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ABSTRACT

Willingness to pay for air quality is a function of health and the costly defensive investments that contribute to health, but there is little research assessing the empirical importance of defensive investments. The setting for this paper is a large US emissions cap and trade market – the NO_x Budget Trading Program (NBP) – that has greatly reduced NO_x emissions since its initiation in 2003. Using rich quasi-experimental variation, we find that the reductions in NO_x emissions decreased the number of summer days with high ozone levels by about 25%. The NBP also led to reductions in expenditures on prescription pharmaceutical expenditures of about 1.9%. Additionally, the summer mortality rate declined by approximately 0.5%, indicating that there were about 2,200 fewer premature deaths per summer, mainly among individuals 75 and older. The monetized value of the reductions in pharmaceutical purchases and mortality rates are each roughly $900 million annually, suggesting that defensive investments are a significant portion of willingness to pay for air quality. Finally, we cautiously conclude that the reductions in ozone are the primary channel for these reductions in defensive investments and mortality rates, which indicates that willingness to pay for ozone reductions is larger than previously understood.

JEL Codes: H4, I1, Q4, Q5, D1
Keywords: willingness to pay for air quality; cap and trade; ozone; pharmaceuticals; mortality; compensatory behavior; human health

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.) and 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; Becker 1965). 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., crime rates and 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., Levitt 1997; Chay and Greenstone 2003a and 2003b; Currie and Neidell 2005; Chen et al. 2012). 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 both 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 any 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.

Figure 1 shows the dramatic effect of this market on NO_x emissions in the states participating in the NBP. In 2002, daily NO_x emissions were fairly flat throughout the calendar year, with a rise when electricity demand peaks in July.[2] 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 the summer of 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 which substantially decreased their NO_x emissions. This market lets us isolate the causal effects of air quality on health because it allows a simple research design. We use a triple-difference estimator which compares pollution and health outcomes in summer versus winter, before versus after 2003, and in the NBP participating and non-participating states.[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 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 hospital admissions or 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, but there is mixed evidence about whether it led to reductions in airborne particulate matter. Consequently, we cautiously utilize the NBP as an instrumental variable for ozone concentrations and find that the elasticity of

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[2] This figure partials out day-of-week fixed effects because additional electricity generation on weekdays adds visible weekly cycles to the image, although the overall picture is unchanged in the raw data.

[3] "Winter" in this paper refers to the combined months of January-April and October-December. Much of the decline in NO_x emissions occurred because several large and dirty coal-fired electricity generating units installed selective catalytic reduction systems—a technology which sprays ammonia or urea into flue gas and then passes the gas through a honeycomb-like catalyst made of vanadium, tungsten, or other materials, to remove over 70% of NO_x emissions. Because these technologies have nonzero operating costs, 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 some electricity to operate. This penalty is between one-twentieth of a percent and six-tenths of one percent (USEPA 2010, p. 5-11), so is too small to appreciably affect the total heat input or gross electricity generation.

medication purchases with respect to mean summer ozone is 0.28. The elasticity of mortality with respect to mean summer ozone is 0.22. When ozone is modeled as the number of summer days where the concentration exceeds 65 ppb, the instrumental variables estimates suggest that an extra high ozone day increases drug purchases by 0.23% and mortality by roughly 1 per 100,000.

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, atmospheric chemistry models of pollution transport, and epidemiological models of dose-response functions (e.g., Muller and Mendelsohn 2009).[5] 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.[6] In 2010, President Obama announced that the EPA would tighten ambient ozone standards. The EPA then missed four deadlines to decide on a new scientifically defensible ozone standard, and in September 2011 announced that it would wait until 2013 to implement new standards. This announcement was followed by 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; Bell, Dominici and Samet 2005; Currie and

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[4] There is an emerging empirical literature that aims to measure defensive investments. Neidell (2009) and Graff-Zivin and Neidell (2009) show that pollution alerts cause people to avoid outdoor zoos and baseball games, and that hot and cold days decrease outdoor leisure time. Graff-Zivin, Neidell, and Schlenker (2011) document an association between bottled water purchase and violations of water quality standards. Deschênes and Greenstone (2011) show that people use additional electricity, presumably for air conditioning, on extremely hot days when mortality risks are elevated. Dickie and Gerking (1991) use data on medical expenditures for 226 persons to find that residents of Los Angeles have substantial willingness-to-pay to decrease ozone pollution.

[5] This study builds on research exploring how emissions markets affect abatement costs and pollution emissions. Several analyses show that the Acid Rain Program – an emissions market for SO_2 – decreased abatement costs (Carlson et al. 2000, Schmalensee et al. 1998). Several papers have studied abatement costs and investment incentives of both the California RECLAIM market for NO_x and the NO_x market studied here (Fowlie 2009, Fowlie 2010, Fowlie, Knittel, and Wolfram 2009). Fowlie, Holland, and Mansur (2011) also show that RECLAIM decreased NO_x emissions relative to emissions from similar facilities outside the market area.

[6] 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.

Neidell 2005; Ito, De Leon and Lippman 2005; Jerrett et al. 2009; Levy, Chemerynski and Sarnat 2005; Neidell 2009; Moretti and Neidell 2011; Lleras-Muney 2010).[7]

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. As we show below, 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. As a consequence, our results are more informative about the possible impacts of new ozone regulation than the existing literature, which has focused on short-run variation in ozone (i.e. daily or weekly) 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.[8] Ozone differs from the other pollutants in three ways that are important for our analysis. First, polluters do not emit ozone directly. Instead, ozone forms through a complex nonlinear function combining two chemical 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.

[7] In contrast, there is more consistent evidence indicating that airborne particulate matter increases mortality rates (Pope, Ezzati, and Dockery 2009; Chay and Greenstone 2003a and 2003b; Chen et al. 2012).

[8] Ground-level ozone should not be confused with ozone in the upper atmosphere, which improves health by blocking ultraviolet radiation from the sun and preventing skin cancer. There is little relationship between the two except that in rare cases high-altitude cities experience increased levels of surface ozone when an "atmospheric inversion" occurs and stratospheric ozone drops to ground 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).[9]

Third, when this market began, national ozone levels changed relatively little since the Clean Air Act first regulated ozone in 1970. By contrast, concentrations of all five other "criteria" pollutants decreased by large amounts between 1973 and 2002 (USEPA 2008). During this period, the EPA imposed numerous regulations on businesses 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 to decrease ozone.

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 which formed in the 1990s. Studies commissioned under the OTC found that ozone levels remained high in the Northeast U.S. 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 which operated in 1999-2002 and produced small declines in summer NO_x emissions.[10] The OTC then created a more stringent version of the NO_x Budget Program which began in 2003 and operated until 2008.[11] The market included 2,500 electricity generating units and industrial boilers, although 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

[9] In response to forecast high-ozone levels, Los Angeles and many other areas issue "smog alert days" which encourage sensitive groups to avoid outdoor air (Graff-Zivin and Neidell 2009). Indoor ozone levels are typically lower than outdoor ozone levels.

[10] 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.

[11] 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. CAIR included both a summer "ozone season" emissions market, and a separate market for winter NO_x emissions. Designers of the winter market intended it to decrease ambient concentrations of particulates. 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.

in the 8 additional states until May 31, 2004.[12] 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).[13] Before the NBP began, about half of NO_x emissions in the 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.[14] At the end of each market season, each source had to give the EPA one allowance for each ton of NO_x emitted.[15] 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).[16]

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.

[12] 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.

[13] 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.

[14] Unused allowances from the NBP could be transferred to the CAIR ozone season program. Research is exploring the potential gains from allowing the value of permits to vary across sources (Fowlie and Muller 2012).

[15] Relatively dirty units in this market have NO_x emissions rates of around 5 lbs NO_x / MWh electricity generated. At mean NO_x permit prices of $2,080/ton NO_x, this implies the units pay a cost of about $5/MWh, or about 10 percent of their typical electricity prices. 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. For each uncovered ton of emitted NO_x, these units had to provide three times as many allowances in the following year (i.e., if a unit emitted 50 tons without allowances in one year, it had to provide 150 additional allowances in the following year).

[16] This paper compares emissions and outcomes in summer versus, so its research design depends on the idea that firms operate NO_x abatement technologies in summer but not winter. Although we show empirically that emissions decreases happened in summer but not winter, it is worth noting that many abatement technologies have substantial operating costs (Fowlie 2010) which lead firms to use these technologies only in summer.

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.

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:

$$max_{X,f,a} u(X,f,s) \quad s.t.\ I + p_w(T - f - s) \geq X + p_a a.$$

The implicit function theorem lets us derive the demand function $a^*(I,p_w,p_a,c)$ for defensive investments. This problem has three first-order conditions for an interior optimum which plays an important role in the final result:[17]

(2) $\partial u / \partial X = \lambda$

(3) $\partial u / \partial f = \lambda p_w$

(4) $\dfrac{p_a}{\partial s / \partial a} = \dfrac{\partial u / \partial s}{\lambda} - p_w$

In these first-order conditions, the Lagrange multiplier λ lets us monetize the benefits of time and health. Condition (2) shows that λ equals the marginal utility of money. Condition (3) shows that the monetized marginal utility of leisure equals the wage rate. Condition (4) shows that defenses are purchased at the market price p_a until their cost equals the additional monetized value of the health and work time they provide.

Rearranging the total derivative of the health production function (1) gives the following expression for the partial effect of ambient pollution on sick days:

[17] 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. The most costly drug (omalizumab, also known as xoliar), for example, which is used to treat rare cases of unusually severe asthma, costs over $10,000 for a year's treatment, and appears rarely in the data. Hence changes in air quality could induce changes in medication purchases for many people.

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

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 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:

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

Expression (6) shows that the marginal willingness to pay for clean air includes three terms. The first is the effect of pollution on productive work time, valued at the wage rage. 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 $\frac{\partial a^*}{\partial c}$.

