Defending Against Environmental Insults:
Drugs, Emergencies, Deaths, and the NO_x Emissions Markets[1]

PRELIMINARY AND INCOMPLETE

Olivier Deschênes
University of California, Santa Barbara, and NBER

Michael Greenstone
MIT and NBER

Joseph S. Shapiro
MIT

July 3, 2011

[1] Thanks to Spencer Banzhaf, Jim Davis, Amy Finkelstein, Meredith Fowlie, Chris Timmins, Mike Wechsler, participants in a CEEPR workshop, MIT development lunch, Census Maryland RDC conference, Federal Reserve Bank of Atlanta conference and seminar participants at MIT, Harvard, Northwestern for insightful comments. Nick Muller generously helped with CRDM, Dan Feenberg, Mohan Ramanujan, and Jean Roth gave considerable help with MarketScan data, and Gabe Chan, Peter Evangelakis, Liz Greenwood, and Paul Youchak provided outstanding research assistance. We gratefully acknowledge funding from NIH Grant 1R21ES019375-01.

Defending Against Environmental Insults:
Drugs, Emergencies, Deaths, and the NO_x Emissions Markets

ABSTRACT

In theoretical models of health behavior, individuals undertake a wide range of actions to protect themselves from risk or harm. It is widely believed that these actions constitute a significant portion of the costs of harms, but there is little research establishing their empirical importance. This paper provides an opportunity to measure these activities in the context of air pollution. Specifically, it examines the impact of a large US emissions trading market – the NO_x Budget Trading Program – on pollution emissions, ambient air quality, medication purchases, hospital admissions and mortality.

Using variation across time and space in the implementation of the emissions market and data on the real world data, rather than relying on chemistry, engineering, or epidemiological models, we find that the reductions in NO_x emissions decreased the number of summer days with harmful ozone levels by more than 35%. These improvements in air quality produced substantial short run health benefits. Drug expenditures decreased by about 1.6% (2.5% percent for respiratory drugs), which are nearly as large as an upper bound estimate of the NO_x Budget Trading Program's abatement costs. Additionally, the summer mortality rate declined by approximately 1.6%, indicating that there were about 7,000 fewer premature deaths per summer, mainly among individuals 75 and older. Models that aim to uncover the loss of life expectancy associated with these premature mortalities lack statistical power. Several placebo tests support the research design: the market had no effect on non-regulated pollutants or on health conditions that are plausibly unrelated to air quality.

I. Introduction

In the canonical models of behavior, individuals trade-off the damages from exposure to harms with investments or costly actions to protect themselves from the harms (Grossman 1972; Becker 1965). For example, 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 the harm itself. However, the empirical literatures have largely focused on the incidence of the harm (e.g., crime rates, 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.[2,]

This paper aims to develop a measure of willingness to pay for reductions in ozone air pollution concentrations that accounts for defensive expenditures, as well as ozone's direct health impacts. As our measure of behavioral changes, we investigate whether medication usage responds to changes in ozone. This is likely to be an especially important measure of defensive expenditures because the annual cost of prescription medications for asthma exceeds the monetized value of any other component of asthma's social cost, including mortality, emergency department admissions, or lost productivity (Weiss and Sullivan 2001). We also provide new evidence on how ozone concentrations affect 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 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 and September. Importantly, NO_x is a primary ingredient in the complex function that produces ozone air pollution.

[2] Additionally, public evaluations of air pollution policy focus largely on premature mortality and hospital admissions as markers of health and generally fail to consider the costs of defensive investments (Pew 2000; US EPA 2005; US EPA 2008a, p. 6-11; US EPA 2008b).

Figure 1 shows the dramatic effect of this market on NO_x emissions. In 2002, NO_x emissions were fairly flat throughout the calendar year, with a rise when electricity demand peaks in July.[3] 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 40 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 Eastern versus Western U.S. (i.e., the states where the NO_x budget program operated versus those where it didn't).[4]

The empirical analysis produces several key results. The reductions in NO_x emissions decreased ozone concentrations by roughly 11% and reduced the number of summer days with harmful ozone levels by more than 35%, or more than half a standard deviation. These improvements in air quality produced substantial short run benefits. Drug expenditures decreased by about 1.6% (2.5% percent for respiratory drugs), which on the aggregate is nearly as large as an upper bound estimate of abatement costs. Further, the summer mortality rate declined by approximately 1.6%, corresponding to 7,000 fewer premature deaths per year, mainly among individuals 75 and older. In contrast, there appears to have been little effect on hospital admissions or charges. Models that aim to explore the gain in life expectancy associated with the reduced mortality rates lack statistical power. Finally, reductions in ozone concentrations appear to be the primary channel, but split sample IV estimates are imprecise.

