and county by season factors.

We also exploit the DDD design to obtain instrumental variables estimates of the impacts of ozone on medication purchases and mortality rates. Specifically, *1(NBP Operating)*$_{cst}$ serves as an instrumental variable for ambient ozone. The version of equation (7) where ozone is the dependent variable is then the first-stage, and the versions with medication purchases or

[24] The data on medication purchases and hospitalization begins in 2001, so for these outcomes, the event-study graphs are for the period 2001-2007.

mortality rates as the outcomes are the reduced-form relationships between the instrument and the outcomes of interest. Below we explore the validity of the required exclusion restriction.

VI. Results

This section reports estimates of the effects of the NBP on pollution emissions, ambient pollution concentrations, medication purchases, hospital costs, and mortality rates. Additionally, it uses the instrumental variables strategy outlined above to estimate the effect of ozone concentrations on medication purchases and mortality rates. The results are organized into separate subsections.

A. Emissions

The NO_x Budget Trading Program required affected units to reduce NO_x emissions. Appendix Figure 2 shows the unadjusted summer-equivalent NO_x emissions, by year (before and after NBP operation) by season (winter and summer) and by NBP status (NBP participating states and non-participating states).[25] Appendix Figure 2 (A) shows that the NBP led to a sharp and discontinuous reduction in summer emissions, starting in 2003 when the emissions market began in 8 Northeastern states and Washington DC. As a result, summer NO_x emissions declined by nearly 20 percent in the summer of 2003, and another 15-20% starting in May 2004, when the market added 11 more Eastern states.[26] Additionally, winter emissions continued their gradual downward pre-2003 trend, with perhaps a modest slowing of that trend post-2003. In contrast, Appendix Figure 2 (B) reveals that summer and winter NO_x emissions in the non-NBP states evolve smoothly over time, with similar downward trends and with no evidence of any

[25] We express the data as summer-equivalent since the summer period has 5 months while the winter period has 7 months. Specifically, the summer equivalent of winter emissions is actual winter emissions multiplied by 5/7.
[26] In 2004, the new states entered the market on May 31, 2004 while the original states began the market on May 1. In subsequent years, the market began in all states on May 1, 2004.

discernible change in 2003 and 2004 when NBP was implemented. In short, NO_x emissions declined in exactly the areas, months, and years that the market design would predict.[27]

Panel A of Table 2 reports estimates of several versions of equation (7) for pollution emissions measured at the county by season by year level. Column (1) includes county-by-season, season-by-year, and state-by-year fixed effects. Column (2) adds binned weather controls. Column (3) replaces the state-by-year fixed effects with county-by-year fixed effects, which causes the parameters of interest to be identified from comparisons of summer and winter emissions within a county by year. Column (4) restricts the sample to 2001-2007, which are the when medication and hospitalization data are available. None of these equations are weighted. The variance-covariance matrix allows for arbitrary autocorrelation within each state by season.

The entries in row 1 report the parameter estimate and standard error associated with the variable $\mathit{1(NBP\ Operating)}_{cst}$. The results suggest that the NBP market decreased NO_x emissions in the average county by 330-380 tons. This is about by 34-38% of 2001-2 mean emissions in NBP counties.[28] (Henceforth, we refer to the 2001-2 mean of variables in NBP counties as the baseline mean.) Appendix Table 1 reports that the qualitative results are unchanged by a series of changes to the specifications, including alternative assumptions about the variance-covariance matrix, restricting the sample to counties with ozone monitors, and adding Maine, New Hampshire, and Vermont to the sample, since they are among the group of states excluded due to ambiguous treatment status in virtue of being outside the NBP region but adjacent to NBP states.

[27] There was a smaller summer NO_x emissions market in New England from 1997-2000. We were unable to detect an appreciable impact of this market on ozone concentrations during its operation.

[28] An ongoing discussion is investigating whether the NBP affected manufacturing employment (Curtis 2012). In regressions not reported here, we detected no effect of the NBP market on electricity prices, which supports the internal validity of the instrumental variables estimator. This result also suggests that the market did not create general equilibrium effects by changing electricity prices (Shapiro 2012).

We also measure whether the NBP market affected emissions of pollutants other than NO_x. Two economic reasons explain why the market might have affected emissions of such co-pollutants. If permits for NO_x emissions cost enough that the market caused natural gas units to displace electricity generation from relatively dirty coal-fired units, then the market could have decreased emissions of pollutants other than NO_x. Second, complementarity or substitutability of NO_x with other pollutants in electricity generation could lead units to change emissions of other pollutants. Any effect of the market on ambient levels of co-pollutants, however, would imply that the market could have affected health through channels other than ozone.

Rows 2 and 3 in Panel A of Table 2 indicate that NBP did not meaningfully affect SO_2 or CO_2 emissions.[29] A couple of the estimates are statistically significant by conventional criteria. However, all of the estimates are economically small; for example, the point estimates in the preferred specifications in columns (3) and (4) are about 1% to 3% of the baseline mean.

B. Ambient Pollution

Panel B in Table 2 reports on how the NBP affected ambient concentrations of ozone and the other pollutants that are most heavily regulated under the Clean Air Act. Columns (1) – (4) have identical specifications to those in Panel A, except that they are weighted by the number of pollution readings from the EPA's ambient air quality monitors in a given year by county. The column (5) estimates are from the same specification as in column (4), except that they are weighted by county population. The remainder of the paper focuses on explaining per capita defensive expenditures, hospitalization costs and the mortality rate; these equations will naturally be weighted by the relevant population to obtain estimated impacts on the average person.

[29] CO_2 emissions have no local effect on health. An impact of the market on CO_2 emissions could indicate that units changed emissions of mercury, toxic chemicals, or other pollutants.

Rows 1 and 2 of in Panel B reveal large and precisely estimated effects of the emissions market on ground-level ozone concentrations (as measured by the maximum 8-hour value). The richest specifications in columns (3) - (5) indicate that the NBP decreased mean summer ozone by about 3 ppb (or 6-7% relative to the baseline average). Importantly, the NBP also decreased the number of high-ozone days (days where the 8-hour value equals or exceeds 65 ppb) by 7.5 to 8.6 days per summer (or 23%-28% of the baseline average).[30] The corresponding event-study figure for the 8-hour ozone reading (Appendix Figure 3 A) exhibits some evidence of differential pre-existing trends in summer ozone concentrations in NBP states. Accounting for these differences increases the magnitude of the NBP's estimated reduction on ozone concentrations, although these models are more demanding of the data and so the estimates are less precise, but remain significant at the conventional level.

The large effect on the number of days with ozone equaling or exceeding 65 ppb that the NBP impacted the distribution of daily ozone concentration in a non-uniform manner, with larger reduction in the upper part of the distribution. Consequently, we also analyze the market's impact on the density function for daily ozone concentrations to explore where in the daily ozone distribution the NBP affected concentrations in Appendix Figure 3 (C). The main result is that the market reduced the number of summer days with high-ozone concentrations (i.e. greater than 50 ppb) and increased the number of days with ozone concentrations less than 50 ppb. It is noteworthy that the EPA has experimented with daily ozone standards of 65, 75, and 85 ppb in

[30] We explored whether the NO_x reductions produced any counterproductive outcomes. When an area has low concentrations of volatile organic compounds relative to NO_x, then decreasing NO_x can <u>increase</u> ozone levels. Such NO_x "disbenefits" may exist in Southern California, where weekend ozone levels exceed weekday ozone levels. There is less consensus on whether they could occur in the Eastern U.S., where most of the NBP-participating states are located. We use two approaches to identify counties where the emissions market might have increased ozone levels. First, we identify a list of such "VOC-constrained" cities from Blanchard (2001). Second, we define a county as VOC-constrained if its mean ratio of weekend/weekday ozone exceeds 1.05. The former approach finds that the change in ozone concentrations is similar in VOC-constrained and -unconstrained regions. The latter indicates a different conclusion: Specifically, it suggests that in VOC-constrained regions of the NBP, the decline in ozone was smaller than in the unconstrained areas. See rows 5 and 6 of Appendix Table 1.

recent years and that the identifying variation in ozone concentrations comes from the part of the distribution where there is great scientific and policy uncertainty.

Rows 3-5 in Panel B of Table 2 test for impacts of NBP on carbon monoxide (CO), sulfur dioxide (SO_2), and nitrogen dioxide (NO_2). CO emissions come primarily from transportation, so it is not surprising that the regressions fail to find evidence that the NBP affected CO concentrations. Further, there is little evidence of an impact on SO_2.[31] Thus, it appears that any impacts of ozone will not be confounded with changes in CO or SO_2 and this supports the use of the NBP as an instrumental variable to identify the effects of ozone on health.

NO_x is a standard term used to describe a mix of two compounds—nitric oxide (NO) and NO_2, but NO_2 is a pollutant subject to its own regulations. Row 5 shows that the market decreased ambient NO_2 levels by 6-7 percent, relative to the baseline. Because NO_2 has limited or possibly no effect on health, this finding seems unlikely to pose a threat to the exclusion restriction necessary to identify the impact of ozone (Lippman 2009).

Air quality models show that atmospheric NO_x can undergo reactions that transform it into a component of particulates. The impact of the NBP on particulates concentrations is of special interest because particulates are widely believed to be the most dangerous air pollutant for human health (Pope, Ezzati, and Dockery 2009; Chay and Greenstone 2003a and 2003b; Chen et al 2013). Further, before its implementation, the EPA projected that 48-53 percent of the projected health benefits from the NBP would come through the channel of reduced particulates concentrations (USEPA 1998). On the other hand, the appendix describes air quality model

[31] Because the Acid Rain Program operated a separate cap-and-trade market for SO_2 during this period, any decrease in summer SO_2 emissions due to the NO_x market would have been offset by a corresponding increase in wintertime SO_2 levels, and such an offset would produce bias in our triple-difference estimator. It supports the research design to detect no significant change in ambient SO_2 concentrations.

simulations in more detail and provides an explanation for why the NBP might not affect particulates concentrations.

Rows 6 and 7 of Panel B in Table 2 empirically examine the impact of the NBP on the concentrations of particles smaller than 10 micrometers (PM_{10}) and 2.5 micrometers ($PM_{2.5}$), both of which are small enough to be respirable. The PM_{10} and $PM_{2.5}$ monitoring networks were just being erected in the late 1990s so to have meaningful samples it is necessary to focus on the 2001-2007 period as in columns (4) and (5). In column (4), where the equation is weighted by the number of monitor observations, there is little evidence that the NBP affected airborne particulate matter concentrations. Alternatively, when the equation is weighted by population, as is the case in the preferred defensive expenditures and health outcomes equations, the entries indicate that the NBP is associated with a 6% reduction in $PM_{2.5}$. However in the smaller sample of counties with PM_{10} monitors, there continues to be no evidence of a meaningful change in PM_{10}.

Overall, the row 6 and 7 results are inconclusive about whether the NBP affected particulates concentrations. These mixed results mean that the subsequent two-stage least squares results of the effects of ozone on defensive expenditures and health outcomes should be interpreted cautiously, because they may reflect the impact of ozone or particulates, or a combination of the two pollutants. Nevertheless, the evidence in Table 2 indicates that the first-order impact of NBP on ambient pollution is through its effect on high ozone.[32]

[32] All of the ambient pollution results are further evaluated and probed in Appendix Table 1, which considers a wide range of specifications, including changes in the method used to compute the standard errors and alternative sample selection rules. In addition, we estimated models that also allowed for differential pre-existing trends in the NBP states during the summer. In general, the models fail to reject the null of no difference in pre-existing trends and cause the standard error on the parameter of interest, γ_1, to increase by a factor of 2 to 3. The only substantive change is that the impact on ozone concentrations is larger in magnitude although the 95% confidence intervals of the estimates from specifications with and without the differential trends overlap.