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 might seem that part of the price of medications is a transfer from consumers to drug firms, and not a social cost. One interpretation of our use of market prices for medications is that 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—a similar induced innovation process as in Finkelstein (2004).

The second important deviation from the neoclassical benchmark is that consumers with insurance generally pay a copayment or deductible for medications. Hence the price exceeds the marginal cost to the consumer, generally by 80-90 percent in these data. 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.[18]

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 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. We compile high frequency data on medications, hospitalizations, mortality, pollution emissions, ambient pollution, and weather for the period 1997-2007. 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.[19]

The U.S. has no national census of local medication purchases, and so we use the best available alternative: confidential data on medication and hospital admissions from the Thompson Reuters MarketScan Research Database. MarketScan contracts with large employers to obtain all insurance-related records for their employees, plus their insured spouses and dependents. The data report the county of the purchaser's home, the purchase date, the National Drug Code (NDC) of the medication, and the money paid from the consumer and insurer to the provider of each medication. An NDC is a unique identifier for a chemical compound, manufacturer, and package type, which helps us to identify the medical condition associated with each medication. Data on the transacted payment for medications, rather than the market price, provides useful information because few patients or insurers pay listed prices for medications.

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[18] Even with health insurance and moral hazard, it remains the case that the market price of medications taken in response to air pollution measures the defensive component of the <u>social</u> willingness-to-pay for clean air. 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.

[19] 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.

We use data from all persons in the 16 covered firms which appear in all seven 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.[20] The MarketScan extract has persons in almost all U.S. counties. 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.[21] 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 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 2003 and 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 2003 and 2006).[22] 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 regularly prescribe medications to treat conditions for which the medications are not indicated, it remains likely that some of these medications were 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.

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[20] The appendix reports estimates from a balanced panel of about 600,000 persons in these firms who appear in all years. For confidentiality reasons MarketScan does not identify the 16 firms, but the firms do cover most sectors of the U.S. economy.

[21] MarketScan is not a random sample. On one hand, it represents people employed in large firms, who might have better health than the average American and so respond less to changes in air pollution. On the other hand, persons in MarketScan can buy costly respiratory medications at low copayment rates, so the response of their medication purchase rates to air pollution might exceed that of the average American. Additionally, emergency department visits may be more likely among uninsured and elderly Americans, and MarketScan has no data on either group. The exclusion of the elderly may be particularly important since we find the largest mortality impacts for the elderly.

[22] 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 relatively 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.

We count hospital admissions 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.[23] 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.

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 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.[24]

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.[25] 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. The EPA audits all of these data to verify their accuracy and internal consistency, and we believe the emissions data 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.

We use a few criteria to select ambient pollution monitoring data from the EPA's detailed Air Quality System. Many pollution monitors operate for only part of a year and for part of the 1997-2007 period. Many ozone monitors operate only in the May-September months. Moreover, monitors operate more when ozone levels increase (Henderson 1996). Many monitors for fine particulates ($PM_{2.5}$) record pollution only 1-2 times per week. To address the incompleteness of these measures, for each pollutant, the main analysis uses monitors which have valid readings for at least 47 weeks in all years 1997-2007. This fairly strenuous selection rule restricts our data to include only the most reliable monitors—it

[23] In all the MarketScan data and the 1997-1998 years of mortality which use ICD9 codes, we define respiratory + cardiovascular conditions as ICD between 390 and 519; neoplasm as ICD9 between 140 and 239; and external as ICD9 between 800 and 999. In the 1999-2007 years of mortality data which use ICD10 codes, we define respiratory + cardiovascular conditions as ICD10 beginning with I or J; neoplasm as ICD10 between C00 and D48; and external as ICD10 beginning with V, W, X, or Y.

[24] Since 1968, the MCOD files provide information on all deaths occurring in the United States. However, information on exact date of death is only available in the public-use data for 1972-1988.

[25] 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.

excludes monitors which operate only during summer, or which operate depending on weekly ozone and weather levels, or which have frequent technical problems. 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 within the day.[26]

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.

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).

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 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 of counties with mean summer ozone above the national median ("high ozone"), and a second with mean summer ozone below the national median ("low ozone"). Row 1 shows

[26] 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.

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 pollutants 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.[27] 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. This implication of Table 1 underscores the need to distinguish the effect of ozone on health from the effects of the other possible 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 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.[28]

Specifically, we estimate the following model:

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

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.

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

[28] The abrupt beginning and end of the market on May 1 and October 1makes a daily regression discontinuity estimator seem appealing. However, because ozone in the Eastern U.S. mainly reaches high levels in July and August, the market is likely to have small effects on April 30 or October 1, and we detect no change in mean daily pollution in small windows around these dates. Auffhammer and Kellogg (forthcoming) analyze daily ozone effects of gasoline regulation in California

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}, 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.[29] 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, it 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, v_{cs}, allow for permanent differences in outcomes across county-by seasons.

The parameter of interest is γ_1 associated with the variable $1(NBP\quad Operating)_{cst}$. This variable is assigned a value of 0.5 in 2003 for all NBP states 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 was assigned to all NBP states, rather than just the implementing states, because NO_x and ozone travel great distances and emissions reductions in one NBP state affected ozone concentrations in many 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.

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.

[29] 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.

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 graph the parameters $\alpha_{1997}\ldots\alpha_{2007}$ from the following model:

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

where $1(NBP \quad Operating)_{cs} = 1$ for all summer observations from NBP states, regardless of the year. These graphs permit a visual and statistical test for pre-trends effects that would raise concern about the validity of the research design. Further, the graphs are also informative about the year-specific effects of the NBP market on the outcomes considered. In all these graphs, the value α_{2001} represents a reference category set to zero.[30]

We also exploit the NBP-based DDD design to obtain instrumental variables estimates of the impacts of ozone on medication purchases and mortality rates. Specifically, $1(NBP \quad Operating)_{cst}$ serves as an instrumental variable for ozone concentrations. In this framework, the version of equation (7) where ozone is the dependent variable is the first-stage, and the versions with medication purchases or mortality rates as the outcomes are the reduced-form relationships between the instrument and the outcomes of interest. We explore the validity of the required exclusion restriction below.

VI. Results

This section reports estimates of the effects of the NBP on pollution emissions, ambient concentrations of pollution, medication purchases, mortality rates and hospital admissions. Additionally, it implements the instrumental variables strategy outlined above to obtain estimates of 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 legally required affected units to reduce NO_x emissions, so it is unsurprising that the market decreased NO_x emissions. At the same time, many analyses of pollution regulations compare emissions levels in a recent year against levels that would be present without the 1990 Clean Air Act Amendments (e.g., USEPA 2009b). Such comparisons make it difficult to identify the contribution of a specific recent policy to total emissions.

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

Figure 2 illustrates the tremendous impact of the NBP on NO_x emissions. The figure 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).[31] The first key point shown in Figure 2 (B) is that summer and winter NO_x emissions in the states excluded from NBP evolve very smoothly over time, with similar downward trends and with no evidence of any discernible change in 2003 and 2004 when NBP was implemented. In contrast, 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.[32] Additionally, winter emissions continued their gradual downward pre-2003 trend, with perhaps a modest slowing of that trend post-2003. In short, NO_x emissions declined in exactly the areas, months, and years that the market design would predict.[33]

Regression analogues of these graphs in Table 2 similarly show that the NBP market decreased NO_x emissions by 34-38%. Like most subsequent tables, Table 2 presents four specifications of each regression, so we explain them here. Column (1) includes no weather controls and includes three sets of two-way fixed effects—it uses state-by-year rather than county-by-year controls. Column (1) implies that the market decreased NO_x emissions in the average county by 362 tons per summer, or 34% relative to baseline. Column (2) adds the full set of binned weather controls. The weather controls increase the point estimates slightly, although the estimates remain precise. Column (3) replaces state-by-year fixed effects with county-by-year fixed effects, which is the most precise control the data allow. The point estimates remain unchanged. Finally, column (4) drops the years 1997-2000 and forces the sample to begin in 2001, since the medication and hospitalization data are only available for the period 2001-2007. The resulting estimated impact of the NBP on NO_x emissions is 32 tons per county smaller than that in column (3), although the difference is not statistically significant. These results for NO_x emissions are unchanged in alternative specifications (see Appendix Table 1). In this and most other tables, we focus on the results from the richest specifications in columns (3) and (4).

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 relatively clean natural gas units to displace electricity generation from relatively dirty coal-fired units, then the market could have decreased

[31] 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.
[32] 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.
[33] 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.

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. Such a finding would violate the exclusion restriction required for the NBP market to serve as a valid instrumental variable for ambient ozone levels.

The data do not provide strong evidence that the market affected emissions of co-pollutants. Columns (1) through (3) of Table 2 show that NBP had no impact on emissions of SO_2 or CO_2.[34] Further, the estimated size effects (point estimate over the mean of the dependent variable) for the co-pollutants are all close to zero: In the preferred specification of column (3), they imply a statistically insignificant decrease in SO_2 or CO_2 emissions of about 2%. The estimates become more precise when the sample is limited to begin in 2001, as shown in column (4). This specification suggests that the market led to small, but significant decreases in SO_2 or CO_2. To assess the relevance of these parameter estimates for the exclusion restriction, subsequent tables measure how the market affected ambient pollution.

B. Ambient Pollution

The panels of Figure 3 show how this emissions market affected ambient pollution levels. Panel A shows an event study for average daily ozone concentrations (as measured by the maximum 8-hour value) for the 1997-2007 period. This event study graph is derived from a regression that adjusts for weather and plots the difference between ozone levels in the NBP and non-NBP states, with the year 2001 normalized to zero. The figure shows that before 2003, the NBP and non-NBP states had roughly similar trends, suggesting that this research design provides a credible counterfactual for measuring the impact of the market on ozone. The vertical line in 2003 marks when the market began. The results for the 2003-2007 period indicate that NBP decreased average ozone concentrations by roughly 3 ppb. In fact, as we show below, the NBP market led to a non-uniform shift in the distribution of summer ozone concentrations.