Several placebo tests support the research design. The market had no effect on non-regulated pollutants. Furthermore, it did not affect health conditions that are plausibly unrelated to air quality.

---

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

[4] "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.

In addition to providing new evidence on the empirical importance of defensive expenditures, this paper makes several contributions.[5] 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., Mendelsohn & Muller 2009).[6]

Second, this study provides the first test of whether the ex ante predictions of an air quality model fit the ex post effects of the market. Several economics papers (e.g., Bayer, Keohane, and Timmins 2008; Shadbegian, Gray, and Morgan 2007) and scores of annual regulations – including most of the Clean Air Act and its subsequent amendments – are based on atmospheric chemistry models which calculate how emissions of pollution from one source affect ambient pollution concentrations elsewhere. We are able to test how the predictions of one leading model compare against the actual results of the market.

Third, the results should be useful for policymakers. National Ambient Air Quality Standards for ozone have changed repeatedly since the Clean Air Act—more than for any other pollutant except particulates.[7] These standards have changed partly because there is substantial uncertainty about how ozone affects health (NRC 2008).[8] The existing literature finds conflicting evidence on the relationship between ozone air pollution and mortality (Bell et al.

---

[5] 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 or 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. Research has also provided indirect evidence of defensive behavior—Moretti and Neidell (2009) show that in Los Angeles, ozone created by the arrival and departure of large boats has a larger effect on emergency department admissions than does non-boat ozone pollution. Deschênes and Greenstone (forthcoming) show that people use additional electricity, presumably for air conditioning, on extremely hot days when mortality risks are elevated.

[6] 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 2010a, Fowlie 2010b, Fowlie and Perloff 2010, Fowlie, Knittle, and Wolfram 2010). Fowlie, Holland, and Mansur (2009) also show that RECLAIM decreased in NO_x emissions relative to emissions from similar facilities outside the market area.

[7] 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. In 2010 the Obama administration withdrew the .075 proposal and instead proposed decreasing the ozone standard to between 0.06 and 0.07 ppm. The EPA has announced numerous delays in deciding the exact level between 0.06 and 0.07.

[8] In contrast, there is more robust evidence indicating that airborne particulate matter increases mortality rates (Pope, Ezzati, and Dockery 2009; Chay and Greenstone 2003a and 2003b;

2004; Currie and Neidell 2005) and a similarly ambiguous association with hospitalization rates (Neidell 2004; Moretti and Neidell 2009; Lleras-Muney forthcoming).[9]

The rest of this paper is organized as follows. Section II reviews the main aspects of ozone formation and provides details on the NOx Trading Budget 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 while Section VII presents calculations on the aggregate costs and health benefits of the NOx Trading Budget Program. 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 which harm health.[10] 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. For example, the National Ambient Air Quality Standards for ozone only 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 effects of ozone on cardiovascular and particularly respiratory health (Lippman 2009).[11]

---

[9] Limited evidence, relying on observational association, links long-run exposure to ozone with increased mortality (Jerrett et al. 2009).

[10] 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.

Third, when this market began, national ozone levels had hardly changed since the Clean Air Act. 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. NO_x Budget Trading Program

The NO_x Budget Trading Program (NBP) grew out the Ozone Transport Commission (OTC), a group of Northeast States which developed in the 1990s. Studies commissioned under the OTC found that ozone levels remained high in the Northeast US partly because NO_x emissions from the industrial Midwest 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.[12] The OTC then created a more stringent version of the NO_x Budget Program which began in 2003 and which operated until 2008. We focus on the 2003-2008 period.[13] 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 partway in 2003 and fully in 2004. The 2003-2008 emissions market originally aimed to cover the 8 Northeast states plus Washington DC (which were the focus of the OTC), plus 11 additional Eastern states. Litigation regarding abatement costs in the Midwest, however, delayed implementation in the 8 additional states until May 31 of 2004.[14] 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 the years 2005-2008. Many firms banked allowances—

---

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

[12] This market also goes under the name NOx 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.