C. Defensive Investments

This section explores the relationship between the NBP market and the resources people devote to defending themselves against air pollution through medication purchases.[33] Figure 2 (A) shows the event study graph for log medication expenditures from the estimation of equation (8). The event study suggests that the market decreased medication expenditures by about 2 percentage points. This impact was roughly constant and is statistically significant at the 7% level or better in each year of the 2004-2007 period, which is when the market was operating in the full set of states. Importantly, there is no evidence of meaningful differences in the trend in summertime medication purchases between NBP and non-NBP states in advance of the market's initiation.

Table 3 reports the estimated reduced-form effect of the market on log medication costs. The richest specification in columns (3) and (4) indicates that the NBP reduced total medication costs by 1.9 percent. The estimate is precise with the full set of controls and has similar magnitude but less precision with less detailed controls. The theoretical model discussed earlier implies that this reduction in defensive expenditures is a key component of total willingness-to-pay for air quality, but it is one that previous research had not measured empirically. Finally, it is worth noting that the column (4) estimate is derived from the subsample of counties with ozone pollution monitors, which is used for the instrumental variables estimation below; this reduces the sample size from 30,926 to 2,338.

We also measure medication purchases separately by cause. As discussed above, the allocation of medications to causes is inexact—doctors can prescribe a medication for many purposes, and the MarketScan data do not identify the cause for which a specific medication was

[33] As emphasized earlier, while medications are the largest category of asthma's typically measured costs, people could engage in other defensive investments such as avoiding outdoor activities and purchasing air filters. Consequently, medication expenditures are a lower bound on the total defensive costs associated with air pollution.

prescribed. The goal of this exercise is to test whether the decline in medication purchases was especially evident among respiratory and cardiovascular medications (although the imprecision of the assignment of causes to medications means that there are good reasons to expect an impact in other categories). The column (3) estimate in row 2 indicates that the NBP decreased expenditures on respiratory and cardiovascular medications by a statistically significant 2.3 percent. In the smaller sample of counties with ozone monitors in column (4), the point estimate is statistically indistinguishable from the column (3) estimate but would not be judged statistically significant at conventional levels. We also use medication costs for gastrointestinal conditions as a placebo test, because we are unaware of evidence linking air pollution exposure to these conditions. Although the column (3) estimate is marginally significant, the results across the columns fail to find a consistent effect of the NBP on medication purchases for gastrointestinal problems.[34]

Finally, we explored the extent of heterogeneity in the log medication results in several ways. First, we separately estimated these regressions for children and obtained results with similar magnitude though less precision. Second using National Drug Codes, we also attempted to distinguish "maintenance" respiratory medications that are taken every day or week to treat chronic respiratory conditions, from "rescue" respiratory medications that are taken once acute respiratory symptoms appear. We again obtained similar negative parameter estimates for both categories though with less precision.

[34] Appendix Table 2 reports the results from a series of robustness checks, none of which alter the qualitative conclusions from Table 3. Specifically, we investigate changing the level of clustering, adding Maine, New Hampshire, and Vermont to the sample, estimating models where the dependent variable is the log number of medications (rather than log medication costs), changing the sample composition to a balanced panel of individuals, using the level instead of the ln of the dependent variable, and using the purchase-specific prices, rather than the average calculated across drug codes. Further, we estimated models that added differential pre-existing trends in the NBP states during the summer; these trends were not statistically significant for any of the three outcome variables and did not cause meaningful changes in the estimated γ_1 coefficients although their standard errors increased by 2 to 3 times making precise inference difficult.

D. Hospital Visits and Mortality

Hospital Visits. Because we seek to compare defensive costs against direct health costs, we also measure how the market affected hospital visits and mortality. Due to the large number of county-year-season observations with ‘zeros’ for hospitalization costs, we focus on the level rather than the log of per capita hospitalization costs.

Overall, our conclusion from these results is that the NBP did not have a meaningful impact on hospitalization costs and we do not pursue this outcome further (Appendix Tables 3-4, Appendix Figure 4). We emphasize however that the MarketScan data exclude uninsured, Medicare, and Medicaid patients whereas these groups are included in some studies which find effects of ozone on hospitalization (Currie and Neidell 2005, Lleras-Muney 2010).

Mortality. In most analyses of air pollution, mortality accounts for the largest share of the regulatory benefits. The results in row 1 of Table 4 suggest that the NBP decreased the all-cause, all-age summertime mortality rate by about 1.6 to 3.0 deaths per 100,000 population, depending on the sample, and would generally be judged to be statistically significant. The effect in the subsample of counties with ozone monitors is larger (see column 4), indicating a reduction of 5.4 deaths per 100,000 population.

The remaining rows divide the overall mortality rate into four independent categories that together account for all causes of death. Reading across row 2, it is apparent that 35% to 56% of the decline in overall mortality is concentrated among cardiovascular/respiratory deaths. Row 4 finds that the market had no effect on external (primarily accidental) deaths, which is a reassuring placebo test. Further, the impacts on neoplasms are small and statistically insignificant (row 3). This result was unknown *ex ante*, since the relationship between ozone and cancer remains uncertain (NRC 2008). Row 5 finds that the NBP is associated with reductions in mortality due to the remaining causes of death. The science of how ozone affects the body is still evolving and this finding may point to new pathways.[35]

Table 5 breaks the entire population into four age groups and separately estimates the effect of the NBP on each group's mortality rate using the full sample and the preferred specification (i.e., column (3) from Table 4). We detect no meaningful effect on the mortality of persons aged 74 and below, although taken literally, the point estimates imply that the market prevented about 375 deaths within this group. The largest impact on mortality occurs among people aged 75 and older; this finding is confirmed visually in Figure 2 (B) although the estimates from individual years are noisy. These results suggest that the NBP prevented about 1,800 deaths each summer among people 75 and older. As with the entire population, respiratory and cardiovascular deaths explain much of the effects on elderly mortality.

The age-group decomposition implies that the NBP prevented 2,175 summer deaths annually. About 80 percent of these were among people aged over 75. By contrast, the overall share of all summer deaths which occur among people aged over 75 is 55%, suggesting that the elderly disproportionately benefited from the NBP

An important question that Table 5 leaves unanswered is the gain in life expectancy associated with these delayed fatalities. Indeed, the question of the magnitude of gains in life expectancy is unanswered in almost all of the air pollution and health literature because it is largely based on changes in mortality rates over relatively short periods of time. The difficulty is

[35] Appendix Table 5 reports on a series of specification checks that leave the qualitative findings unchanged. Specifically, we investigate changing the level of clustering, adding Maine, New Hampshire, and Vermont to the sample, estimating models where the dependent variable is the log mortality rate (rather than the simple mortality rate), and adjusting the mortality rate for the age distribution of the population. Further, at conventional significance levels we cannot reject that a separate time trend for summer observations from NBP states has no predictive power for all-cause or respiratory-cardiovascular mortality rates. Moreover, the addition of this variable causes the standard errors for the estimates of γ_1 to roughly triple. We conclude that this model is over-determined and that the data do not support the inclusion of these NBP by summer trends.

that it is possible and perhaps likely that the relatively sick benefited and that their lifespans were extended only modestly, given their age. In the extreme, the NBP might merely have moved the date of these deaths to the winter months immediately following the market.[36]

We explored two approaches to investigate the empirical relevance of this short-term 'seasonal' displacement hypothesis. First, we experimented with redefining each "year" to begin on May 1 of one calendar year and conclude on April 30 of the following calendar year. This redefined "year" compares each summertime season against the seven following months. Second, we estimated differences-in-differences regressions where each observation represents a calendar year (as opposed to a calendar-season-year), and where we measure the change in mortality rates by NBP status pre vs. post. We also combined these two approaches to estimate differences-in-differences models with the restructured year.

These approaches do not provide strong support for the short-term displacement hypothesis. In most cases, the estimated effect of the market on mortality was negative and had similar magnitude to the models reported in the paper, but these estimates were imprecise and we could not reject the null hypothesis that the NBP had no long-run impact on mortality. Overall, we conclude that this research design lacks power to measure the effect of ozone on life expectancy beyond the five month length of the NBP's summer season. Nevertheless, this paper's focus on the summertime mortality rate is an advance from the previous literature that has primarily estimated how ozone affects same-day or same-week mortality rates.[37]

[36] The paper's triple-difference estimator compares summer and winter deaths within a year. If some of the deaths are displaced from summer to October-December of the same year, then the estimator will overstate the decline in mortality.

[37] Currie and Neidell (2005) are an important exception in that they estimate monthly and quarterly mortality regressions.

E. Instrumental Variables (IV)

The preceding sections measure the reduced-form effects of the NBP market on pollution, defenses, and health. We now turn to an IV approach to measuring the effect of ozone on defensive expenditures and mortality rates. These relationships are central to determining the social cost of marginal reductions in ozone, which is widely used in economic and policy analysis (e.g., Fowlie, Knittel and Wolfram 2009).[38] However, we want to underscore that these results should be interpreted cautiously due to the mixed evidence of an impact of the NBP on particulates concentrations.

Panel A of Table 6 reports an analysis of the association between ozone and medication purchases (columns 1 - 3) and between ozone and the all-age mortality rate (columns 4 – 8). The analysis is based on the fitting of ordinary least squares (OLS) models that are standard in the pollution-health effects literature. Each observation represents a county-year-season as in the above analysis. Further, the estimates are from separate regressions of the outcome on alternative measures of ozone concentrations and are adjusted for county-by-season fixed effects, county-by-year fixed effects, season-by-year fixed effects, and detailed weather controls.

The OLS results have varying signs. The 8-hour ozone measure has a positive and statistically insignificant association with all three measures of medication purchases. By contrast, the number of days with ozone at or above 65 ppb is a positive and statistically significant predictor of all measures of medication purchases, including the gastrointestinal drugs, which are not expected to respond to air pollution. For mortality, the only statistically significant association suggests that ozone concentrations increase external deaths, which are

[38] On the regulatory side, these IV estimates are most directly applicable to EPA ozone control programs in the Eastern US because they affect essentially the same populations as NBP. This includes CAIR, the EPA Transport Rule, the Cross-State Air Pollution Rule, and the successors that the EPA is designing after courts have struck down several of these rules.

expected to have no relationship to pollution. Although such OLS associations are commonplace in the previous literature, we interpret this as evidence against the reliability of OLS to infer the ozone-health relationship. These unstable estimates may reflect the feature highlighted in Table 1 that counties with high ozone differ substantially from counties with low ozone.

The two-stage least squares (2SLS) or IV estimates are adjusted for the same controls as in the OLS specifications but the endogenous ozone variable (either average 8-hour ozone concentration or the number of days equaling or exceeding 65 ppb) is instrumented with $1(NBP\ Operating)_{cst}$. The entries indicate a strong relationship between ozone concentrations and medication purposes. For example, the estimates imply that a 10% decline in the average 8-hour ozone measure relative to the Table 1 mean of 48.06 ppb leads to a 3.3% reduction in spending on drugs. Analogously, they suggest that a 10% decline in days with ozone concentrations exceeding 65 ppb reduces drug spending by 4.7%. Finally, all of these estimates would be judged to be statistically significant by conventional criteria.