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.[35] Figure 3B shows the pre-NBP market (i.e., 2001-2002 average) distribution of summer ozone daily concentration in the NBP

[34] CO_2 emissions have no local effect on health, and they are only monitored to measure their contribution to climate change. But an impact of the market on CO_2 emissions could indicate that units changed emissions of mercury, toxic chemicals, or other pollutants.

[35] The market's impact on the right tail of ozone is difficult to predict *ex ante*. On one hand, because the market price of NO_x emission permits is roughly constant throughout the summer and the wholesale price of electricity spikes on high-pollution days, one could have expected the market to have the least effect on the right tail of ozone. At the same time, the nonlinearity of ozone formation in its precursors, the differing abatement strategies used by various electricity generating units, and the ability of NO_x to be deposited several days after it is emitted make it possible that the market could have mainly affected the upper tail of the ozone distribution. This *ex ante* ambiguity provides an additional motivation to examine the market's impact on the ozone distribution.

states. It divides the support of the daily 8-hour ozone distribution into 11 bins. The first bin, for example, counts the number of summer days with ozone between 0 and 10 ppb and the second counts the number of summer days with ozone between 10 and 20 ppb. The remaining bins are defined similarly. For the typical county in the NBP states, about 90 summer days (out of a possible 153) have daily ozone concentrations between 30 and 60 ppb, and about 25 summer days have concentrations in excess of 70 ppb (i.e., the last 4 bins).

Figure 3 (C) shows the estimated effect of the NBP market on the number of summer days in each of the 11 bins (thick line with markers), along with the 95% confidence intervals (dashed lines). The market reduced the number of summer days with ozone concentrations greater than 60 ppb and increased the number of days with ozone concentrations less than 60 ppb.[36] It is noteworthy that the EPA has experimented with daily ozone standards of 65, 75, and 85 ppb in 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.

Table 3 statistically summarizes the impact of the NBP on ambient concentrations of ozone and the other pollutants that are most heavily regulated under the Clean Air Act. Electricity generation emits all of these pollutants except CO, and NO_x can undergo reactions to form all of these pollutants except CO and SO_2. If ozone is the only pollutant affected by the NBP, then it may be appropriate to use the NBP as an instrumental variable to identify the impact of ozone concentrations on defensive expenditures and health.

Columns (1) through (4) repeat the specifications from Table 2 and, for efficiency reasons, weight the equation by the square root of the number of monitor observations. The impact of the NBP on ambient pollution concentrations is interesting in its own right. However, the remainder of the paper is focused on explaining per capita defensive expenditures and hospitalization costs and the mortality rate; these equations will naturally be weighted by the relevant population to obtain estimated impacts on the average person. For this reason, column (5) repeats the column (4) specification but uses the population as the weight, instead of the number of monitor observations.

Rows 1 and 2 of Table 3 reveal large and precisely estimated effects of the emissions market on ground-level ozone concentrations. The richest specifications in columns (3) - (5) indicate that the NBP decreased mean summer ozone by 6-7 percent. Importantly, the NBP market also decreased the number of days with ozone above 65 ppb by 7.5 to 8.6 per summer (or 23%-28%).[37]

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[36] These bins are response variables, and each bin estimate results from a separate regression. Although the sum of bin-specific effects must add up to zero, we do not need to normalize the coefficient on any bin to zero. This differs from the use of bins as explanatory variables (e.g., Deschênes and Greenstone 2011).

[37] 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

Rows 3-5 test for impacts 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.[38] Thus, it appears that any impacts of ozone will not be confounded with changes in CO or SO_2.

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. Because NO_2 has limited or possibly no effect on health, this is not a clear problem for the exclusion restriction necessary to identify the impact of ozone.[39]

Air quality models show that atmospheric NO_x can undergo reactions which transform it into a component of particulates. The impact of the NBP on particulates concentrations is of especial 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 2012). 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 simulations in more detail and provides an explanation for why the NBP might not affect the particulates concentrations. We 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, in rows 6 and 7 of Table 3.

The results about particulates concentrations are mixed. 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}

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.

[38] 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.

[39] Lippman (2009, p. 830), in the third edition of his widely-cited reference text on the health effects of pollution, summarizes the evidence as follows: "[G]iven the available epidemiological evidence, it is not possible to provide an unequivocal conclusion regarding adverse health effects of NO_2. There have been both positive and negative findings at various levels of NO_2 exposure."

monitors, there continues to be no evidence of a meaningful change in PM_{10}.[40] Overall, these 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.[41]

C. Defensive Investments

This section explores the relationship between the NBP market and the resources people devote to defending themselves against air pollution. This relationship is important in its own right as a partial measure of the NBP's social benefits, and in the instrumental variables framework where it may also be valid to interpret it as the reduced-form relationship between the instrument and each outcome. Figure 4 provides a graphical answer: It plots the difference in log medication purchases per person-season in the NBP and non-NBP states during the summer versus winter, after adjustment for the detailed weather controls, county-by-year, season-by-year and county-by-season fixed effects (as in column (5) of Table 3). The 2001 difference is normalized to zero. The graphs show little change in 2002, before the market began. After the market began to operate in 2003, the estimate on the difference in expenditures on medications ranges between 0% and 4% in each of the subsequent years; notably, the annual declines for 2005-7 are all statically significant at the 7% level or better.

Table 4 reports regression analogues of this graph: It shows the reduced-form effect of the market on log medication costs. The richest specification in column (3) indicates that the NBP reduced total medication costs by 1.9 percent. This estimate is precise with the full set of controls, and has similar magnitude but less precision with less detailed controls. Column (4) reports the results from fitting the column (3) specification on the smaller sample of counties with ozone monitors that have a 2004 population of 97 million; the results are similar to those in column (3). 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.[42]

[40] Current EPA regulations focus on $PM_{2.5}$. As a result, PM_{10} monitors only satisfy the monitor selection criteria in 39 counties in this period (Table 1).

[41] 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.

[42] We separately estimated these regressions for children and obtained results with similar magnitude though less precision. Based on National Drug Codes, we also attempted to distinguish "maintenance" respiratory medications, which are taken every day or week to treat chronic respiratory conditions, from "rescue" respiratory medications, which are taken once acute respiratory symptoms appear. We again obtained similar negative parameter estimates for both categories, though with less precision.

We also measure medication purchases separately by cause. As discussed earlier, 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 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 estimates in row 2 indicate that the NBP decreased expenditures on respiratory and cardiovascular medications by 2.3 percent in column (3). This estimate would 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, these results together suggest that the NBP had little impact on medications for gastrointestinal problems.

Appendix Table 2 reports the results from a series of robustness checks, none of which alter the qualitative conclusions. All the results are from Table 4's column (3) specification and sample. Four specifications change the level of clustering; statistical precision is similar with most alternatives, though generally lower with state clusters. Using data on the number of medications, rather than on medication costs, produces similar patterns. The MarketScan balanced panel of people implies slightly smaller effects on medication purchases. Using medication levels or dollars per person, rather than logs, produces results that are generally similar, although the distribution of medication purchases is skewed, making the log specification more appropriate. The rest of the paper uses the average paid-cost by National Drug Code, to aggregate over measurement error from individual reports. Using purchase-specific costs obtains similar results, although it also produces a large estimate for gastrointestinal drugs.

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. Figure 5 repeats the exercise from Figure 4, but per person-season hospitalization costs is the dependent variable. The line is estimated imprecisely but it is nearly flat, indicating that there is little evidence that the NBP affected hospitalization costs.

The corresponding regression estimates confirm the visual impression. Column (3) of Table 5 reports that the market decreased hospitalization costs by about \$6.00 per person-year or roughly 1%, and that this estimate is not statistically significant. We find a similar result when the log of hospitalization costs is used as the dependent variable (see Appendix Table 3). The sign of the parameter estimates suggest that the market decreased cardiovascular and respiratory hospitalizations, but this result also is imprecise. A different story is evident in column (4), which restricts the sample to the 168 counties with ozone monitors that account for 37% of the population in the column (3) sample; these entries indicate large and statistically significant declines in hospitalizations costs. Overall, our judgment is that the balance of evidence suggests that the NBP did not have a detectable impact on hospitalization costs, and we do not pursue this outcome further.

Mortality. Finally, we assess the NBP's impact on mortality. In most analyses of air pollution, mortality accounts for the largest share of the regulatory benefits. Figure 6 repeats the event-study graph from Figures 4 and 5 for the mortality rate (deaths per 100,000 population) for people aged 75 and over; this section will demonstrate that the effect on the overall mortality effect is concentrated in this population. Although the estimates are noisy, it is evident that summer mortality rates are lower after the market began operating in the NBP states.

The statistical results are reported in Tables 6 and 7. In the full sample, the emissions market 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, indicating a reduction of 5.4 deaths per 100,000 population.

Across the columns, an analysis of cause-specific mortality rates reveals that 35% to 56% of the decline in overall mortality is concentrated among cardiovascular/respiratory deaths. We find that the market had no effect on external (primarily accidents) deaths, which is a reassuring placebo test. Further, the impacts on neoplasms are small and statistically insignificant. This result was unknown *ex ante* since the relationship between ozone and cancer remains uncertain (NRC 2008). We also consider all causes of mortality other than respiratory, cardiovascular, and neoplasm. There is evidence that deaths from all other causes significantly declined also. Appendix Table 4 reports on a series of specification checks that leave the qualitative findings unchanged, although the statistical significance of the mortality effect is more sensitive to assumptions about the variance-covariance matrix.

Table 7 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) in Table 6). 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. 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 (column (2)).