[13] 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 concentration s of particulates. The EPA Transport Rule is now replacing CAIR.

[14] In 2003 the emissions cap applied to Connecticut, Delaware, Maryland, Massachusetts, New Jersey, New York, Pennsylvania, Rhode Island, and 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.

in each year of the market, about 250,000 tons of allowances were saved unused for subsequent years (USEPA 2009a). 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 (Fowlie 2011). 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.[15] At the end of each market season, each source had to give the EPA one allowance for each ton of NO_x emitted. 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 permit price was \$2080 per ton of NO_x, which we use to establish an upper bound on NO_x emissions.[17]

III. Model of Willingness-to-Pay

We use a simple theoretical model built on Becker (1965), Grossman (1972), Cropper and Freeman (1991), and Freeman (2003) to highlight the role of defensive investments in the measurement of willingness-to-pay for clean air. This model shows that accurate measurement of willingness-to-pay requires knowledge of both how pollution affects health outcomes like mortality and how it affects defensive investments that maintain health, but otherwise generate no utility, like medications.

[15] Unused allowances from NBP could be transferred to the CAIR ozone season program.

[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.

[17] Relatively dirty units in this market have NO_x emissions rates around 5 lbs NO_x / MWh electricity generated. At mean NO_x permit prices of \$2080/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).

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.

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

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 play an important role in the final result:[18]

(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:

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

Equation (5) combines the effect of pollution on health in the absence of defenses, and the preventative effect of defenses. A parameter like ∂s/∂c is reported in Currie and Neidell (2005)

[18] 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.

for schoolchildren. This is purely a health parameter—without additional information, it does not represent utility in monetary terms.

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

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

Expression (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 which 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 & Sullivan 2001), they represent an important component of defensive investments.

IV. Data

This analysis has compiled an unprecedented set of files to assess the impacts of the NO_x Budget Program. To the best of our knowledge, this study represents the first time any analysis has linked health data directly to emissions and air quality measures in order to evaluate an emissions market. We compile high frequency data on medications, emergencies, mortality, pollution emissions, ambient pollution, and weather in the period 2001-2007. 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 US 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. The data include insured spouses and dependents of the worker. The data report the county of the purchaser's home, the prescription

[19] The main analysis excludes Alaska, Georgia, Hawaii, Iowa, Maine, Mississippi, Missouri, New Hampshire, Vermont, and Wisconsin, though the Appendix reports similar estimates with other sample selection rules.

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 identify the medical condition associated with each medication. Each observation in these data represents a prescription or refill. 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.

We use data from all persons in the 16 firms which appear in all seven years 2001-2007 of MarketScan. 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]

Medications, unlike hospital visits or death counts, are not linked to a single International Classification of Disease code (e.g., ICD9). We define an NDC as respiratory if it satisfies any of three criteria: if it is listed in the Third Treatment Guidelines for Asthma (NHLBI 2007), in a recent New England Journal of Medicine guide to asthma treatment (Fanta 2009), or 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, neoplasm, and gastrointestinal medications by their corresponding therapeutic groups in Red Book.[22] This broad approach to identifying respiratory 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

---

[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. The firms do cover much of the economy—the complete MarketScan dataset identifies each firm with one of seven sectors, and the 16 firms include at least one from each of the seven sectors.

[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.

medications were prescribed for non-respiratory conditions, and that medications prescribed for respiratory conditions are not in this list.

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 if the either of the two ICD9 diagnosis codes is in the range 460-519. 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 2001-2007 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.[23]

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.[24] These 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 NBP only must report NO_x emissions 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 2001-2007 period, units in 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 2001-2007 period. Many ozone monitors operate only in the May-September months. Moreover,

---

[23] 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.

[24] 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.

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 2001-2007. This fairly strenuous selection rule restricts our data to include only the most reliable monitors—it 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 other monitor selection rules. For ozone, we focus on a concentration measure which the EPA regulates—for each day, we calculate an "8-hour value" as the maximum rolling 8-hour mean within the day.[25]

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 developed a rule to select the weather stations that requires monitors to operate for a minimum number of days. 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 a 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. Ambient ozone data are only available for 158 counties, $PM_{2.5}$ data in 256 counties, and data on other pollutants in similar numbers of counties. The smaller sample for pollution than for health leads us to use two-sample instrumental variables to measure how ozone affects health, as the next section explains.