The IV mortality estimates in column (4) also imply large direct effects of ozone. They suggest that a 1 ppb increase in ozone pollution leads to 2.6 additional summertime deaths per 100,000 people, or an elasticity of mortality with respect to ozone of 0.31. The analogous elasticity for the days greater than 65 ppb measure of ozone is 0.06.[39] In interpreting these elasticities, recall that the reduced form relationship between the NBP and mortality rates is substantially larger in the counties with ozone monitors than in the full sample of counties with mortality data (recall Table 4), which could be due to smaller reductions in ozone in the non-monitored counties. Further, it is worth underscoring that the counties with ozone monitors account for an important share of the country as they have a population of 97 million, which is

[39] Multiplying the IV 8-hour coefficient by the mean mortality and ozone values from Table 1 gives 2.60 * (48.06 / 402.42) =0.31. Similarly for the 65-ppb ozone measure, we have 1.03*(23.6/402.42)=0.06.

37% of the 262 million people in the counties covered by the mortality data. The IV estimates indicate a positive relationship between ozone and mortality due to respiratory and cardiovascular causes, although this relationship is not statistically significant at conventional criteria.[40]

If it is appropriate to interpret these estimates causally, they would substantially change alter our understanding about the welfare consequence of exposure to ozone. For example, the most prominent ozone-mortality study (Bell et al. 2004) finds an elasticity of weekly ozone with respect to daily mortality rates that is smaller than the elasticity implied by Table 6.[41] Further, we are unaware of any large-scale evidence on the relationship between ozone and defensive expenditures measured by medication purchases or any other goods.

VII. A Cost-Benefit Analysis of the NBP and Cautious Estimates of Willingness to Pay for Ozone Reductions

This paper's results allow us to conduct a simple cost-benefit analysis for the entire NBP, with the caveat that data restrictions prevent us from measuring all health outcomes and defensive expenditures. The estimates in Table 2 imply that the NBP market decreased NO_x emissions by 365,750 tons per summer and the average cost of a NO_x permit was \$2,080/ton.[42] The permit price should reflect an upper bound on abatement costs per ton, because firms should only use abatement technologies that cost less than the permit price. Thus, an upper bound estimate is

[40] This paper treats the emissions market as spatially homogenous and ignores geographic differentiation. We explored regressions which predict a larger impact of the market on states bordering the Atlantic, or in New England, or in counties which an air quality model (CRDM) predicted to have larger decreases in ozone. Across these specifications, we did not find statistically larger effects of the market on air quality in these areas, and correspondingly, we also did not detect statistically different effects of the market on health in these areas.

[41] Bell et al. (2004) is not directly comparable to our study however since it uses a distributed lag model. Attempts to recover the long-run relationship between ozone and mortality generality obtain larger estimates (Jerrett et al. 2009).

[42] This figure is calculated by applying the estimated impact of NPB on NO_x emissions (-0.366) from Table 2, Column (3), to the mean summer 2002 NO_x emissions for NBP counties (841 tons) and then summing over all NBP 1,185 counties.

that the market caused firms to spend $759 million (=$2080 x 365,750) annually to abate NO_x and this is reported in Table 7. Defining 2003 to have half a year of typical abatement costs, we obtain an upper bound on 2003-2007 total abatement costs of $3.4 billion (=759 x 4.5).

We now turn to estimating the NBP's social benefits. As we discussed above, it may seem natural to assume that a change in pharmaceutical purchases are simply a transfer from consumers to pharmaceutical firms and thus have zero social cost. However, reductions in air pollution concentrations decrease the demand for medications that protect individuals from air pollution. Dynamically, this decline in demand will reduce the resources used to develop these medication types and will allow these resources to be applied to more productive uses.

Column (1) of Table 7 Panel B reports average annual reduction in drug expenditures, as well as the sum over the NBP's life. Specifically, we take the estimated 1.9% reduction in medication purchases from the regression result in column (3) and row 1 of Table 3 and multiply that by the annual mean medication purchases. This calculation suggests that the NBP market led to a decrease in medication expenditures of almost $900 million per year or $4 billion when summed over the 4.5 years that the NBP operated. It is unclear whether this extrapolation from the MarketScan population is an under- or over-statement of the effect on the full population.[43]

Taken literally, the Table 5 mortality estimates imply that the market prevented about 2,200 deaths annually. The value of a statistical life (VSL) determines the monetary value assigned to these deaths. To provide one approach to monetization, we use Ashenfelter and Greenstone's (2004) upper bound VSL of $1.93 million (2006$) for a prime age person and Murphy and Topel's (2006) method to develop estimates of the VSL for each age group in our analysis. This adjustment is especially consequential in this setting where the avoided fatalities

[43] Recall, the medication estimates represent the Americans employed in large firms and their dependents, who appear in the MarketScan data; these people may have better baseline health than the average American, but may also have better health insurance and hence spend more on medications than the average American.

are largely individuals 75 and over. The implied VSLs are as follows: $1.9 million (infants), $1.5 million (ages 1-64), $0.6 million (ages 65-74), and $0.2 million (ages 75+). The application of this approach implies that the value of the mortality avoided by the NBP is $900 million per year, or $4 billion in the period 2003-2007 (columns (2a) and (2b) of Table 7 Panel B).[44]

The entries in Panels A and B provide the basis for a comparison of the costs and benefits. The upper bound on the NBP's aggregate abatement costs is $3.4 billion, but by themselves the value of the reduced drug purchases of $3.9 billion exceeds these costs. It is apparent that, at least in this context, defensive investments are economically important. Once the value of the reduced rates of mortality is added in, the benefits of the market are more than twice as large as the upper-bound of its abatement costs (i.e., $7.9 billion in benefits and $3.4 billion in costs). It appears that the NBP's social benefits easily exceeded its abatement costs.

Finally, estimates of willingness to pay for a reduction in ozone would be of tremendous practical importance as the EPA is currently considering revising the ozone standard. Noting that they must be interpreted cautiously due to uncertainty about the validity of the exclusion restriction, the IV ozone results suggest that each 1 ppb decrease in the mean 8-hour summer ozone concentration in the Eastern U.S. is worth approximately $1.7 billion in social benefits annually. Similarly, one fewer day per summer in the Eastern US with an ozone concentration exceeding 65 ppb would yield roughly $700 million of benefits annually (Table 7, Panel C).

[44] We thank Kevin Murphy and Bob Topel for sharing the data underlying Figure 3 of their paper. The VSL used here is lower than the $7.4 million VSL ($2006) used by the EPA, which is not age-adjusted. Our primary goal is not to endorse a specific VSL value, but to demonstrate the results that come from one choice of VSL and age-adjustment. Using the $7.4 million VSL rather than the $1.93 million VSL implies that the mortality benefits of NBP were larger: $3.3 billion per year or $14.8 billion for the 2003-2007 total.

VIII. Conclusions

Theoretical models make clear that willingness to pay (WTP) for well-being in a variety of contexts is a function of factors that enter the utility function directly (e.g., the probability of mortality, school quality, local crime rates, etc.) and the costly investments that help to determine these factors. One approach to developing measures of WTP is to find a single market that captures individuals' full valuation, as can be the case with property markets under some assumptions (see, e.g., Chay and Greenstone 2005; Greenstone and Gallagher 2008). All too frequently though, the data and/or a compelling research design for the key market are unavailable, making it necessary to develop measures of WTP by summing its components.

However, across a wide variety of applied literatures, the empirical evidence on WTP has almost exclusively focused on the factors that enter the utility function directly. The resulting measures of willingness to pay are thus generally underestimated and the extent of this underestimation is unknown. This paper has demonstrated that defensive expenditures are an important part of willingness to pay for air quality. Indeed in the context of the NO_x Budget Program, the improvement in air quality generates reductions in medication purchases that are as large as the value of the observed reduction in mortality rates. A fruitful area for research is to explore whether individuals' compensatory behavior and resulting defensive investments account for such a large fraction of willingness to pay in other settings.

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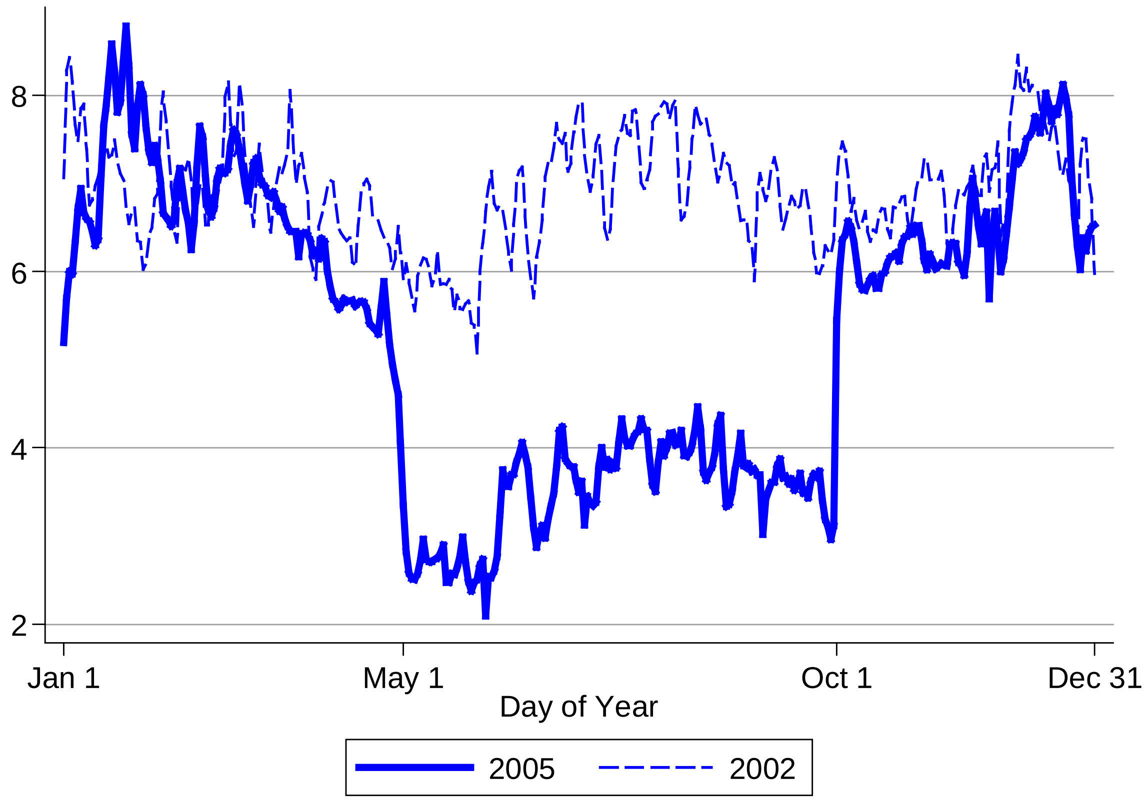
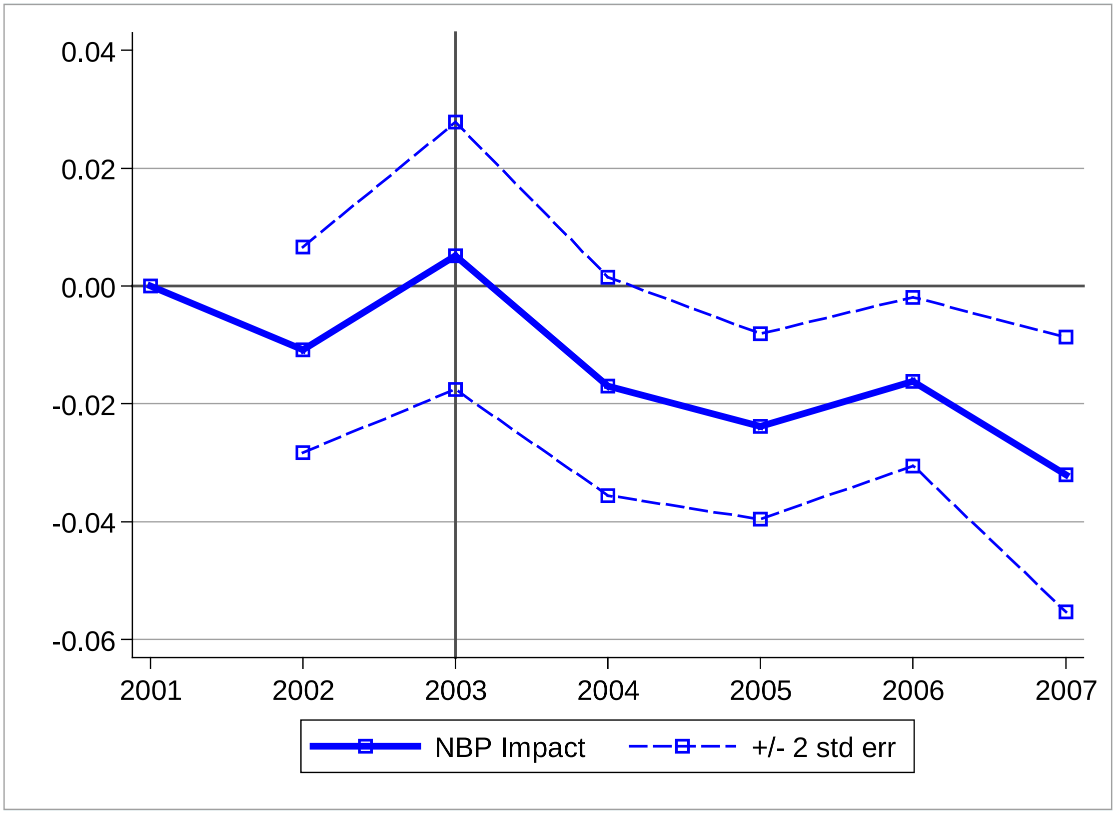
Figure 1. Total Daily NO_X Emissions in NBP-Participating States