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%. These comparisons suggest that the market had larger effects on the mortality rates of the elderly than of the non-elderly. Moreover, because baseline mortality rates are relatively high for the elderly, the absolute number of deaths prevented by this market is especially concentrated among the elderly.

These results suggest that the NBP market prevented deaths which would have occurred during the summer. But the people who die from ozone pollution may have pre-existing respiratory, cardiovascular, or other medical conditions which cause them to have limited life expectancies, even for people in this age category. In the extreme, the market could merely have moved the date of these deaths to the winter months immediately following the market. Because the regressions reflect a triple-difference estimator which compares summer and winter deaths within a year, any deaths displaced from summer to October-December of the same year would cause the triple-difference estimator to overstate the impact by a factor of two.[43]

We explored two approaches to investigate the empirical relevance of this possibility of 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 did 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. Nonetheless, these estimates were imprecise and could not reject the null hypothesis that the market had no long-run impact on mortality.

The focus of this paper on the summertime mortality rate is an advance from the previous literature which has primarily estimated how ozone affects same-day or same-week mortality rates.[44] Because the approaches described above obtained imprecise estimates of the market's long-run effect on mortality, however, 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.

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[43] For example, if the market displaced one death per 100,000 from July to December of the same year, then the triple-difference regression would imply a regression coefficient of two since the market would have both raised winter deaths and decreased summertime deaths.

[44] Currie and Neidell (2005) 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 measure the "structural" effect of ozone on health. This parameter – the social cost of marginal reductions in ozone – is widely used in economic and policy analysis (e.g., Fowlie, Knittel, and Wolfram 2009). 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. Definitive evidence of an impact of NBP on particulates concentrations would violate the IV approach's exclusion restriction.

Panel A of Table 8 first reports a simple association of ozone with medication purchases and with mortality rates for the elderly. The OLS and IV regressions use the same data, so each observation represents a county-year-season. These results are from regressions of the indicated outcome on alternative measures of ozone concentrations and are adjusted for county fixed effects, year fixed effects, and detailed weather controls. The OLS medication regressions have varying signs, and the only statistically significant associations suggest ozone concentrations purchases of gastrointestinal medications, which are 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. OLS estimates do detect some effects of ozone on overall mortality.

The OLS mortality regressions are more consistent across the two measures of ozone and suggest that there is a positive association between ozone concentrations and mortality rates. However, they also detect effects of ozone on external causes of death, which raises concerns about whether these OLS regressions are biased by omitted variables.

Two-stage least squares estimates use the same sample as OLS and detect significant effects of ozone on medication purchases, with a semi-elasticity of 0.007 for average 8-hour ozone and .002 for the number of days when the ozone concentration exceeds 65 ppb. These estimates imply that a 10% increase in mean ozone leads to a 2.2% increase in medication purchases. There is also a significant effect for respiratory/cardiovascular related medication purchases but no effect on gastrointestinal medications.

The mortality estimates also imply large direct effects of ozone. The 2SLS point estimates suggest that a 1 ppb increase in ozone pollution leads to 2.6 additional summertime deaths per 100,000 people. This implies an elasticity of mortality with respect to ozone of 0.22.[45] These elasticities may seem large: However, 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, which could reflect 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 37% of the 262 million people in the counties covered by the mortality data.[46]

If it were appropriate to interpret these estimates causally, they would lead to a substantial change in 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 what we obtain.[47] Further, we are unaware of any evidence on the relationship between ozone and defensive expenditures measured by medication purchases.

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

The results of this paper let us report a simple cost-benefit analysis for the entire NO_x Budget Trading Program, with the caveat that we only calculate some of the health benefits of this market. Nevertheless, as we emphasized before, our analysis includes a larger set of health outcomes than most of the previous literature. The estimates in Table 2 imply that the NBP market decreased NO_x emissions by 365,750 tons per summer.[48] The average cost of a NO_x permit during the market was $2,080/ton. Because firms should only use abatement technologies which cost less than the permit price, the permit price represents an upper bound on the abatement cost. Specifically, this approach implies that the market required firms to spend some amount less than $759 million per year to abate NO_x. 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 * 4.5). These costs are reported in Panel A of Table 9.[49]

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[45] Multiplying the 2SLS coefficient by weighted mean ozone divided by weighted mean mortality rate in the 2SLS sample gives 1.682 * (40.73 / 309.73) = 0.22.

[46] We explored estimates with two-sample instrumental variables (TSIV), which use the 168 counties with ozone monitors for the first-stage and the 2,539 counties with mortality data for the reduced-form, then combine them in a Wald estimator. This approach has disadvantages because it assumes that the first-stage is the same in counties with and without ozone monitors—an assumption at odds with most atmospheric chemistry models of ozone formation.

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

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

[49] Our measurement of abatement costs is based on permit prices. Recent research using aggregated labor data suggests that the NBP decreased employment in regulated industries (Curtis 2012).

We can now turn to estimating the social benefits of the NBP. As we discussed above, it is tempting to assume that a change in pharmaceutical purchases are simply a transfer from consumers to pharmaceutical firms and thus have zero social cost. However, lower levels of air pollution and the resulting decline in medication purchases that protect individuals from air pollution will free resources used to develop these types of drugs and allow them to be applied to more productive uses. Monetizing the social value of these freed resources is not straightforward, so we use the value of the drug purchases as a proxy. Table 9 shows that this emissions market let Americans decrease medication expenditures by about \$900 million per year, or \$4 billion when summed over the 4.5 years during which NBP was implemented.

If the mortality estimates are taken literally, they imply that the market prevented about 2,200 deaths annually. The monetary value assigned to these deaths depends on the value of a statistical life (VSL). In Table 9, we take Ashenfelter and Greenstone's (2004) upper bound VSL of \$1.93 million (\$2006\$) for a prime age person and use Murphy and Topel's (2006) method to develop estimates of the VSL for each age group in our analysis. This is especially important in this setting where the avoided fatalities are largely coming from 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.[50]

The final column of Table 9 allows for a comparison of the costs and benefits. An 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. This finding demonstrates that defensive investments are economically important in this context. Once the value of the reduced rates of mortality are added in, the benefits of the market exceeded the upper-bound of its abatement costs by 232% (7.9 / 3.4). 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 with an expected announcement of an updated standard in 2013. 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

[50] 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. Because Murphy and Topel calculate a VSL for each 1-digit age, to obtain a VSL for the four aggregated age categories in Table 7, we calculate the weighted average of the 1-digit age VSLs within each of the four age categories, with weight equal to the share of deaths from each 1-digit age group. 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.

decrease in the mean summer ozone concentration in the Eastern U.S. is worth approximately $1.3 billion in social benefits. Similarly, one fewer day per summer nationally with an ozone concentration exceeding 65 ppb would yield roughly $500 million of benefits.

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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Appendix: 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)

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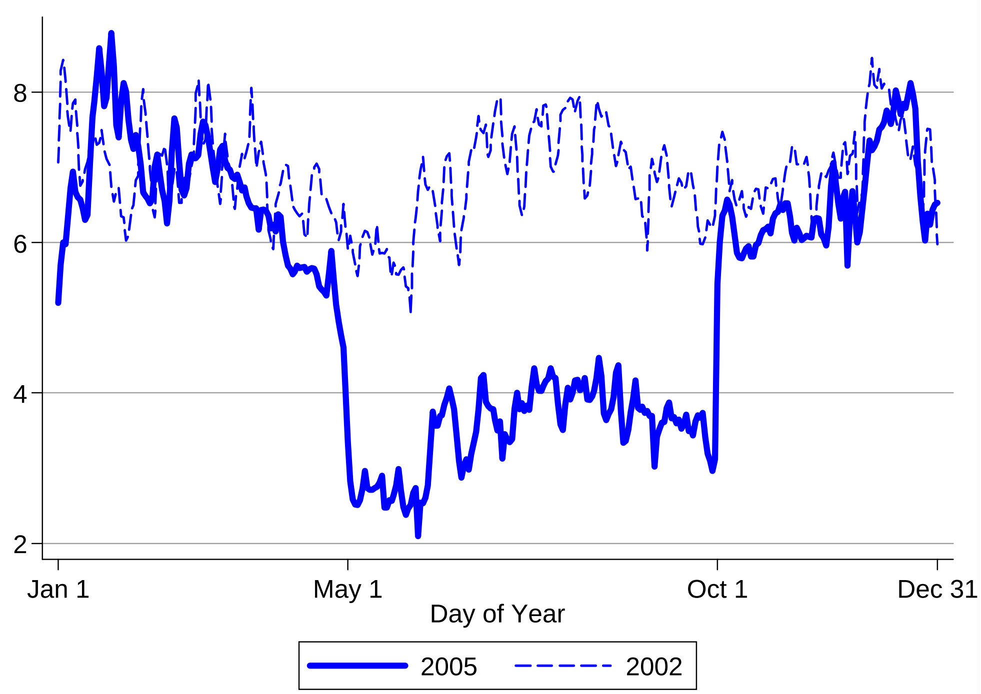
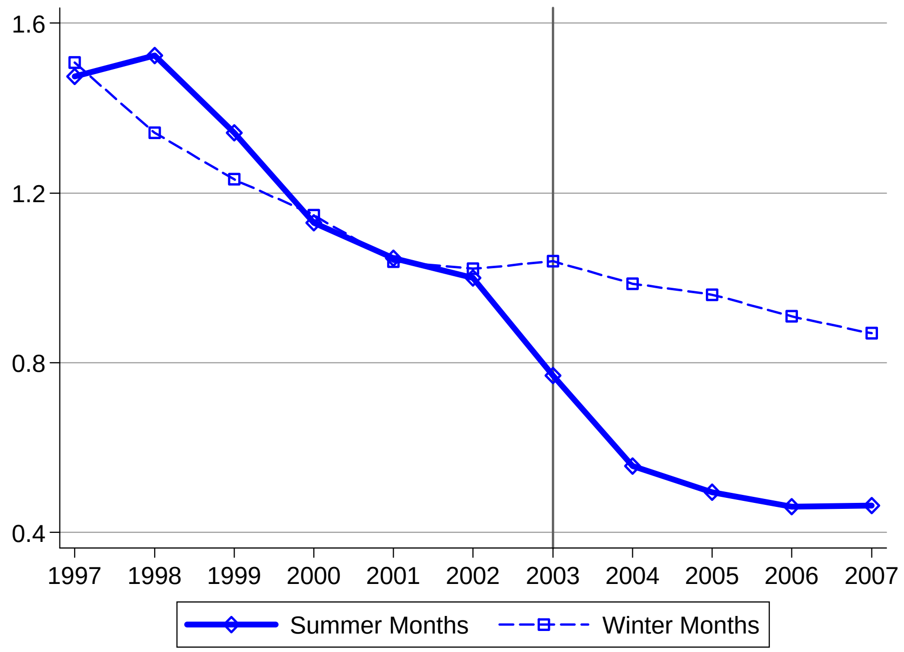
Figure 1. Total Daily NO_X Emissions in NBP-Participating States