Summary statistics in Table 1 also provide a benchmark to measure the economic importance of medications and the emissions market. In summer, ozone averages 50 ppb. The

[25] 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 pollutants, 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 total number of underlying pollution readings.

proposed EPA air quality standard stipulates that a county can 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, 23 days every summer exceed 65 ppb. The average person spends $500 per summer on medications, and about the same on hospital admissions. Six to nine percent of medications, emergency department admissions, and deaths occur due to respiratory causes. Cardiovascular causes represent about 20 percent of total hospitalization and medication costs, and about 36 percent of deaths.

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 that counties with high regulated NO_x emissions are slightly *underrepresented* in the high-ozone counties, which highlights 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.[26] The finding that so many of these observed county characteristics covary with ozone suggests that that an observational association of ozone with health is likely to reflect the contributions of other unobserved variables. 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 to measure the "structural" effect of ozone on health. This estimator exploits three sources of temporal and geographical variation in the emission and health data. First, we compare pre versus post NBP enactment. Eight states plus DC began this market in 2003 while the remaining 11 states began in 2004. This market did not

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

operate before 2003. Second, we compare East versus West. We include all 19 states plus DC as "East." Third, we compare summer versus winter.[27]

Hence we estimate the following model:

$$(7)\qquad Y_{cst} = \gamma_1 T_c S_s Post_t + \gamma_2 T_c S_s + W_{cst}^{'}\beta + \mu_{ct} + \eta_{st} + \varepsilon_{cst}$$

In this model, the outcomes Y vary by county c, season s, and year t. We define s as a binary indicator for May 1-September 30. Because the NBP market stated partway in 2003, we define Post=0.5 in 2003 and Post=1.0 in 2004 through 2007.

Because ozone formation depends on weather conditions, 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.[28] For each county-season-year observation in the data, we then calculate the share of days which fall into each of the 20 quantiles.

The set of fixed effects μ_{ct} for each pair of county and year form an important control variable. These fixed effects adjust for annual unemployment, manufacturing activity, health insurance, government policy, and all other factors which vary within a county and year. The use of these fixed effects implies that all regressions in this paper are comparing across summer and winter, <u>within</u> a county and year.

The season-by-year fixed effects η_{st} and the interaction $T_c S_s$ make this within-county-year comparison between the East and West, and before and after the market began. For each outcome we report the parameter γ_1, which represents the market's reduced-form impact on Y. For example, in regressions where ozone is the response variable, γ_1 represents the effect of the market on ozone.

We also report variants on this approach. Equation (7) is not the only implementation of a triple-difference estimator—other versions can change the level of county, year, and season controls, and the detail of weather controls. The main tables report equation (7) along with three variants, and Appendix Tables (1)-(4) report additional variations.

[27] The abrupt beginning and end of the market on May 1 and October 1 makes a daily regression discontinuity estimator seem appealing. However, because ozone in the Eastern US mainly reaches high levels in July and August, the market is likely to have small effects on 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.

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

Given the potential for temporal and spatial autocorrelation, we use a few approaches for inference. Pollution and health data are available for each county. States decided whether to enter the market. In at least two cases, a region surrounding one city entered the market but the remainder of the state did not.[29] So in main tables we report regressions clustered by metropolitan statistical area (MSA), where all non-urban counties in each state are combined into their own MSAs. Appendices report estimates allowing for arbitrary autocorrelation within counties and states.

Although our tables focus on the triple-difference parameter γ_1 from equation (6), separate measures of the market's effect in each year provide additional useful information. Hence, for most outcomes, we graph the parameters $\alpha_{2002} \ldots \alpha_{2007}$ from the following model:

$$(8) \qquad Y_{cst} = \sum_{t=2002}^{2007} \alpha_t T_c S_s Y_t + \alpha_2 T_c S_s + W_{cst}^{'} \beta + \mu_{ct} + \eta_{st} + \varepsilon_{cst}$$

These "event study" graphs permit a visual test for pre-trends and for the effect of the market. In these graphs, the value α_{2001} represents a reference category set to zero.

Because the set of available MarketScan firms increases substantially in the year 2001, we begin the analysis in most figures and tables in 2001. However, mortality data are available beginning in 2000, so mortality results also show estimates using a sample which begins in 2000.