Notes: This graph depicts values from an OLS regression of NO_x emissions on 6 day-of-week indicators and a constant. We control for day-of-week fixed effects since additional electricity generation on weekdays adds visible weekly cycles to the image, although the overall picture is unchanged in the raw data. The values in the graph equal the constant plus the regression residuals, so that the graph depicts fitted values for the reference category (Wednesday). Y-axis is measured in thousands of tons. Data include Acid Rain Units. NBP participating states include: Alabama, Connecticut, Delaware, District of Columbia, Illinois, Indiana, Kentucky, Maryland, Massachusetts, Michigan, Missouri, New Jersey, New York, North Carolina, Ohio, Pennsylvania, Rhode Island, South Carolina, Tennessee, Virginia, and West Virginia. See the text for more details.

Figure 2. NBP Market Impacts

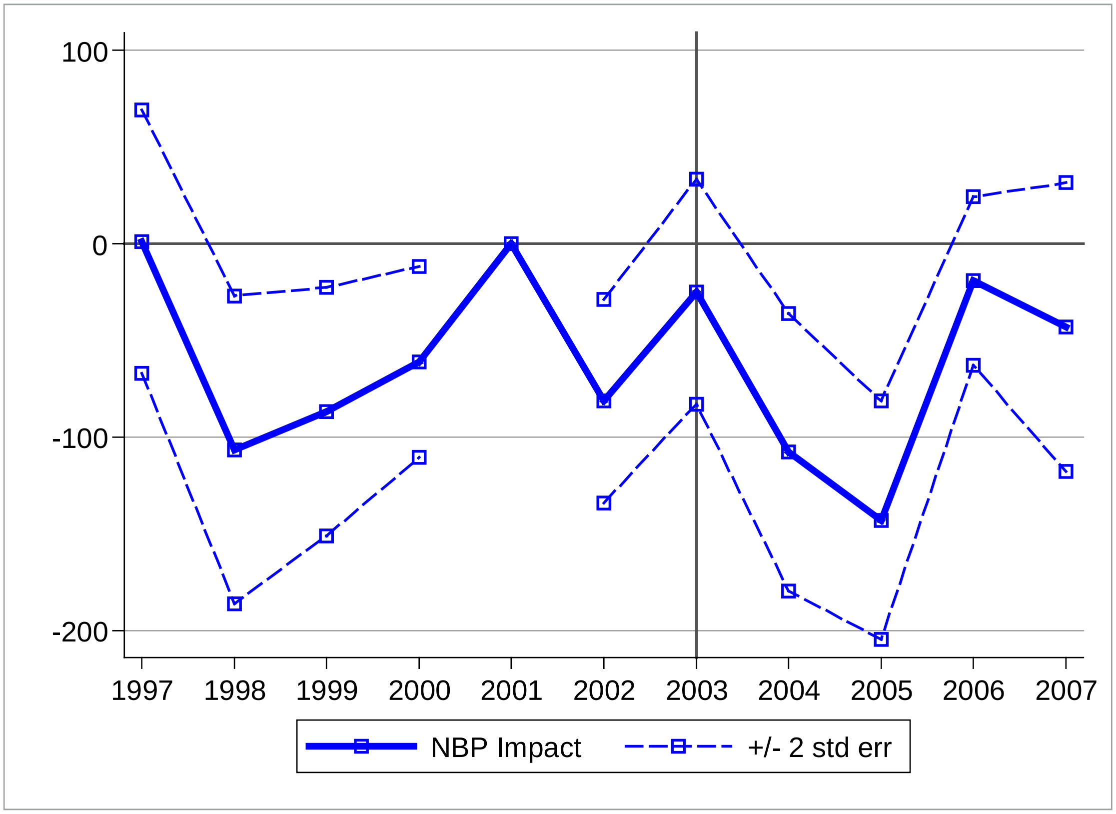
(A) Event Study for Log Medication Costs ($2006)



Notes: Log medication cost is the log of total medication costs per person-season in a county. Costs are in 2006 dollars, deflated using the BLS CPI for urban consumers. Estimate for year 2001 restricted to take a value of 0. Regression models include detailed weather controls, and a full set of county*year, season*year, and county*season fixed effects. Regression is GLS weighted by the square root of MarketScan population in a given county-year-season. Standard errors based on covariance matrix allows arbitrary autocorrelation within each state-season. See text for NBP participation status designation.

Figure 2. NBP Market Impacts (Continued)

(B) Event Study for Elderly Mortality Rates



Notes: The dependent variable is the all-cause mortality rate for persons aged 75+ per 100,000 persons aged 75+. Estimate for year 2001 restricted to take a value of 0. Regression models include detailed weather controls, and a full set of county*year, season*year, and county*season fixed effects. Regression is GLS weighted by the square root of the relevant population in a given county-year. Standard errors based on covariance matrix allows arbitrary autocorrelation within each state-season. See text for NBP participation status designation.

Table 1. Mean Summer Values of Pollution, Weather, and Health, by Ozone Level

	All Counties			Low Ozone			High Ozone			
	Counties With Data	Mean	s.d.	Counties With Data	Mean	s.d.	Counties With Data	Mean	s.d.	p-value of H_0: (8)-(5)=0
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Pollution Emissions (000's of tons/summer)										
NO_x Emissions	2,539	0.52	(1.99)	84	1.67	(3.26)	84	1.30	(4.14)	[0.09]
SO_2 Emissions	2,539	1.50	(6.52)	84	2.92	(6.20)	84	1.41	(4.04)	[0.00]
CO_2 Emissions	2,539	384	(1,299)	84	1,263	(1,896)	84	918	(2,030)	[0.00]
Ambient Pollution										
Ozone 8-Hour Value	168	48.06	(9.28)	84	41.28	(6.10)	84	54.85	(6.58)	[0.00]
Ozone Days $\geq$65 (ppb)	168	23.60	(22.64)	84	10.93	(9.41)	84	36.28	(24.81)	[0.00]
NO_2 (ppb)	110	11.45	(5.39)	34	8.67	(4.57)	37	12.15	(4.85)	[0.00]
CO (ppm)	125	0.44	(0.24)	35	0.46	(0.22)	33	0.42	(0.17)	[0.06]
$PM_{2.5}$ ($\mu g/m^3$)	298	13.33	(4.19)	47	10.70	(3.01)	45	11.63	(4.45)	[0.00]
PM_{10} ($\mu g/m^3$)	39	27.28	(6.26)	4	25.14	(3.85)	6	29.70	(6.86)	[0.00]
SO_2 (ppb)	150	3.26	(2.27)	32	2.04	(1.49)	33	2.60	(1.97)	[0.00]
Weather										
Temperature (°F)	2,539	70.59	(5.79)	84	73.82	(7.40)	84	72.40	(5.90)	[0.00]
Precipitation (1/100")	2,539	11.46	(5.37)	84	13.91	(8.59)	84	7.35	(6.12)	[0.00]
Dew Point Temp. (°F)	2,539	58.31	(7.58)	84	62.36	(8.59)	84	55.28	(9.57)	[0.00]
Medication Costs ($ Per Person)										
All	2,435	338.53	(302.10)	84	269.69	(84.92)	84	284.89	(107.62)	[0.01]
Respiratory + Cardio.	2,435	87.84	(97.86)	84	69.33	(28.66)	84	70.94	(30.18)	[0.35]
Hospitalizations ($ Per Person)										
All	2,435	502.62	(2120.44)	84	474.77	(418.56)	84	484.25	(703.12)	[0.78]
Respiratory + Cardio.	2,435	99.69	(768.61)	84	92.47	(250.19)	84	73.58	(142.45)	[0.11]
Mortality (Deaths Per 100,000 People)										
All	2,539	402.42	(121.32)	79	331.26	(89.47)	79	316.25	(76.94)	[0.00]
Respiratory + Cardio.	2,539	180.80	(69.93)	79	144.31	(45.37)	79	137.08	(39.59)	[0.00]

Notes: All currency in 2006 dollars deflated using the US CPI for urban consumers. Emissions, medications, and deaths are totals per summer. Ambient pollution and weather are mean summer values. Low and High ozone are based on comparisons to the county with median summer ozone. Means are across counties (i.e., not weighted). All data 2001-2007.