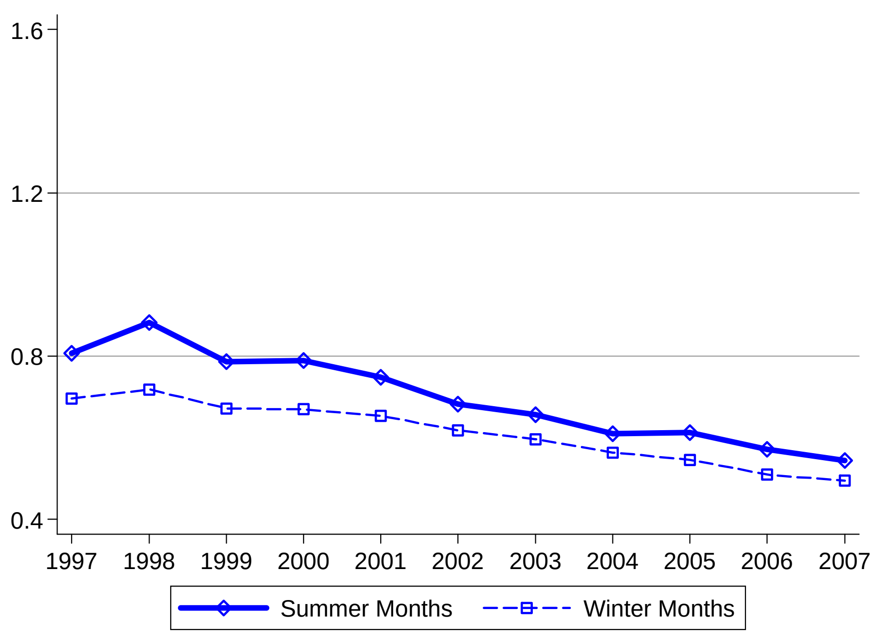
Notes: Graph depicts values from an OLS regression of NO_x emissions on 6 day-of-week indicators and a constant. We control for day-of-week fixed effects since additional electricity generation on weekdays adds visible weekly cycles to the image, although the overall picture is unchanged in the raw data. 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. Summer-Equivalent Seasonal NO_x Emissions (Mil. Tons)

(A) States Participating in NBP



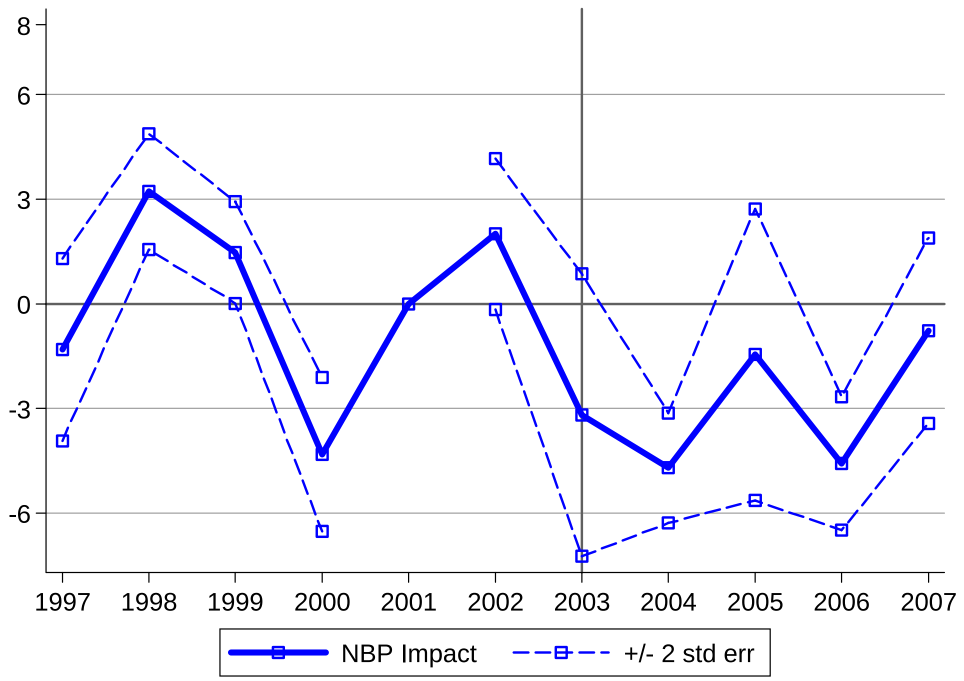
(B) States Non-Participating in NBP



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. 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. States not participating in NBP include: Arkansas, Arizona, California, Colorado, Florida, Idaho, Kansas, Lousiana, Minnesota, Montana, Nebraska, Nevada, New Mexico, North Dakota, Oklahoma, Oregon, South Dakota, South Carolina, Texas, Utah, Washington, Wyoming. Alaska, Georgia, Hawaii, Iowa, Maine, Mississippi, Missouri, New Hampshire, Vermont, and Wisconsin are excluded from the main analysis sample. See the text for more details.

Figure 3. NBP Market Impact on Ambient Ozone Pollution

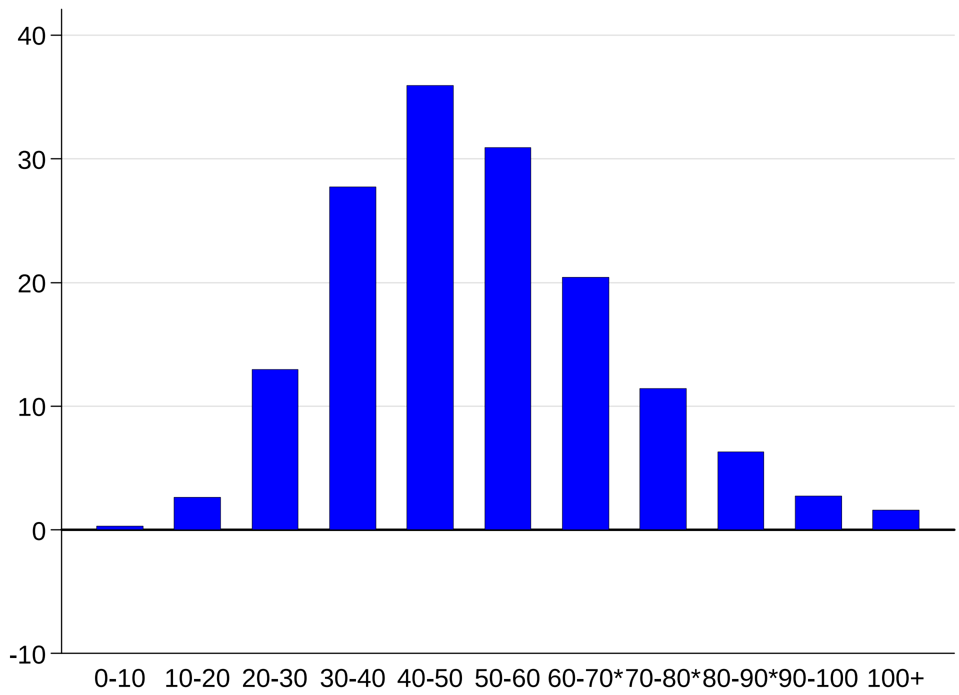
(A) Event Study for Daily Ozone 8-Hour Values, 1997-2007