The triple-difference estimators test the main hypotheses of the paper—they measure whether defenses are an economically important response to changes in air quality; they apply a new way to evaluate emissions markets; they let us quantify the benefits of this specific emissions market; and they let us evaluate the accuracy of an air quality model. However, the one goal the triple-difference estimators do not achieve is to measure the costs of ozone specifically, as distinct from other pollutants.

Because the market targeted ozone pollution, it can provide a plausible instrumental variable to measure how ambient ozone affects health. But ozone data monitoring is available for only 160 counties while health outcomes data are available in 2500 counties. Hence, use of a standard instrumental variables estimator to measure how ozone affects health would have to discard most health data. Although we report instrumental variables estimates using the 90%

[29] A large area around Birmingham in Northern Alabama participated in the market and southern Alabama did not. The industrial areas of Southern Michigan entered the market and the rest of Michigan did not. In 2007, the area around St Louis entered the market but the rest of Missouri did not. We define all of Alabama and Michigan as having participated in the market, and we exclude Missouri as adjacent to the market region.

smaller sample, we also use what we believe is a new approach to deal with this common issue in environmental and spatial economics—we use two-sample instrumental variables.[30]

To obtain two-stage instrumental variables estimates, we first estimate equation (7) with ambient ozone as the dependent variable, and estimate the first-stage regression using all 160 counties where ozone data is available. We then specify equation (7) with our measures of health outcomes as dependent variables, and estimate equation (7) using all 2500 counties where health data is available. Let $(\hat{\gamma}_1^{ozone}, \hat{\gamma}_1^{health})$ represent these first-stage and reduced-form estimates, respectively. Because this model is exactly identified, the following Wald estimator equals the "structural" effect of ozone on health:[31]

$$(12) \qquad \hat{\pi} = \frac{\hat{\gamma}_1^{health}}{\hat{\gamma}_1^{ozone}}$$

We use a clustered bootstrap to estimate standard errors for $\hat{\pi}$ in equation (12). Specifically, we estimate $\hat{\gamma}_1^{ozone}$ by drawing with replacement the total number of clusters in the ozone data. We then estimate $\hat{\gamma}_1^{health}$ by drawing with replacement the total number of clusters in the health data. We form an estimate $\hat{\pi}^{bs}$ of π by taking the ratio $\hat{\gamma}_1^{health} / \hat{\gamma}_1^{ozone}$. We repeat this procedure 100 times, and calculate the standard error of $\hat{\pi}$ according to the standard deviation of the vector $(\hat{\pi}_1^{bs}, \dots \hat{\pi}_{100}^{bs})$.[32]

VI. Results

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

[30] We emphasize the triple-difference estimates because they test the more important hypotheses of the paper, as discussed above. We also emphasize them because we view the assumptions required for IV estimates as fairly strong in this setting. The two key IV assumptions are the exclusion restriction (NBP affected no pollutants besides ozone) and the applicability of TSIV (i.e., the first-stage is the same in counties with ozone monitors as in counties without ozone monitors).
[31] This approach is similar to Dee and Evans' (2003) application of two-sample instrumental variables to teen drinking.
[32] Monte carlo simulations in Cameron, Gelbach and Miller (2008) suggest that this type of procedure produces tests with correct size when using OLS with data that have autocorrelation.

present without the 1990 Clean Air Act Amendments (e.g., USEPA 2009). Such comparisons make it difficult to identify the contribution of a specific recent policy to total emissions.

Figure 2 illustrates the tremendous impact of the NBP on NOx emissions. The figure shows the unadjusted summer-equivalent NOx emissions, by year (before and after NBP operation) by season (winter and summer) and by region (Eastern and Western state).[33] The first key point is that emissions in the Western states are unaffected by the NBP, as shown by the smooth and moderate downward trend in both winter and summer emissions. In comparison, the NBP lead to a sharp and discontinuous reduction in summer emissions, starting in 2003 when the emissions market began in 8 Northeastern states and DC. As a result, summer NOx emissions declined by about 20 percent in the summer of 2003, and another 20% starting in May 2004, when the market added 11 more Eastern states.[34] Additionally, winter emissions continued to decline on their gradual downward pre-2003 trend. In short, NO_x emissions declined in exactly the areas, months, and years that the emissions market design would predict.