Table 2. Effect of NBP Emissions Market on NBP Source Emissions and Ambient Pollution

	(1)	(2)	(3)	(4)	(5)
A. Pollution Emissions					
1. NO_x	-0.36***	-0.38***	-0.37***	-0.33***	---
	(0.05)	(0.05)	(0.07)	(0.07)	
2. SO_2	-0.08**	-0.12	-0.07	-0.07**	---
	(0.04)	(0.07)	(0.05)	(0.03)	
3. CO_2	-3.34	-19.04	-6.19	-12.65*	---
	(4.38)	(16.07)	(6.13)	(6.61)	
B. Air Quality (Ambient Pollution)					
1. Ozone 8-Hour Value	-2.91***	-4.22***	-2.97***	-3.25***	-3.43***
	(0.77)	(1.24)	(0.75)	(0.60)	(0.60)
2. Ozone Days ≥ 65	-7.40***	-8.26***	-7.46**	-8.40***	-8.62***
	(2.50)	(2.75)	(2.96)	(2.55)	(2.51)
3. CO: Carbon Monoxide	-0.05**	-0.04	-0.04	-0.02	0.00
	(0.02)	(0.03)	(0.04)	(0.03)	(0.03)
4. SO_2: Sulfur Dioxide	0.16	0.16	0.10	0.11	0.12
	(0.12)	(0.25)	(0.18)	(0.16)	(0.15)
5. NO_2: Nitrogen Dioxide	-1.13***	-0.020	-1.21***	-1.00***	-1.25**
	(0.21)	(0.90)	(0.40)	(0.37)	(0.49)
6. $PM_{2.5}$: Particulates Less than 2.5 Micrometers	n.a.	n.a.	n.a.	-0.38	-1.01***
	n.a.	n.a.	n.a.	(0.28)	(0.28)
7. PM_{10}: Particulates Less than 10 Micrometers	n.a.	n.a.	n.a.	-0.90	0.11
	n.a.	n.a.	n.a.	(1.02)	(1.25)
County-by-Season FE	x	x	x	x	x
Summer-by-Year FE	x	x	x	x	x
State-by-Year FE	x	x			
County-by-Year FE			x	x	x
Detailed Weather Controls		x	x	x	x
Data Begins in 2001				x	x
Weighted by Emission/Pollution Monitors (B. only)	x	x	x	x	
Weighted by Population (B. only)					x

Notes: The entries report the coefficient and standard error associated with *1(NBP Operating)$_{cst}$* from separate regressions. The dependent variable is thousands of tons (panel A) or concentration of ambient pollution (panel B). The variance-covariance matrix allows for arbitrary autocorrelation within each state-season. For Panel A., winter emissions are multiplied by 5/7, so all values are summer-equivalent. For Panel A, columns (1) through (3) have 55,858 observations and column (4) has 35,546 observatoins. For Panel B, number of observations for each pollutant based on 1997-2007 sample (2001-2007 sample for PM) is 3,124 (Ozone); 2,244 (CO); 4,172 (PM2.5); 546 (PM10); 2,684 (SO2); 1,782 (NO2). Unless otherwise noted, the sample period begins in 1997. Asterisks denote p-value < 0.10 (*), <0.05 (**), <0.01 (***).

Table 3. Effect of NBP Emissions Market on Log Medication Costs

	(1)	(2)	(3)	(4)
A. Medication Purchases				
1. All Medications	-0.008	-0.026	-0.019***	-0.019***
	(0.011)	(0.021)	(0.006)	(0.006)
2. Respiratory + Cardiovascular	-0.005	-0.019	-0.023***	-0.015
	(0.014)	(0.023)	(0.006)	(0.010)
3. Gastrointestinal	0.012	-0.004	-0.011*	-0.001
	(0.014)	(0.027)	(0.006)	(0.014)
County-by-Season FE	x	x	x	x
Summer-by-Year FE	x	x	x	x
State-by-Year FE	x	x		
County-by-Year FE			x	x
Detailed Weather Controls		x	x	x
Only Counties With Ozone Monitors				x
Weighted by Population	x	x	x	x

Notes: The entries report the coefficient and standard error associated with $1(NBP\ Operating)_{cst}$ from separate regressions. The dependent variable is log of medication costs per MarketScan person in each county-year-season cell. The estimating equations are weighted by the square root of MarketScan population in a given county-year-season. The variance-covariance matrix allows for arbitrary autocorrelation within each state-season. All currency in 2006 dollars deflated using BLS CPI for urban consumers. Number of observations is as follows: Row 1 columns (1) to (3): 30,926. Row 1 column (4): 2,338. Row 2 columns (1) to (3): 28,784. Row 2 column (4): 2,324. Row 3 columns (1) to (3): 24,080. Row 3 column (4): 2,296. Data begin in 2001. Asterisks denote p-value < 0.10 (*), <0.05 (**), <0.01 (***).

Table 4. Effect of NBP Emissions Market on All-Age Mortality Rates

	(1)	(2)	(3)	(4)	(5)
1. All Deaths	-2.15**	-3.03	-1.56*	-5.41***	-2.67*
	(0.94)	(3.47)	(0.81)	(1.83)	(1.54)
2. Respiratory + Cardiovascular	-0.75	-1.70	-0.55	-2.28*	-1.11
	(0.49)	(1.81)	(0.68)	(1.23)	(1.00)
3. Neoplasm	0.09	0.15	0.10	-0.17	-0.14
	(0.28)	(0.75)	(0.27)	(0.40)	(0.40)
4. External	0.31	-0.07	0.12	-0.66	0.17
	(0.21)	(0.37)	(0.31)	(0.66)	(0.38)
5. All Other	-1.49***	-1.49	-1.11**	-2.96***	-1.41*
	(0.38)	(1.09)	(0.43)	(0.78)	(0.72)
County-by-Season FE	x	x	x	x	x
Summer-by-Year FE	x	x	x	x	x
State-by-Year FE	x	x			
County-by-Year FE			x	x	x
Detailed Weather Controls		x	x	x	x
Counties With Ozone Monitors				x	
Data Begins in 2001					x

Notes: The entries report the coefficient and standard error associated with *1(NBP Operating)*$_{cst}$ from separate regressions. The dependent variable is deaths per 100,000 population in each county-year-season cell. The estimating equations are weighted by the square root of population in a given county-year-season. The variance-covariance matrix allows for arbitrary autocorrelation within each state-season. "All Other" row corresponds to all causes of death other than respiratory, cardiovascular, neoplasm, and external. Number of observations is 55,858 for columns (1) through (3); 3,124 for column (4); and 35,546 for column (5). Unless otherwise noted, data begin in 1997. Asterisks denote p-value < 0.10 (*), <0.05 (**), <0.01 (***).

Table 5. Effect of NBP Emissions Market on Mortality Rates, by Age

	Cause of Death	
	All	Respiratory & Cardiovascular
	(1)	(2)
1. Age 0 (Infants)	-4.61	-1.85
	(6.28)	(1.21)
Response Var Mean	306	13
Estimated Change in 2005 Deaths	-81	-33
2. Ages 1-64	-0.14	0.24
	(0.50)	(0.26)
Response Var Mean	104	30
Implied 2005 Deaths	-168	281
3. Ages 65-74	-1.49	-3.18
	(6.00)	(3.51)
Response Var Mean	964	417
Estimated Change in 2005 Deaths	-132	-282
4. Ages 75+	-20.70*	-11.20
	(10.85)	(9.84)
Response Var Mean	3,182	1,795
Estimated Change in 2005 Deaths	-1,794	-970

Notes: The entries report the coefficient and standard error associated with *1(NBP Operating)*$_{cst}$ from separate regressions that correspond to the column (3) specification of Table 4. The dependent variable is deaths per 100,000 population in each county-year-season cell, where deaths and population are calculated for the indicated age groups. The estimating equations are weighted by the square root of population in a given county-year-season. The variance-covariance matrix allows for arbitrary autocorrelation within each state-season. In 2005, market-area population levels in millions were 1.8 (infants), 116.5 (1-64), 8.9 (65-75), and 8.7 (75-99). Number of observations is 55,770 for row 1.; 55,858 for rows 2-3; and 55,836 for row 4. Data begin in 1997. Asterisks denote p-value < 0.10 (*), <0.05 (**), <0.01 (***).

Table 6. Effect of Ambient Ozone On Medication Purchases and All-Age Mortality Rate: Ordinary Least Squares and Instrumental Variables Estimates, 2001-2007

	Log Medication Costs			Mortality				
	All	Respiratory + Cardio.	Gastrointestinal	All	Respiratory + Cardio.	Neoplasm	External	All Other
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A: OLS								
8-Hour Ozone	0.001	0.001	0.001	0.24	-0.02	0.08	0.02	0.18
	(0.001)	(0.001)	(0.001)	(0.19)	(0.11)	(0.06)	(0.03)	(0.12)
Days ≥65 ppb	0.000*	0.000***	0.001***	0.01	0.00	-0.01	0.01*	0.02
	(0.000)	(0.000)	(0.000)	(0.04)	(0.02)	(0.01)	(0.01)	(0.03)
B: 2SLS								
8-Hour Ozone	0.007***	0.005***	0.000	2.60**	1.19	0.00	0.23	1.40***
	(0.001)	(0.002)	(0.003)	(1.18)	(0.77)	(0.23)	(0.18)	(0.32)
Days ≥65 ppb	0.002***	0.002**	0.000	1.03*	0.48	0.00	0.09	0.56***
	(0.001)	(0.001)	(0.001)	(0.58)	(0.35)	(0.09)	(0.08)	(0.19)

Notes: The entries report the coefficient and standard error associated with $Ozone_{cst}$ from separate regressions that correspond to the column (4) specification of Table 4. The dependent variable is deaths per 100,000 population in each county-year-season cell. The estimating equations are weighted by the square root of population in a given county-year-season. The variance-covariance matrix allows for arbitrary autocorrelation within each state-season. Number of observations is as follows: 2,338 for column (1); 2,324 for column (2); 2,296 for column (3); and 2,212 for columns (4) through (8). Data begin in 2001. Asterisks denote p-value < 0.10 (*), <0.05 (**), <0.01 (***).

Table 7. Estimates of Welfare Impacts of the NBP and the Social Benefits of Ozone Reductions

	Medications ($ Million)	Mortality:		Total ($ Million)
		Number of Deaths	Monetized Value ($ Million)	
A. An Upper Bound Estimate of NBP's Social Costs				
Upper Bound Per Year				$759
Upper Bound, 2003-2007 Total				$3,414
B. Estimates of the NBP's Benefits				
Total Per Year	$873	2,175	$883	$1,756
Total 2003-2007	$3,929	9,788	$3,973	$7,902
C: The Social Benefits of Ozone Reductions in the Eastern US				
1 ppb Ozone Decrease	$312	3,524	$1,431	$1,743
1 Less Day With Ozone > 65 ppb	$106	1,402	$569	$675

Notes: All currency in 2006 dollars deflated using BLS CPI for urban consumers. Mortality dollar impact uses the VSL of $1.93 million (2006 dollars) from Ashenfelter and Greenstone (2004) and the age adjustments from Murphy and Topel (2006, p. 888). The implied VSLs are as follows: $1.9 million (infants); $1.5 million (age 1-64); $0.6 million (age 65-74); $0.2 million (age 75+). Total 2003-7 decrease due to NBP assumes impact is for half of 2003 summer and for all of summers 2004-2007. NBP cost upper bound is based on the mean permit price of $2,080/ton and estimated total abatement quantity of 412,380 tons. Panel A multiplies the estimate from Table 2, Column (3) by mean summer NOx emissions for NBP area to calculate decrease in NOx due to NBP. Panel B uses estimate from Table 3, column (4) to measure change in medication purchase; and from Table 5, Column (1) to measure mortality. Panel C takes the IV estimates from Table 6, Panel B, Columns (1) and (4), and applies them to the full population of the NBP region.