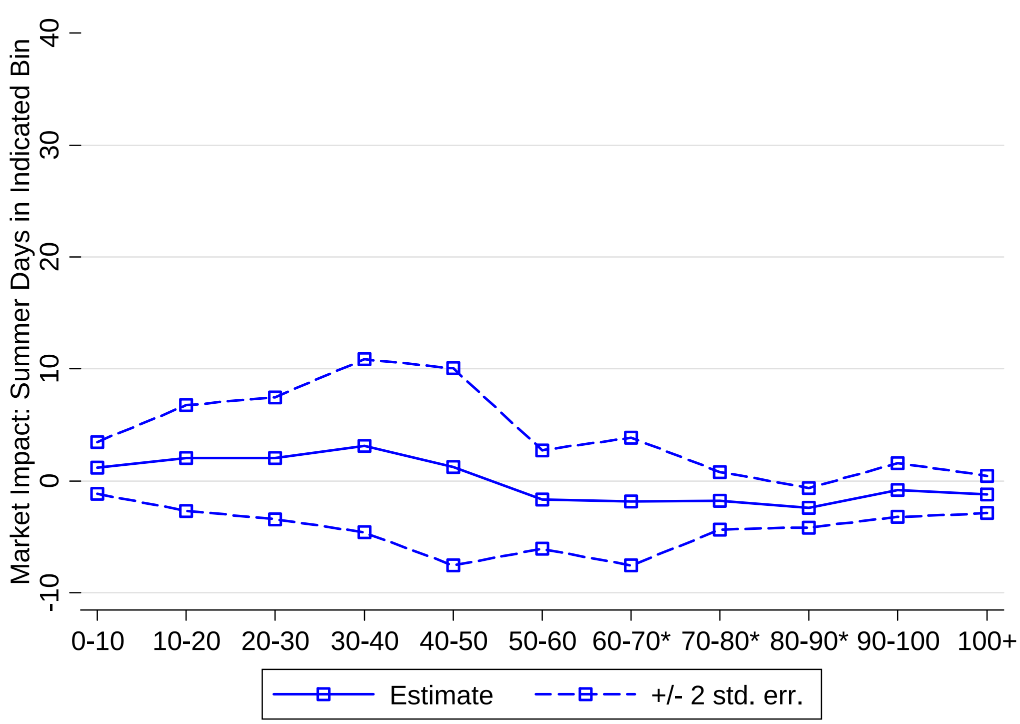
Notes: Ozone 8-hour value is measured as the maximum rolling 8-hour mean of hourly values within each day, which is the statistic used in EPA non-attainment designations. Estimate for year 2001 restricted to take a value of 0. Regression models include detailed weather controls, and a full set of county*year, season*year, and county*season fixed effects. Regression is GLS weighted by the square root of the number of underlying pollution readings. Standard errors based on covariance matrix allows arbitrary autocorrelation within each state-season. See Figure 2 notes or text for NBP participation status designation. See Appendix Table 5 for the full set of estimates underlying this figure.

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

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



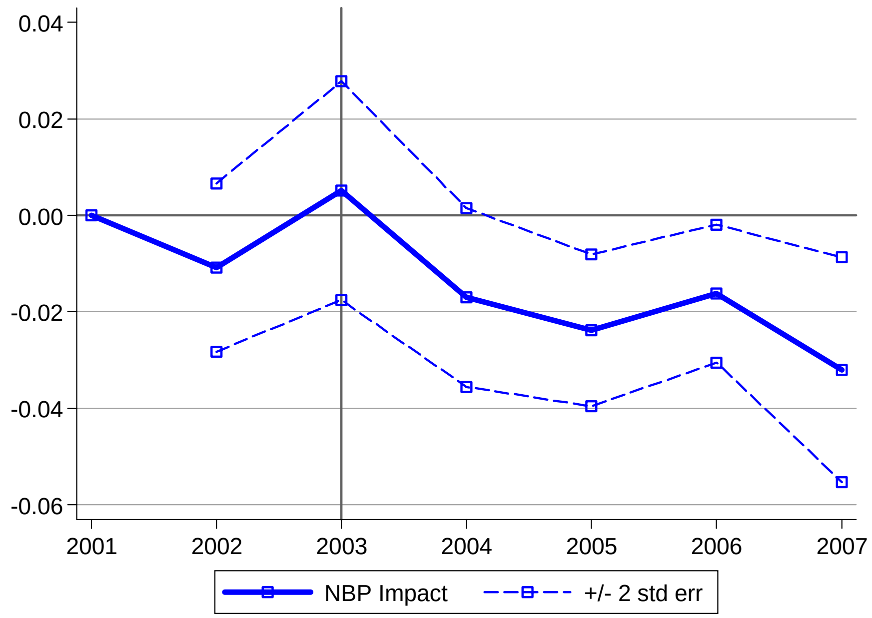
(C) NBP Market Impact on Number of Summer Days in 11 Ozone Bins



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

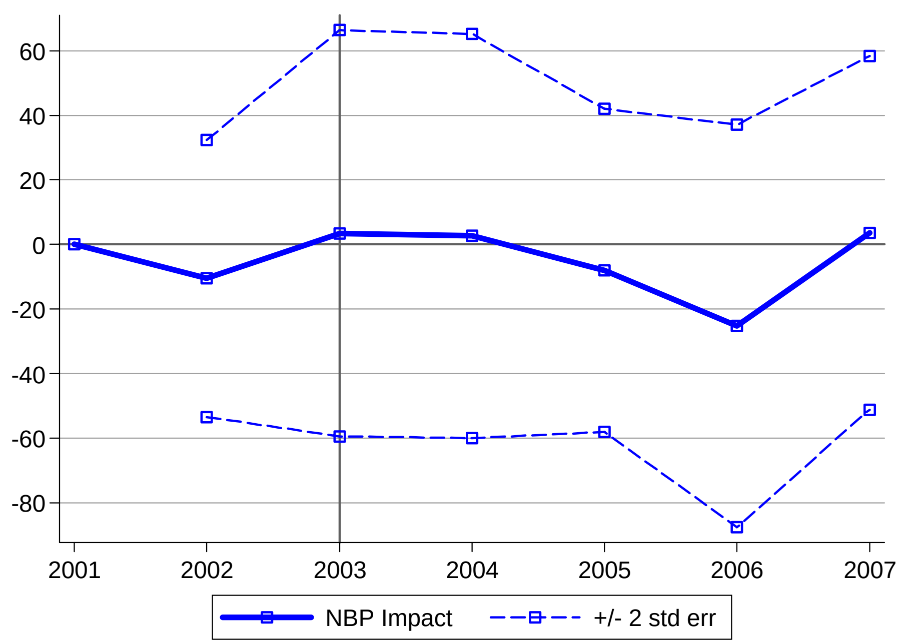
2001-2002 (pre-NBP period). Panel C shows the estimated impact of NBP on the number of summer days in 11 categories for daily ozone 8-hour value. The asterisks in the x-axis of Panel C represent EPA non-attainment standards in ppb: 85 (1997 standard), 75 (2008 standard), and 60-70 (2010 proposed standard). Estimates in Panel C are based on regression models that include detailed weather controls, and a full set of county*year, season*year, and county*season fixed effects. Regression in Panel C is GLS weighted by the square root of the number of underlying pollution readings. Standard errors based on covariance matrix allows arbitrary autocorrelation within each state-season. See Figure 2 notes or text for NBP participation status designation.

Figure 4. Impact of NBP Market on Log Medication Costs ($2006)



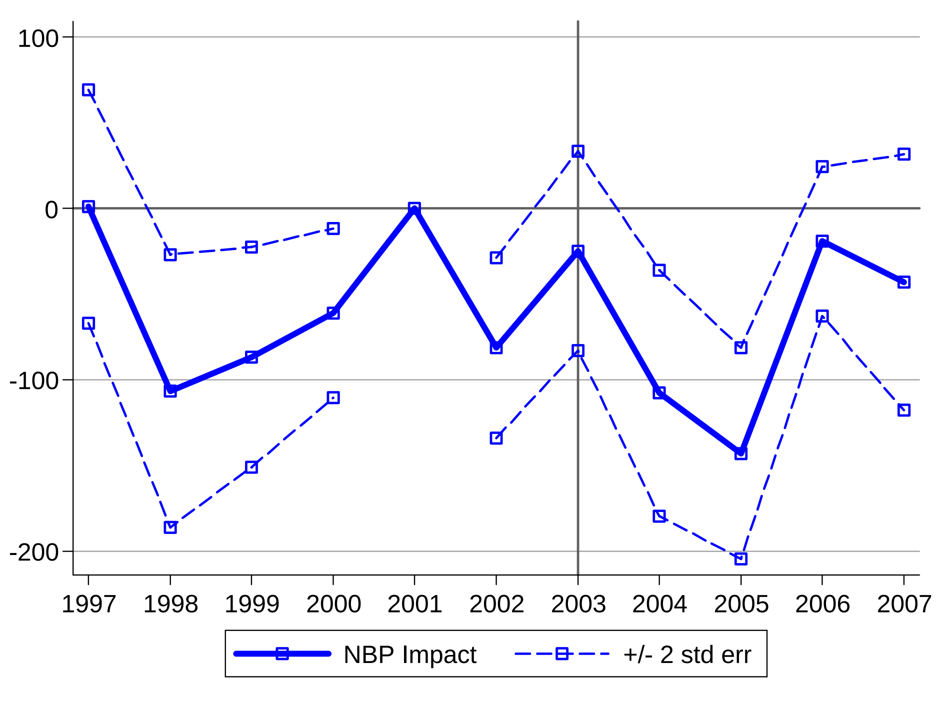
Notes: Log medication cost is the log of total medication costs per person-season in a county. All medication and hospital costs are in 2006 dollars, deflated using the BLS CPI for urban consumers. Estimate for year 2001 restricted to take a value of 0. Regression models include detailed weather controls, 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 Figure 2 notes or text for NBP participation status designation.

Figure 5. Impact of NBP Market on Hospital Costs ($2006)



Notes: Hospitalization costs are total hospitalization costs per person-summer in a county. All medication and hospital 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 Figure 2 notes or text for NBP participation status designation.