Regression analogues of these graphs in Table 2 show similar patterns. 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 dummy variables along with the county-year fixed effects, which makes this a basic triple-difference estimator. It finds that the market decreased NO_x emissions in the average county by 343 tons per summer. Column (2) includes more precise controls, though still no weather variables—it replaces S_sY_{post} and S_s with summer-by-year fixed effects η_{st}. In this table, columns (1) and (2) have nearly identical point estimates and confidence regions. Column (3) adds three weather variables which control for mean temperature, precipitation, and dew point temperature in each observation. Column (4) adds the full set of binned weather controls. The weather controls attenuate the point estimates by a fourth of a standard deviation, although the estimates remain highly precise. These results are unchanged in numerous alternative specifications (Appendix Table 1).

We also measure whether the market affected emissions of pollutants other than NO_x. Two economic reasons explain why the market might have affected emissions of such copollutants. If permits for NO_x emissions cost enough that the market caused relatively clean

[33] We express the data as summer-equivalent since the summer period has 5 months while the winter period has 7 months.
[34] 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.

natural gas units to displace electricity generation from relatively dirty coal-fired units, then the market could have decreased emissions of pollutants other than NO_x. Second, complementarity or substitutability of NO_x with other pollutants in electricity generation could lead units to change emissions of other pollutants. Any effect of the market on emissions of copollutants, 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 market to serve as a valid instrumental variable for ozone.

The data, however, show that the market did not affect emissions of copollutants. Columns (3) and (4) of Table 2 show that NBP had no impact on emissions of SO_2 or CO_2.[35] The estimated size effects (point estimate over the mean of the dependent variable) for the copollutants are all close to zero—while we precisely estimate a 37 percent decrease in NO_x emissions. In contrast, the estimates imply only a statistically insignificant decrease in SO_2 or CO_2 emissions of about 2%. For copollutants, the confidence intervals from the richest specifications rule out declines of more than about six percent relative to the baseline level. These results suggest that the NBP changed emissions primarily by encouraging the use of retrofitted abatement technologies for NO_x, and not by changing the amount of electricity that each unit generates.

B: Ambient Pollution

Figure 3 shows how this emissions market affected ambient pollution levels. Panel A shows an event study for ambient ozone.[36] It adjusts for weather and plots the difference between ozone levels in the Eastern and Western US, with the 2001 difference normalized to zero. In 2001-2002, the East and West had roughly similar trends, suggesting that this research design provides a credible counterfactual to measure the impact of the market on ozone. The vertical line in 2003 marks when the market began. In 2003, when the market limited emissions from 8 Northeastern states plus DC, mean ozone levels dropped by 3 ppb. In 2004-2007, when the market restricted emissions in 11 additional Eastern states, ozone levels dropped an additional 1 ppb.

[35] 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. We also detect no effect of the market on total electricity generation.
[36] Appendix Table 5 shows the regression values for event study estimates.

Because epidemiological evidence finds that ozone has a non-linear dose-response function, we also analyze the market's impact on the density function for daily ozone concentrations.[37] Panel B of Figure 3 divides the support of the daily 8-hour ozone distribution into 11 bins. The first bin, for example, counts the share of summer days with ozone between 0 and 10 ppb. The second bin counts the share of summer days with ozone between 10 and 20 ppb. The remaining bins are defined similarly. The thick line shows the estimated effect of the market on the share of summer days in each bin, while the dashed lines show the 95% confidence interval. The three vertical lines at 65, 75, and 85 ppb represent the three different levels where the EPA has set National Ambient Air Quality Standards for ozone in recent years.[38]

Panel B of Figure 3 shows that the emissions market affected ozone in <u>exactly</u> the part of the ozone distribution which epidemiology suggests harms health. The market reduced the share of days with ozone between 65 and 100 ppb and increased the share of days with ozone between 10 and 60 ppb. Panels C and D present the same data recalculated to show the effect of the market on the number of days in a typical summer with ozone in each of the 11 bins. In a typical summer, this market caused an average county in the Eastern US to have 8 fewer days with ozone between 70 and 90 ppb. It produced smaller decreases in the number of days with ozone above 90 ppb.

Table 3, which measures how the market affected ambient pollution, reveals large and precisely estimated effects of the emissions market on ozone. As reported in the richest specification (column (4), the market significantly decreased mean summer ozone in the Eastern US by about 8 percent. The market also decreased the number of days with ozone above 65 ppb – the level believed to harm health – by 40 percent.

We measure the effect of the market on pollutants other than ozone for two reasons. First, these estimates measure reduced-form effects of the emissions market, which is important in any ex post evaluation of the market. In particular, the ex ante estimates of the market's impact on

[37] 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 for us to examine the market's impact on the ozone distribution.