NOT FOR PUBLICATION Appendix For:

Defensive Investments and the Demand for Air Quality: Evidence from the NO_x Budget Program and Ozone Reductions

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Appendix 1: The NO_x Budget Trading Program and Particulate Matter

This appendix provides one explanation based in atmospheric chemistry as to why the NO_x Budget Trading Program might have little or no effect on particulate matter. We begin by defining the relevant compounds:

PM_{10} and $PM_{2.5}$: particulate matter
NO_x: nitrogen oxides
NO: nitric oxide, a component of NO_x
NO_2: nitrogen dioxide, a component of NO_x
NH_4NO_3: ammonium nitrate, the component of $PM_{2.5}$ and PM_{10} which NO_x can form
NO_3: nitrate, a derivative of NO_x
NH_4: ammonium
SO_4: sulfate, formed as a byproduct of electricity generation
NH_{4e}: excess ammonium, i.e., ammonium which remains after NH_4 has bonded with SO_4
NH_3: ammonia
HNO_3: nitric acid, a derivative of NO_x

A summary is that excess ammonium (NH_{4e}) is the necessary ingredient for nitrate (NO_3) to become ammonium nitrate (NH_4NO_3), which is a component of particulates. In the absence of NH_{4e}, NO_x and NO_3 do not form particulate matter. NH_{4e} levels were low in the Eastern U.S. during the operation of the NO_x Budget Trading Program because levels of sulfate (SO_4) were high enough to absorb much of the available NH_4 so that little sulfate remained to bond with nitrate.

A more detailed explanation follows. For NO_x to become a component of PM_{10} or $PM_{2.5}$, NO_x must decompose to nitrate (NO_3). Nitrate then must undergo a reaction with excess ammonium (NH_{4e}) to form ammonium nitrate (NH_4NO_3). Ammonium nitrate is a component of particulate matter but nitrate is not. So a necessary condition for NO_x to increase particulate matter is the presence of sufficient excess ammonium to convert nitrate into ammonium nitrate.

To assess the empirical relevance of this explanation, we calibrated an air quality model (CRDM) using the 2002 National Emissions Inventory, as in Muller and Mendelsohn (2012). According to calculations from CRDM, the Eastern U.S. had relatively low levels of NH_{4e} during the operation of the NO_x Budget Trading Program. Excess ammonium levels were low in part because NH_4 preferentially bonds with SO_4, which is a byproduct of sulfur emissions. Even with the Acid Rain program, sulfur levels were high enough in the Eastern U.S. in 2003-2007 that little NH_4 remained as NH_{4e} after the NH_4-SO_4 reaction occurred.

According to calculations using CRDM, in the period 2003-2007, the Eastern U.S. had relatively low levels of excess ammonium, which could explain why we fail to find consistent evidence consistently that the NO_x Budget Program affected particulate levels. Pandis and Seinfeld (2006), a widely-cited atmospheric chemistry text, note that this phenomenon is well-established:

> "The formation of ammonium nitrate is often limited by the availability of one of the reactants. Figure 10.24 shows the ammonium concentration as a function of the total

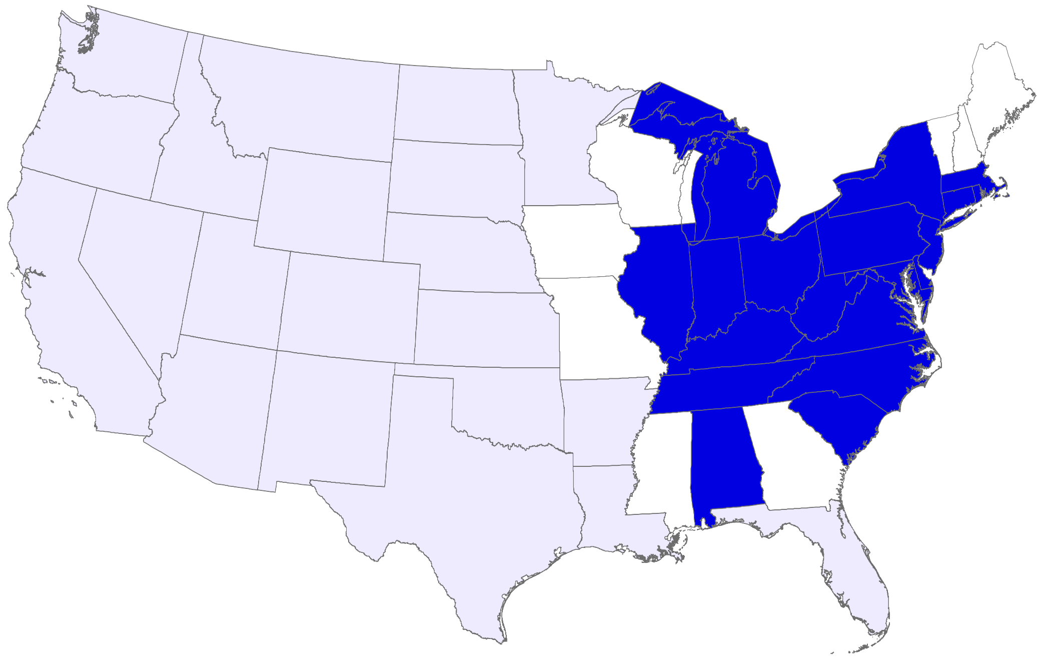
available ammonia and the total available nitric acid for a polluted area. The upper left part of the figure (area A) is characterized by relatively high total nitric acid concentrations and relatively low ammonia. Large urban areas are often in this regime. The isopleths are almost parallel to the y-axis in this area, so decreases in nitric acid availability do not affect significantly the NH_4NO_3 concentration in this area." (p. 483)

Appendix 1 References:

Pandis, Spyros N. and John H. Seinfeld (2006). Atmospheric Chemistry and Physics: From Air Pollution to Climate Change (2nd Edition). NY, NY, USA: John Wiley & Sons, Inc.

Appendix 2: Supplementary Figures and Tables

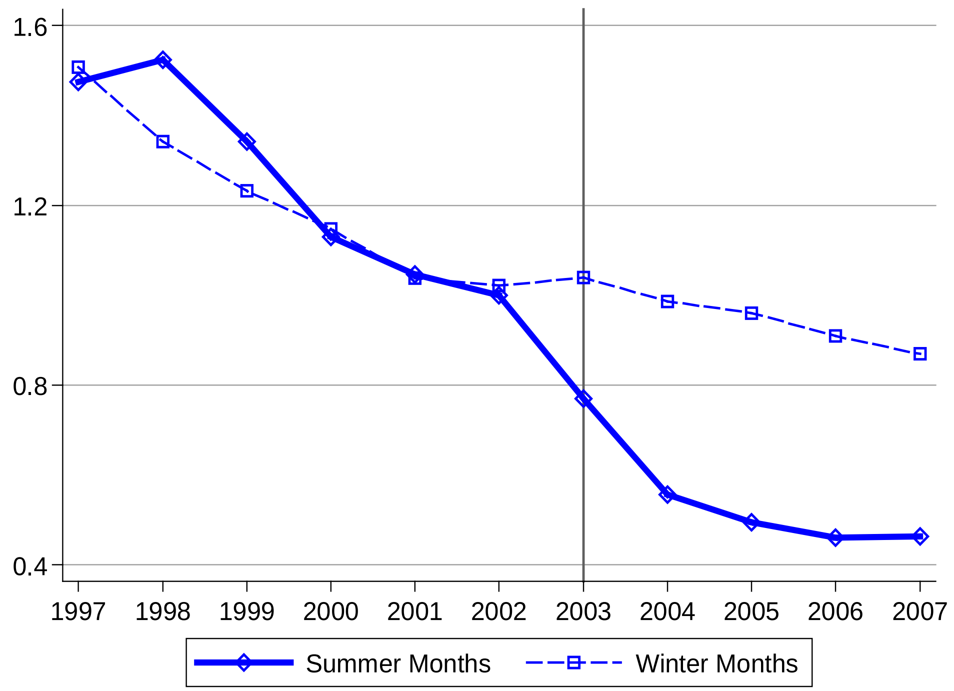
Appendix Figure 1. Participation in NBP by State



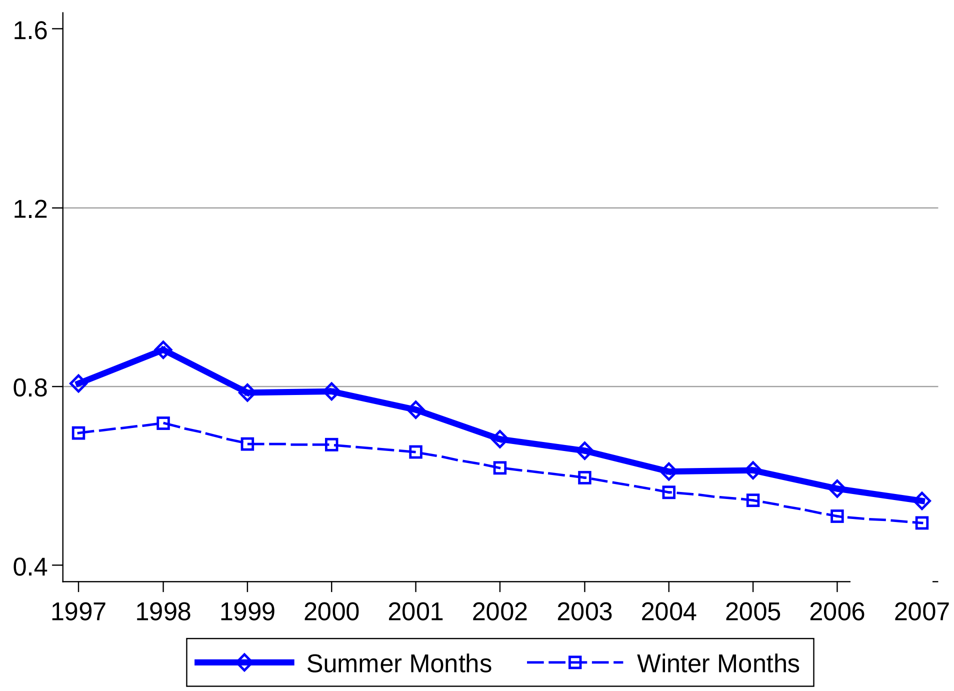
Notes: Dark blue states are those participating in NBP during the 2003-2007 period (NBP states). Light blue states are not participating (non-NBP states). White states are excluded from the main analysis sample.