Figure 6. Impact of NBP Market on Mortality Rates: Elderly Mortality



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 Figure 2 notes or 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)	[0.090]
SO_2 Emissions	2,539	1.50	(6.52)	84	2.92	(6.20)	84	1.41	(4.04)	[0.000]
CO_2 Emissions	2,539	384	(1,299)	84	1,263	(1,896)	84	918	(2,030)	[0.003]
Ambient Pollution										
Ozone 8-Hour Value	168	48.06	(9.28)	84	41.28	(6.10)	84	54.85	(6.58)	[0.000]
Ozone Days ≥65 (ppb)	168	23.60	(22.64)	84	10.93	(9.41)	84	36.28	(24.81)	[0.000]
NO_2 (ppb)	110	11.45	(5.39)	34	8.67	(4.57)	37	12.15	(4.85)	[0.000]
CO (ppm)	125	0.44	(0.24)	35	0.46	(0.22)	33	0.42	(0.17)	[0.058]
$PM_{2.5}$ ($\mu g/m^3$)	298	13.33	(4.19)	47	10.70	(3.01)	45	11.63	(4.45)	[0.002]
PM_{10} ($\mu g/m^3$)	39	27.28	(6.26)	4	25.14	(3.85)	6	29.70	(6.86)	[0.002]
SO_2 (ppb)	150	3.26	(2.27)	32	2.04	(1.49)	33	2.60	(1.97)	[0.001]
Weather										
Temperature (ºF)	2,539	70.59	(5.79)	84	73.82	(7.40)	84	72.40	(5.90)	[0.000]
Precipitation (1/100")	2,539	11.46	(5.37)	84	13.91	(8.59)	84	7.35	(6.12)	[0.000]
Dew Point Temp. (ºF)	2,539	58.31	(7.58)	84	62.36	(8.59)	84	55.28	(9.57)	[0.000]
Medication Costs ($ Per Person)										
All	2,435	338.53	(302.10)	84	269.69	(84.92)	84	284.89	(107.62)	[0.007]
Respiratory + Cardio.	2,435	87.84	(97.86)	84	69.33	(28.66)	84	70.94	(30.18)	[0.348]
Hospitalizations ($ Per Person)										
All	2,435	502.62	(2120.44)	84	474.77	(418.56)	84	484.25	(703.12)	[0.779]
Respiratory + Cardio.	2,435	99.69	(768.61)	84	92.47	(250.19)	84	73.58	(142.45)	[0.112]
Mortality (Deaths Per 100,000 People)										
All	2,539	402.42	(121.32)	79	331.26	(89.47)	79	316.25	(76.94)	[0.003]
Respiratory + Cardio.	2,539	180.80	(69.93)	79	144.31	(45.37)	79	137.08	(39.59)	[0.005]

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 Emitted Pollution

	(1)	(2)	(3)	(4)
1. NO_x	-0.362***	-0.375***	-0.366***	-0.330***
	(0.053)	(0.053)	(0.071)	(0.066)
Effect / Mean	-0.344	-0.356	-0.348	-0.384
2. SO_2	-0.077**	-0.115	-0.071	-0.069**
	(0.037)	(0.070)	(0.048)	(0.033)
Effect / Mean	-0.027	-0.040	-0.024	-0.027
3. CO_2	-3.338	-19.036	-6.187	-12.647*
	(4.384)	(16.070)	(6.127)	(6.610)
Effect / Mean	-0.008	-0.043	-0.014	-0.029
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
Data Begin in 2001				x

Notes: Each observation represents a county-year-season. Winter emissions are multiplied by 5/7, so all values are summer-equivalent. Response variable measured in thousands of tons. Mean represents 2001-2002 summer in NBP areas. Covariance matrix allows arbitrary autocorrelation within each state-season. 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 Ambient Pollution

	(1)	(2)	(3)	(4)	(5)
1. Ozone 8-Hour Value	-2.910***	-4.223***	-2.965***	-3.250***	-3.428***
	(0.773)	(1.236)	(0.747)	(0.597)	(0.600)
Effect / Mean	-0.057	-0.082	-0.058	-0.063	-0.068
2. Ozone Days ≥ 65	-7.395***	-8.264***	-7.461**	-8.401***	-8.621***
	(2.504)	(2.746)	(2.964)	(2.546)	(2.511)
Effect / Mean	-0.229	-0.255	-0.231	-0.251	-0.278
3. CO: Carbon Monoxide	-0.048**	-0.036	-0.042	-0.017	0.000
	(0.023)	(0.027)	(0.035)	(0.026)	(0.028)
Effect / Mean	-0.091	-0.068	-0.081	-0.033	0.000
4. SO_2: Sulfur Dioxide	0.159	0.157	0.097	0.106	0.123
	(0.122)	(0.248)	(0.183)	(0.157)	(0.148)
Effect / Mean	0.034	0.034	0.021	0.023	0.029
5. NO_2: Nitrogen Dioxide	-1.130***	-0.023	-1.210***	-0.995***	-1.249**
	(0.209)	(0.895)	(0.397)	(0.370)	(0.485)
Effect / Mean	-0.067	-0.001	-0.072	-0.061	-0.068
6. $PM_{2.5}$: Particulates Less than	n.a.	n.a.	n.a.	-0.382	-1.011***
2.5 Micrometers	n.a.	n.a.	n.a.	(0.278)	(0.277)
Effect / Mean	n.a.	n.a.	n.a.	-0.023	-0.062
7. PM_{10}: Particulates Less than 10	n.a.	n.a.	n.a.	-0.896	0.114
Micrometers	n.a.	n.a.	n.a.	(1.018)	(1.249)
Effect / Mean	n.a.	n.a.	n.a.	-0.030	0.004
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 Begin in 2001				x	x
Weighted by Population					x

Notes: Each observation represents a county-year-season. Pollution readings are mean values. Regressions are GLS weighted by the square root of the number of underlying pollution readings unless otherwise noted. Insufficient PM data are available for the 1997-2007 period. Mean is for 2001-2002 summers in NBP States. Covariance matrix allows arbitrary autocorrelation within each state-season. Unless otherwise noted, data begin in 1997. 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). Asterisks denote p-value < 0.10 (*), <0.05 (**), <0.01 (***).

Table 4. Effect of NBP Emissions Market on Log Medication Costs

	(1)	(2)	(3)	(4)
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
Counties With Ozone Monitors				x

Notes: All currency in 2006 dollars deflated using BLS CPI for urban consumers. Dependent variable is log of medication costs per person-season-year in a county. Regressions are GLS with weight equal to square root of MarketScan population in a given county-year-season. Covariance matrix allows arbitrary autocorrelation within each state-season. Asterisks denote p-value < 0.10 (*), <0.05 (**), <0.01 (***). 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.

Table 5. Effect of NBP Emissions Market on Hospitalization Costs

	(1)	(2)	(3)	(4)
1. All Hospitalizations	-5.317	-0.470	-5.997	-78.509***
	(17.127)	(17.438)	(18.948)	(23.759)
2. Respiratory + Cardiovascular	-8.148*	-8.256	-8.702	-44.872***
	(4.728)	(5.226)	(5.717)	(9.822)
3. External	-2.749	-2.931	-3.629	-15.494
	(3.755)	(4.425)	(6.486)	(9.366)
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
Counties With Ozone Monitors				x

Notes: All currency in 2006 dollars deflated using BLS CPI for urban consumers. Dependent variable is dollars per person-season-year in each county-year-season cell. Regressions are GLS with weight equal to square root of MarketScan population in a given county-year-season. Covariance matrix allows arbitrary autocorrelation within each state-season. Asterisks denote p-value < 0.10 (*), <0.05 (**), <0.01 (***). Number of observations is 31,822 for columns (1) to (3) and 2,352 for column (4). Number of observations differs from Table 4 because the log response variable of Table 4 excludes cells with no drug purchases.

Table 6. Effect of NBP Emissions Market on Mortality Rates

	(1)	(2)	(3)	(4)	(5)
1. All Deaths	-2.145**	-3.033	-1.557*	-5.410***	-2.666*
	(0.937)	(3.469)	(0.813)	(1.825)	(1.539)
2. Respiratory + Cardiovascular	-0.745	-1.700	-0.547	-2.282*	-1.113
	(0.492)	(1.810)	(0.675)	(1.229)	(0.997)
3. Neoplasm	0.089	0.153	0.099	-0.172	-0.142
	(0.280)	(0.752)	(0.268)	(0.401)	(0.395)
4. External	0.307	-0.073	0.115	-0.658	0.174
	(0.206)	(0.368)	(0.309)	(0.657)	(0.382)
5. All Other	-1.488***	-1.486	-1.109**	-2.956***	-1.411*
	(0.379)	(1.094)	(0.425)	(0.781)	(0.715)
Observations	55,858	55,858	55,858	3,124	35,546
Clusters	82	82	82	48	82
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 Begin in 2001					x

Notes: Dependent variable is deaths per 100,000 population in each county-year-season cell. Regressions are GLS with weight equal to square root of population in a given county-year-season. Covariance matrix allows arbitrary autocorrelation within each state-season. "All Other" row corresponds to all causes of death other than respiratory, cardiovascular, and neoplasm. Unless otherwise noted, data begin in 1997. Asterisks denote p-value < 0.10 (*), <0.05 (**), <0.01 (***). Asterisks denote p-value < 0.10 (*), <0.05 (**), <0.01 (***).

Table 7. Effect of NBP Emissions Market on Mortality Rates, by Age

Cause of Death	All	Respiratory + Cardio.
	(1)	(2)
1. Age 0 (Infants)	-4.612	-1.853
	(6.277)	(1.212)
Response Var Mean	306	13
Estimated Change in 2005 Deaths	-81	-33
2. Ages 1-64	-0.144	0.241
	(0.503)	(0.257)
Response Var Mean	104	30
Implied 2005 Deaths	-168	281
3. Ages 65-74	-1.492	-3.175
	(5.997)	(3.505)
Response Var Mean	964	417
Estimated Change in 2005 Deaths	-132	-282
4. Ages 75+	-20.700*	-11.198
	(10.846)	(9.841)
Response Var Mean	3,182	1,795
Estimated Change in 2005 Deaths	-1,794	-970

Notes: Dependent variable is deaths per 100,000 population in each county-year-season cell. Regressions are GLS with weight equal to square root of population in a given county-year-season. Covariance matrix allows 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). Sample includes 1997-2007 data. Asterisks denote p-value < 0.10 (*), <0.05 (**), <0.01 (***).