[38] 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 any bin to zero. This differs from the use of bins as explanatory variables (e.g., Deschênes and Greenstone 2010).

mortality were largely predicted to occur due to reductions in particulates, so it is important to know whether these effects occurred. Second, the validity of the NBP as an instrumental variable for ozone depends on an exclusion restriction. If the market affected health through any channel other than ozone, then an instrumental variables estimator will not consistently estimate the ozone-health relationship. Because pollutants other than ozone are a plausible channel through which the market can affect health, we test whether the market affected ambient concentrations of such pollutants.

Table 3 shows that the market had no effect on <u>any</u> pollutant besides ozone. Because electricity generation contributes substantially to all the pollutants in Table 3 except Carbon Monoxide (CO), and because this market was among the most important air quality regulations for electricity generation in this period, we view this finding as particularly striking.

For example, emitted NO_x produces ozone but can also undergo atmospheric reactions to produce nitrogen dioxide (NO_2), a pollutant subject to its own regulations. Table 3 shows that even though NO_x levels decreased dramatically, ambient NO_2 experienced little or no change. Carbon monoxide (CO) emissions come primarily from transportation and this market should not affect them. Unsurprisingly, Table 3 reveals no impact of the market on CO levels.

Table 3 also shows small and statistically insignificant effects of the market on particulates, which is particularly surprising. Taken literally, these numbers imply that the NBP decreased levels of particulates smaller than 2.5 microns ($PM_{2.5}$) by 2.4 percent relative to the baseline mean, and it decreased levels of particulates smaller than 10 microns (PM_{10}) by 11 percent.[39] Among all the pollutants in this study, current research suggests that $PM_{2.5}$ is the most harmful to health, and more monitors record $PM_{2.5}$ than record any other pollutant, including ozone. The estimate for $PM_{2.5}$ is only somewhat precise—we can reject the hypothesis that the market caused any more than a 6.6 percent decline in $PM_{2.5}$. But the small and insignificant estimate for $PM_{2.5}$ is surprising because in ex ante simulations of the market, the predicted decrease in particulates was the primary pathway through which the market was predicted to affect health (USEPA 1998).[40] Air quality models show that atmospheric NO_x can undergo reactions which transform it into a component of fine particulates. An Appendix available from

[39] EPA regulations focus on $PM_{2.5}$ and PM_{10} monitors only satisfy the monitor selection criteria in 17 counties in this period (Table 1), so $PM_{2.5}$ estimates are more representative of potential effects of the market on particulates and health than are PM_{10} estimates.

[40] The market was not predicted to have an especially large effect on particulate matter, but epidemiological evidence suggests that particulates have more effect on mortality than ozone does.

the authors describes air quality model simulations in more details and provides one explanation for why the market had little or no effect on particulates.

Table 3 also reveals no impact of NBP on ambient sulfur dioxide levels. Because the Acid Rain Program operated a separate cap-and-trade market for SO_2 during this period, any decrease in summer SO_2 levels due to the NO_x market would have been offset by a corresponding increase in wintertime SO_2 levels. Because 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.

Importantly, we show in Appendix Table 1 that the results in Table 3 are robust to a wide range of specification analysis, including changes in the method used to compute the standard errors, the sample weights used in the regression, the summer-winter-comparison, the set of excluded states, and the pollution monitor selection rule.

Finally, we explore whether these reductions in NO_x produced any counterproductive outcomes. When an area has low concentrations of volatile organic compounds relative to NO_x, then decreasing NO_x can increase ozone levels. Such NO_x "disbenefits" may exist in Southern California, where weekend ozone levels exceed weekday ozone levels. There is less consensus on whether they could occur in the Eastern US. 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" MSAs from Blanchard (2001). Second, we define a county as VOC-constrained if its mean ratio of weekend/weekday ozone exceeds 1.05.

These tests suggest that the emissions market may have produced smaller ozone decreases in these VOC-constrained areas, though the market still decreased ozone (Appendix Table 1). The differences are not statistically significant, which fails to yield any support for the empirical relevance of "NO_x disbenefits".

In sum, ambient pollution data show that the NBP caused a large decrease in ambient ozone but no detectable change in other pollutants. The point estimates for other pollutants are small. Overall, these findings suggest that the market is a plausible instrument for ozone, and that any bias from changes in other pollutants is likely to be limited.