Appendix Figure 2. Summer-Equivalent Seasonal NO_x Emissions (Mil. Tons)

(A) States Participating in NBP



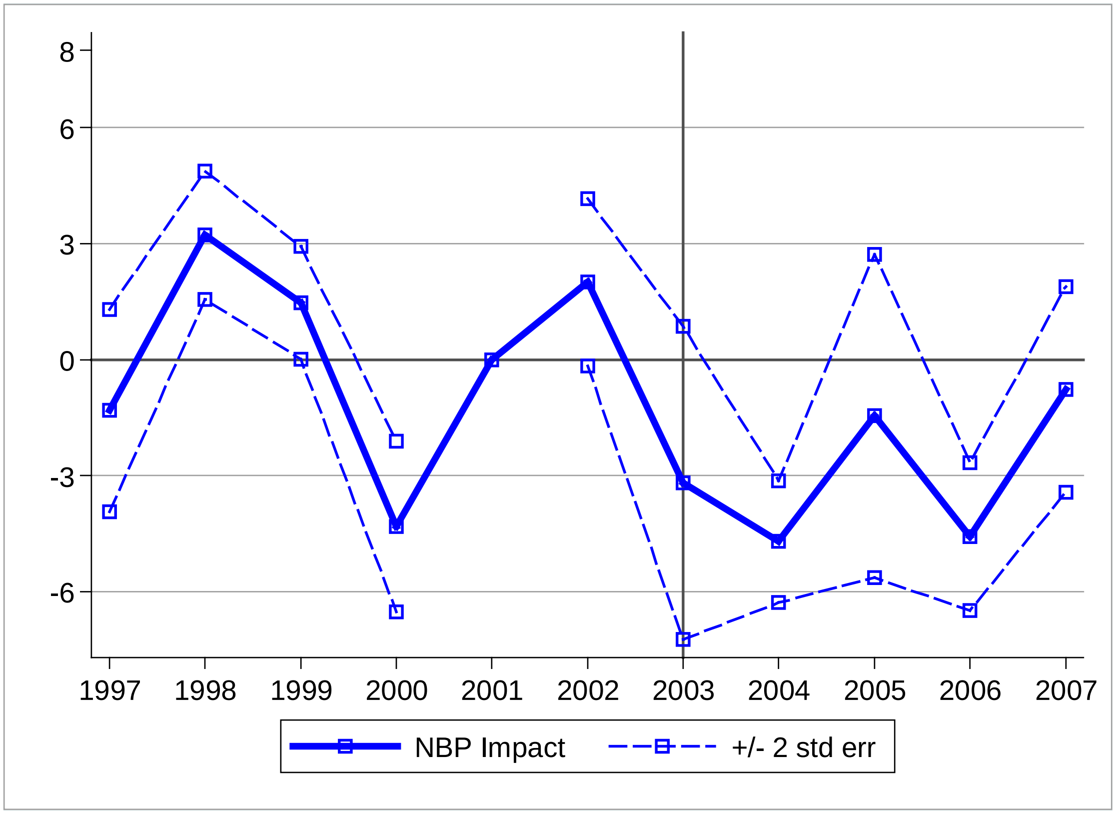
(B) States Not Participating in NBP



Notes: The data show raw, unadjusted emissions totals. The y-axis is in millions of tons of summer-equivalent NO_x emissions. Summer is defined as May-September, winter as January-April and October-December. Summer-equivalent multiplies the winter total by 5/7. See the text and Appendix Figure 1 for a description of NBP and non-NBP states.

Appendix Figure 3. NBP Market Impact on Ambient Ozone Concentrations

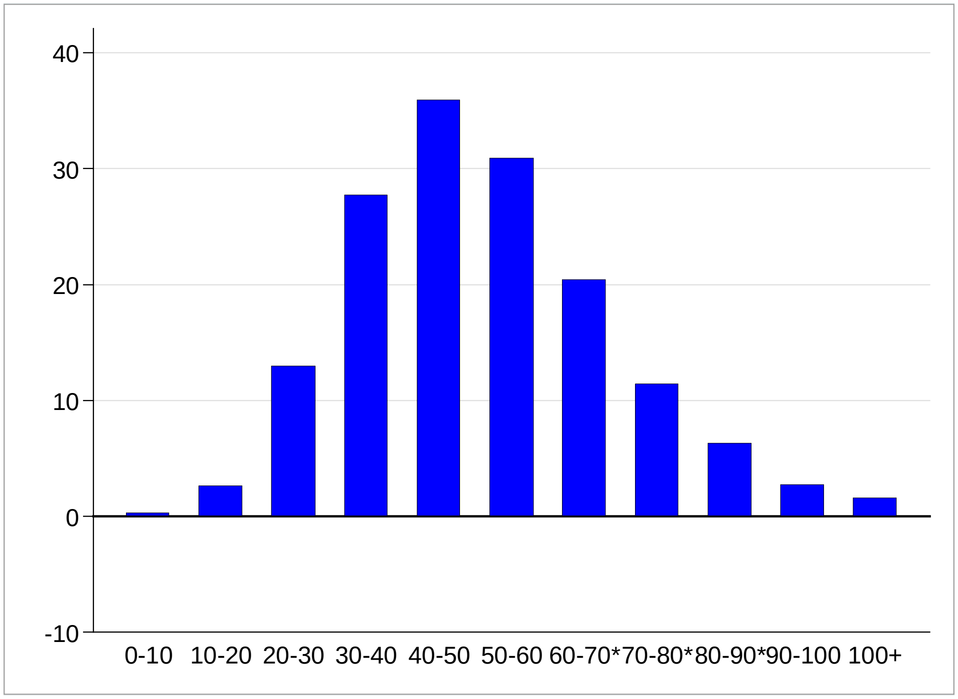
(A) Event Study for Daily Ozone 8-Hour Values, 1997-2007



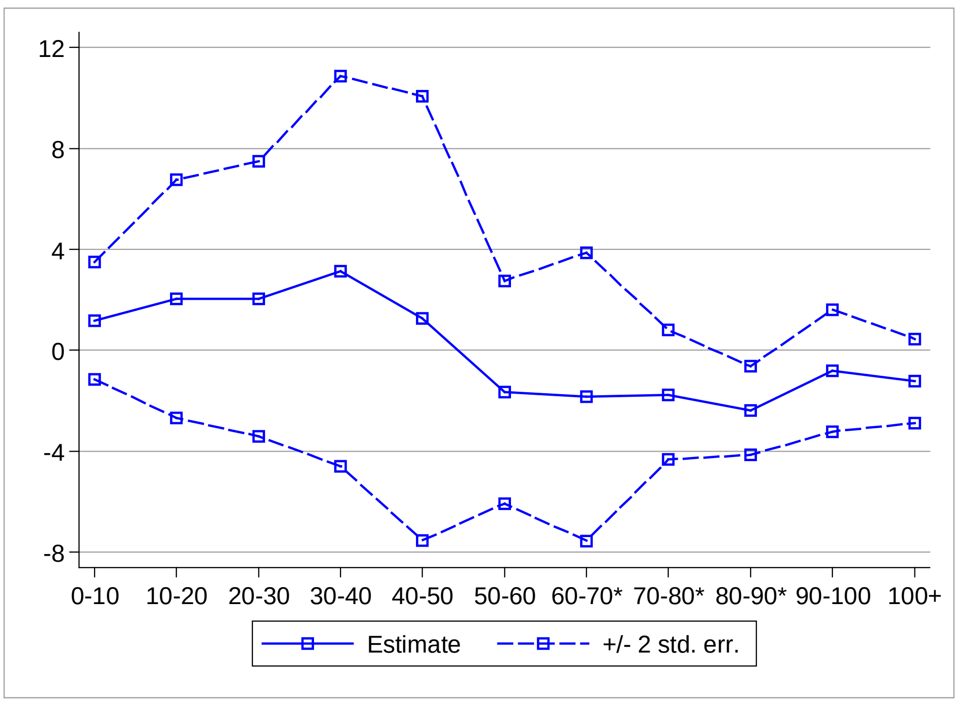
Notes: The graph depicts the coefficients and standard errors associated with α_t*1{NBP State and Summer}*$_{cs}$ for each year $_t$. This corresponds to the specification of Table 2, column (3). The dependent variable is the 8-hour ozone value, measured as the maximum rolling 8-hour mean of hourly values within each day, which is the statistic used in EPA non-attainment designations. The variance-covariance matrix allows for arbitrary autocorrelation within each state-season. Estimate for year 2001 restricted to take a value of 0. See text for NBP participation status designation.

Appendix Figure 3. NBP Market Impact on Ambient Ozone Concentrations (Continued)

(B) Number of Summer Days in 11 Ozone Bins, NBP Participating States, 2001-2002

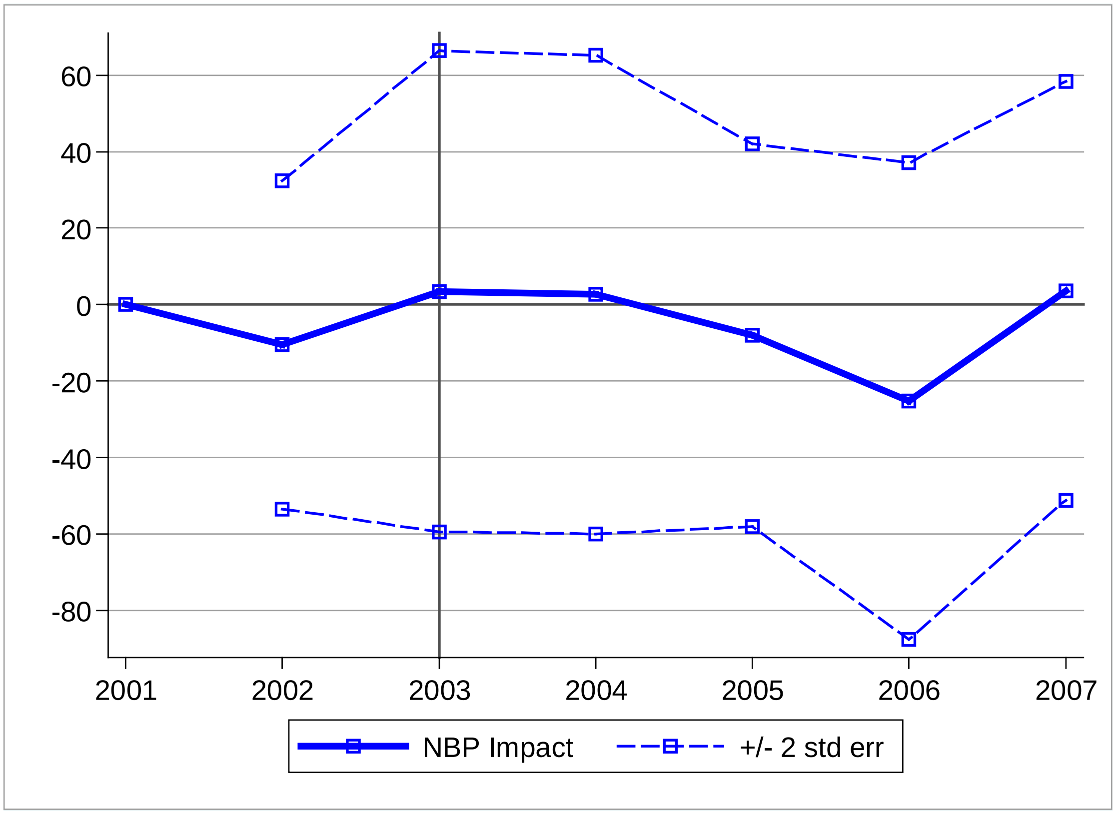


(C) NBP Market Impact on Number of Summer Days in 11 Ozone Bins



Notes: Ozone 8-hour value is measured as the maximum rolling 8-hour mean of hourly values within each day, which is the statistic used in EPA non-attainment designations. Panel B shows the average number of summer days (out of a possible 153 days) in 11 categories for daily ozone 8-hour value in the NBP states in 2001-2002 (pre-NBP period). Panel C shows the estimated impact of NBP on the number of summer days in 11 categories for daily ozone 8-hour value. Asterisks in the x-axis of Panel C represent EPA non-attainment standards in ppb: 85 (1997 standard), 75 (2008 standard), and 60-70 (2010 proposed standard). Estimates in Panel C report the coefficient and standard error associated with *1(NBP Operating)*$_{cst}$ from separate regressions that correspond to the column (3) specification of Table 2. The regressions underlying Panel C are weighted by the square root of the number of pollution readings in a given county-year-season. Standard errors based on covariance matrix that allows for arbitrary autocorrelation within each state-season. See text for NBP participation status designation.