Table 8. Effect of Ambient Ozone on Medication Purchases and Mortality: Ordinary Least Squares and Instrumental Variables Estimates, 2001-2007

	Log Medication Costs			Mortality			
	All	Respiratory + Cardio.	Gastrointestinal	All	Respiratory + Cardio.	External	All Other
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: OLS							
8-Hour Ozone	-0.002	-0.002	-0.003*	0.271***	0.081*	0.054**	0.133***
	(0.001)	(0.001)	(0.001)	(0.084)	(0.049)	(0.021)	(0.030)
Days ≥65 ppb	0.000	0.000	0.000	0.113***	0.035**	0.014**	0.058***
	(0.000)	(0.000)	(0.000)	(0.025)	(0.016)	(0.007)	(0.008)
Panel B: 2SLS							
8-Hour Ozone	0.007***	0.005**	0.001	2.596**	1.194	0.234	1.401***
	(0.001)	(0.002)	(0.003)	(1.183)	(0.769)	(0.184)	(0.318)
Days ≥65 ppb	0.002***	0.002**	0.000	1.033*	0.475	0.093	0.557***
	(0.001)	(0.001)	(0.001)	(0.581)	(0.351)	(0.075)	(0.194)

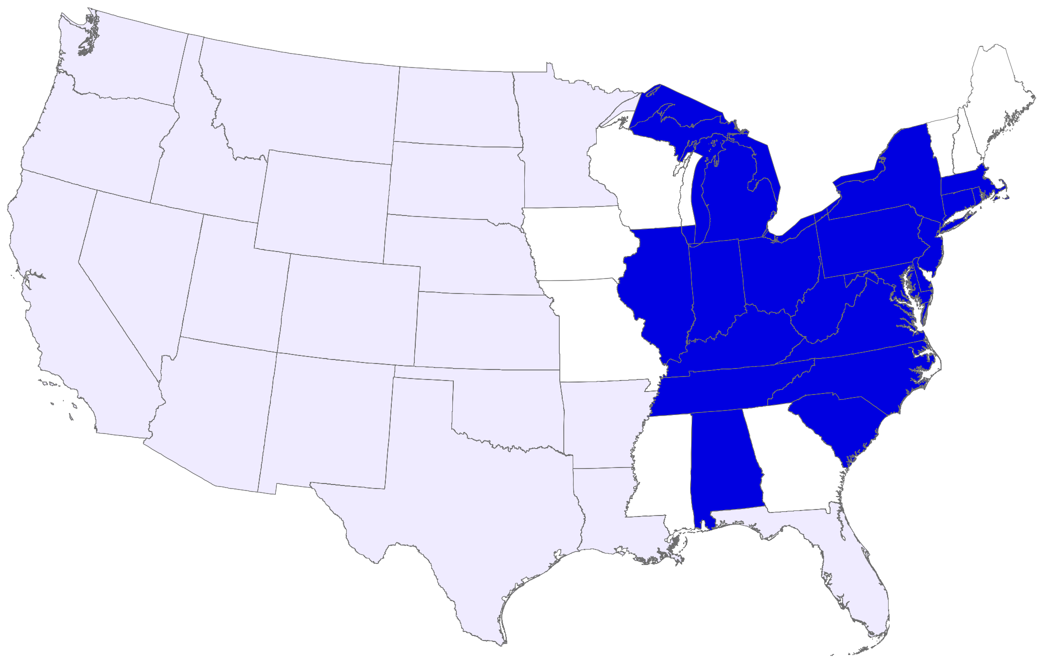
Notes: Endogenous variable is ozone. Excluded instrument is Summer*Post*NBP. OLS includes county fixed effects, year fixed effects, and detailed weather control variables. Data includes population of all ages. IV regression includes specification of Table 6, column (5). GLS weights equal square root of the relevant population. Regressions use counties with ozone monitors. Covariance matrix allows arbitrary autocorrelation within each state-season. Asterisks denote p-value < 0.10 (*), <0.05 (**), <0.01 (***).

Table 9. The Welfare Impacts of the NBP and the Social Benefits of Ozone Reductions

	Medications ($ Million)	Mortality		Total ($ Million)
		Number of Deaths	Monetized Value ($ Million)	
Panel A. An Upper Bound Estimate of NBP's Social Costs				
Upper Bound Per Year				$759
Upper Bound, 2003-2007 Total				$3,414
Panel 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
Panel 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 C takes the IV estimates from Table 8 and applies them to the full population of the NBP region.

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 Table 1. Sensitivity Analysis: Emitted and Ambient Pollution

	Emitted Pollution			Ambient Pollution						
	NO_x	SO_2	CO_2	Ozone	Ozone≥65	CO	$PM_{2.5}$	PM_{10}	SO_2	NO_2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1. Original	-0.330	-0.069	-12.647	-3.250	-8.401	-0.017	-0.382	-0.896	0.106	-0.995
State-Season Clusters	(0.066)***	(0.033)**	(6.610)*	(0.597)***	(2.546)***	(0.026)	(0.278)	(1.018)	(0.157)	(0.370)***
County Clusters	(0.075)***	(0.054)	(7.598)*	(0.535)***	(2.442)***	(0.033)	(0.311)	(1.229)	(0.236)	(0.474)**
State Clusters	(0.093)***	(0.047)	(9.406)	(0.842)***	(3.591)**	(0.036)	(0.390)	(1.443)	(0.221)	(0.523)*
State-Year Clusters	(0.050)***	(0.041)*	(6.465)*	(1.205)***	(3.770)***	(0.029)	(0.487)	(1.404)	(0.178)	(0.408)**
County-Season Clusters	(0.053)***	(0.038)*	(5.372)**	(0.382)***	(1.747)***	(0.024)	(0.223)*	(0.874)	(0.169)	(0.338)***
2. Counties With Ozone	-0.228*	-0.251	-69.209	-3.250***	-8.401***	-0.016	-0.583	-4.133	0.152	-1.111*
Monitors	(0.121)	(0.204)	(45.352)	(0.597)	(2.546)	(0.029)	(0.411)	(5.807)	(0.251)	(0.569)
3. Including ME, NH, and	-0.330***	-0.068**	-12.373*	-3.250***	-8.401***	-0.019	-0.380	-1.067	0.106	-0.995***
VT	(0.066)	(0.032)	(6.415)	(0.597)	(2.546)	(0.025)	(0.273)	(1.053)	(0.157)	(0.370)
4. Monitors Operating ≥				-2.962***	-10.872***	-0.018	-0.519**	-0.055	0.098	-0.649*
30 weeks				(0.451)	(1.900)	(0.023)	(0.260)	(1.183)	(0.143)	(0.388)
5. Summer*Post*NBP				0.220	1.026					
*VOC-Constrained				(1.179)	(4.631)					
6. Summer*Post*NBP*				1.537***	4.936**					
(High Weekend O_3)				(0.572)	(2.290)					

Notes: Unless otherwise noted, each table entry shows the coefficient on Summer*Post*NBP from a separate regression. Regression uses specification and sample of Tables 2-3 column (4) unless otherwise noted. 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. Regressions use 2001-2007 data. Asterisks denote p-value < 0.10 (*), <0.05 (**), <0.01 (***).

Appendix Table 2. Sensitivity Analysis: Medications

	All	Respiratory + Cardio.	Gastrointestinal
	(1)	(2)	(3)
1. Original	-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, and 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: Each table entry shows the coefficient on Summer*Post*NBP from a separate regression. Regressions use specification of Table 4 column (3) unless otherwise noted. 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. “Medications” uses counts of medication purchases, rather than cost measures. "Panel of People" uses the much smaller panel of persons who appear in all observations of the MarketScan sample. "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. Sensitivity Analysis: Hospitalization Costs

	All	Respiratory + Cardio.	External
	(1)	(2)	(3)
1. Original	-5.997	-8.702	-3.629
State-Season Clusters	(18.948)	(5.717)	(6.486)
County Clusters	(21.937)	(8.813)	(7.007)
State Clusters	(26.942)	(8.127)	(9.223)
State-Year Clusters	(20.316)	(7.732)	(6.673)
County-Season Clusters	(15.525)	(6.236)	(4.958)
2. Including ME, NH, and VT	-1.538	-6.084	-3.224
	(18.198)	(5.473)	(6.208)
3. Hospitalizations (Not Costs)	0.000	-0.002**	0.000
	(0.003)	(0.001)	(0.001)
4. Panel of People	1.077	3.009	0.635
	(7.176)	(4.141)	(2.635)
5. Logs (Not Levels)	0.007	-0.116	-0.107
	(0.038)	(0.086)	(0.103)

Notes: Each table entry shows the coefficient on Summer*Post*NBP from a separate regression. The entries after row 1 present different levels of clustering for standard errors. Regressions use specification and sample of Table 5 column (3) unless otherwise noted. "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. Regressions use 2001-2007 data. Asterisks denote p-value < 0.10 (*), <0.05 (**), <0.01 (***).

Appendix Table 4. Sensitivity Analysis: Mortality

	All	Respiratory + Cardio.	External
	(1)	(2)	(3)
1. Original	-1.557	-0.547	0.115
State-Season Clusters	(0.813)*	(0.675)	(0.309)
County Clusters	(1.155)	(0.777)	(0.338)
State Clusters	(1.157)	(0.960)	(0.439)
State-Year Clusters	(1.645)	(1.116)	(0.357)
County-Season Clusters	(0.816)*	(0.550)	(0.239)
2. Including ME, NH, and VT	-1.699**	-0.671	0.146
	(0.792)	(0.656)	(0.301)
3. Logs (Not Levels)	-0.006***	-0.008**	0.007
	(0.002)	(0.003)	(0.012)
4. Age-Adjustment	-1.504*	-0.762	0.116
	(0.848)	(0.673)	(0.305)

Notes: Each table entry shows the coefficient on Summer*Post*NBP from a separate regression. Regressions show specification and sample of Table 6 column (3) unless otherwise noted. 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. "Logs (Not Levels)" specifies the response variable in logs rather than levels. “Age-Adjustment” modifies the response variable to use age-adjusted mortality counts, rather than total deaths per population. Regressions use 1997-2007 data. Asterisks denote p-value < 0.10 (*), <0.05 (**), <0.01 (***).