Appendix Figure 4. Impact of NBP Market on Hospital Costs ($2006)



Notes: The graph depicts the coefficients and standard errors associated with α_t*1{NBP State and Summer}*$_{cs}$ for each year $_t$. This corresponds to the specification of Table 3, column (3). The dependent variable is the total hospitalization cost per person-summer in a county. Costs are in 2006 dollars, deflated using the BLS CPI for urban consumers. The estimating equations are weighted by the square root of population in a given county-year-season. The variance-covariance matrix allows for arbitrary autocorrelation within each state-season. Estimate for year 2001 restricted to take a value of 0.

Appendix Table 1. Sensitivity Analysis: Emitted and Ambient Pollution

	Emitted Pollution			Air Quality (Ambient Pollution)						
	NO_x	SO_2	CO_2	Ozone	Ozone Days ≥65ppm	CO	$PM_{2.5}$	PM_{10}	SO_2	NO_2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1. Baseline Sample	-0.33	-0.07	-12.65	-3.25	-8.40	-0.02	-0.38	-0.90	0.11	-1.00
State-Season Clusters	(0.07)***	(0.03)**	(6.61)*	(0.60)***	(2.55)***	(0.03)	(0.28)	(1.02)	(0.16)	(0.37)***
County Clusters	(0.08)***	(0.05)	(7.60)*	(0.54)***	(2.44)***	(0.03)	(0.31)	(1.23)	(0.24)	(0.47)**
State Clusters	(0.09)***	(0.05)	(9.41)	(0.84)***	(3.59)**	(0.04)	(0.39)	(1.44)	(0.22)	(0.52)*
State-Year Clusters	(0.05)***	(0.04)*	(6.47)*	(1.21)***	(3.77)***	(0.03)	(0.49)	(1.40)	(0.18)	(0.41)**
County-Season Clusters	(0.05)***	(0.04)*	(5.37)**	(0.38)***	(1.75)***	(0.02)	(0.22)*	(0.87)	(0.17)	(0.34)***
2. Counties With Ozone	-0.23*	-0.25	-69.21	-3.25***	-8.40***	-0.02	-0.58	-4.13	0.15	-1.11*
Monitors	(0.12)	(0.20)	(45.35)	(0.60)	(2.55)	(0.03)	(0.41)	(5.81)	(0.25)	(0.57)
	-0.33***	-0.07**	-12.37*	-3.25***	-8.40***	-0.02	-0.38	-1.07	0.11	-1.00***
3. Including ME, NH, VT	(0.07)	(0.03)	(6.42)	(0.60)	(2.55)	(0.03)	(0.27)	(1.05)	(0.16)	(0.37)
4. Monitors Operating ≥				-2.96***	-10.87***	-0.02	-0.52**	-0.06	0.10	-0.65*
30 weeks				(0.45)	(1.90)	(0.02)	(0.26)	(1.18)	(0.14)	(0.39)
5. Summer*Post*NBP				0.22	1.03					
*VOC-Constrained				(1.18)	(4.63)					
6. Summer*Post*NBP*				1.54***	4.94**					
(High Weekend O_3)				(0.57)	(2.29)					

Notes: The table entries report the coefficient and standard error associated with *1(NBP Operating)*$_{cst}$ from separate regressions that correspond to the column (4) specification of Table 2 unless otherwise noted. The dependent variable in columns (1)-(3) is thousands of tons. The dependent variable in columns (4)-(10) is the concentration of ambient pollution. The estimating equations are weighted by the square root of population in a given county-year-season. The variance-covariance matrix allows for arbitrary autocorrelation within each state-season. Regressions use 2001-2007 data. The entries after row 1 present different levels of clustering for standard errors. "Including ME, NH, and VT" redefines the regression sample to include data from these three states. "Monitors Operating ≥ 30 weeks" uses a monitor selection rule which requires each monitor to have valid readings in 30 weeks of each year in the data, rather than the 47-week rule used in the main results. "Summer*Post*NBP*VOC-Constrained" reports the interaction of the main triple-difference term with an MSA indicator for being VOC constrained based on Blanchard (2001). "Summer*Post*NBP*(High Weekend O_3) interacts the main triple-difference term with an indicator for whether the weekend/weekday ozone ratio of a county exceeds 1.05. This provides an alternative indicator of VOC-constrained regions. Asterisks denote p-value < 0.10 (*), <0.05 (**), <0.01 (***).

Appendix Table 2. Sensitivity Analysis: Medications

	All	Respiratory & Cardiovascular	Gastrointestinal
	(1)	(2)	(3)
1. Baseline Sample	-0.019	-0.023	-0.011
State-Season Clusters	(0.006)***	(0.006)***	(0.006)*
County Clusters	(0.006)***	(0.006)***	(0.011)
State Clusters	(0.008)**	(0.009)**	(0.008)
State-Year Clusters	(0.007)***	(0.008)***	(0.010)
County-Season Clusters	(0.005)***	(0.005)***	(0.008)
2. Including ME, NH, VT	-0.018***	-0.023***	-0.009
	(0.006)	(0.006)	(0.006)
	-0.015***	-0.022***	-0.019***
3. Log Medications (Not Costs)	(0.005)	(0.005)	(0.005)
4. Panel of People	-0.013*	-0.018**	-0.001
	(0.007)	(0.007)	(0.010)
5. Levels (Not Logs)	-10.129***	-2.542***	-1.260***
	(2.115)	(0.642)	(0.316)
6. Purchase-Specific Costs	-0.016***	-0.022***	-0.023***
	(0.006)	(0.005)	(0.008)

Notes: The table entries report the coefficient and standard error associated with $1(NBP\ Operating)_{cst}$ from separate regressions that correspond to the column (3) specification of Table 3 unless otherwise noted. The dependent variable is log of medication costs per MarketScan person in each county-year-season cell. The estimating equations are weighted by the square root of population in a given county-year-season. The variance-covariance matrix allows for arbitrary autocorrelation within each state-season. Regressions use 2001-2007 data. All currency in 2006 dollars deflated using BLS CPI for urban consumers. The entries after row 1 present different levels of clustering for standard errors. "Including ME, NH, and VT" redefines the regression sample to include data from these three states. "Levels (Not Logs)" specifies the response variable in levels rather than logs. "Purchase-Specific Costs" uses the raw reported prices, rather than averaging across national drug codes to deal with outliers as in the main analysis. Asterisks denote p-value < 0.10 (*), <0.05 (**), <0.01 (***).

Appendix Table 3. Effect of NBP Emissions Market on Hospitalization Costs

	(1)	(2)	(3)	(4)
1. All Hospitalizations	-5.32	-0.47	-6.00	-78.51***
	(17.13)	(17.44)	(18.95)	(23.76)
2. Respiratory + Cardiovascular	-8.15*	-8.26	-8.70	-44.87***
	(4.73)	(5.23)	(5.72)	(9.82)
3. External	-2.75	-2.93	-3.63	-15.49
	(3.76)	(4.43)	(6.49)	(9.37)
County-by-Season FE	x	x	x	x
Summer-by-Year FE	x	x	x	x
State-by-Year FE	x	x		
County-by-Year FE			x	x
Detailed Weather Controls		x	x	x
Only Counties With Ozone Monitors				x
Weighted by Population	x	x	x	x

Notes: The table entries report the coefficient and standard error associated with *1(NBP Operating)*$_{cst}$ from separate regressions. The dependent variable is hospital costs per MarketScan person in each county-year-season cell. The estimating equations are weighted by the square root of population in a given county-year-season. The variance-covariance matrix allows for arbitrary autocorrelation within each state-season. Regressions use 2001-2007 data. All currency in 2006 dollars deflated using BLS CPI for urban consumers. Asterisks denote p-value < 0.10 (*), <0.05 (**), <0.01 (***).

Appendix Table 4. Sensitivity Analysis: Hospitalization Costs

	All (1)	Respiratory & Cardiovascular (2)	External (3)
1. Baseline Sample	-6.00	-8.70	-3.63
State-Season Clusters	(18.95)	(5.72)	(6.49)
County Clusters	(21.94)	(8.81)	(7.01)
State Clusters	(26.94)	(8.13)	(9.22)
State-Year Clusters	(20.32)	(7.73)	(6.67)
County-Season Clusters	(15.53)	(6.24)	(4.96)
2. Including ME, NH, VT	-1.54	-6.08	-3.22
	(18.20)	(5.47)	(6.21)
3. Hospitalizations (Not Costs)	0.00	-0.00**	0.00
	(0.00)	(0.00)	(0.00)
4. Panel of People	1.08	3.01	0.64
	(7.18)	(4.14)	(2.64)
5. Logs (Not Levels)	0.01	-0.12	-0.11
	(0.04)	(0.09)	(0.10)

Notes: The table entries report the coefficient and standard error associated with *1(NBP Operating)*$_{cst}$ from separate regressions that correspond to the column (3) specification of Appendix Table 3 unless otherwise noted. The dependent variable is hospital costs per MarketScan person in each county-year-season cell. The estimating equations are weighted by the square root of population in a given county-year-season. The variance-covariance matrix allows for arbitrary autocorrelation within each state-season. Regressions use 2001-2007 data. All currency in 2006 dollars deflated using BLS CPI for urban consumers. The entries after row 1 present different levels of clustering for standard errors. "Including ME, NH, and VT" redefines the regression sample to include data from these three states. "Hospitalizations (Not Costs)" uses counts of hospitalizations, rather than cost measures. "Panel of People" uses the much smaller panel of persons who appear in all observations of the MarketScan sample. "Logs (Not Levels)" specifies the response variable in logs rather than levels. Asterisks denote p-value < 0.10 (*), <0.05 (**), <0.01 (***).

Appendix Table 5. Sensitivity Analysis: Mortality

	All (1)	Respiratory & Cardiovascular (2)	External (3)
1. Baseline Sample	-1.56	-0.55	0.12
State-Season Clusters	(0.81)*	(0.68)	(0.31)
County Clusters	(1.16)	(0.78)	(0.34)
State Clusters	(1.16)	(0.96)	(0.44)
State-Year Clusters	(1.65)	(1.12)	(0.36)
County-Season Clusters	(0.82)*	(0.55)	(0.24)
2. Including ME, NH, VT	-1.70**	-0.67	0.15
	(0.79)	(0.66)	(0.30)
3. Logs (Not Levels)	-0.01***	-0.01**	0.01
	(0.00)	(0.00)	(0.01)
4. Age-Adjustment	-1.50*	-0.76	0.12
	(0.85)	(0.67)	(0.31)

Notes: The table entries report the coefficient and standard error associated with *1(NBP Operating)*$_{cst}$ from separate regressions that correspond to the column (3) specification of Table 4 unless otherwise noted. The dependent variable is deaths per 100,000 population in each county-year-season cell. The estimating equations are weighted by the square root of population in a given county-year-season. The variance-covariance matrix allows for arbitrary autocorrelation within each state-season. Asterisks denote p-value < 0.10 (*), <0.05 (**), <0.01 (***).