C. Defensive Investments

The previous section established that this emissions market provides a good opportunity to measure how high levels of ozone pollution affect health outcomes and health behaviors. We now ask whether the declines in ozone pollution caused by this market have allowed people to devote fewer resources to defending themselves against air pollution. Figure 4 Panels A and B provide a graphical answer. They compare medication purchases in the Eastern versus Western US, and in summer versus winter. They then plot this comparison in each year, with 2001 normalized to zero. These graphs show little difference in 2002, before the market began. After the market began, in 2003, expenditures on medications and number of medications purchased both decreased by over 1 percent. These comparisons stayed relatively constant through 2007.

Table 4 reports regression analogues of these graphs—it shows the reduced-form effect of the market on log medication costs. We estimate that the market significantly decreased total medication costs by 1.6 percent. The Grossman model discussed earlier implies that this is a lower-bound on total willingness-to-pay for air quality, but it is a component of willingness-to-pay which previous research has not measured.

We also measure medication purchases separately by cause. 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 allocation is to test whether the decline in medication purchases was large for respiratory medications. We also test whether the market's effect was small for medications which treat gastrointestinal conditions, which we believe should be unrelated to ozone.

Our estimates indicate that NBP decreased expenditures on respiratory medications by 2.5 percent, although the estimate is only significant at 92% confidence. The market's effects on medication purchases are slightly larger in areas with ozone monitors, which generally have higher ambient ozone levels (Appendix Table 2).

We also estimate one placebo test—we test whether the emissions market created any apparent effect on purchases of gastrointestinal medications. We find no detectable effect, and a point estimate of -0.011. This is consistent with the observe changed in overall and respiratory medications operating through the reduction in ambient ozone concentrations.

Appendix Table 2 reports other specifications which obtain similar results, and which we mention here. Two specifications change the level of clustering—precision is similar with county clusters but 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 similar effects on medication purchases. Using medication levels rather than logs produces large and unstable estimates, which reflect the fact that medication purchases are highly skewed. The main tables use the average paid-cost by National Drug Code, to aggregate over measurement error from individual reports. Using purchase-specific costs obtains similar results. We find that the effects for respiratory drugs are somewhat larger for rescue medications, which are used after an acute respiratory episode, than for maintenance medications, which are used as a daily response to chronic respiratory conditions. Finally, we find that copayment costs are similar to total costs.

We also check whether air conditioning serves as a complementary defense. Because people with air conditioning may be more likely spend time indoors on hot days when ozone is high, air conditioning may also decrease exposure to ambient ozone. However, Appendix Tables 1-2 show both that the market has little effect on ozone in areas where air conditioning is high, and that the market has no impact on medication purchases in these areas.[41] Because the market's effects on ozone are muted in areas with high air conditioning, this research design lacks power to measure the importance of air conditioning as a defense.

Doctors generally distinguish two types of respiratory medications—one ("maintenance") is taken regularly regardless of respiratory symptoms, while the other is taken in response to acute respiratory episodes ("rescue"). Appendix 2 investigates the use of both types in response to the emissions market. Rescue medications generally respond more to the emissions market than maintenance medications do, although the confidence intervals are wide enough that we typically cannot reject equal effects for the two types of medications. This is consistent with the hypothesis that the emissions market prevented asthma patients from experiencing acute episodes which air pollution had caused before the market began.

D. Hospital Visits and Mortality

Hospital Visits. Because the form of the relationship between ozone and health remains controversial, and because we seek to compare defensive costs against direct health costs, we also measure how the market affected hospital visits and mortality. Figure 5 plots the East-West

[41] These estimates use county-level data on the share of the population with home air conditioning from the 1980 US Population Census, as summarized in ICPSR Study Number 2896.

Summer-Winter difference in hospital admissions in each year, with 2001 normalized to zero. A visual comparison of the points to the left and right of the vertical line shows no pronounced difference, although the estimates are imprecise. These estimates suggest that if the market produced any effects on hospital admissions, we cannot detect them.

Corresponding statistical estimates of how the market affected hospital admissions also give small and imprecise results. Column (4) of Table 5 literally implies that the market decreased hospitalization costs by about $6.60 per person-year, but the estimates are not statistically significant. We obtain similar results when looking only at respiratory admissions, cardiovascular admissions, or admissions for injuries. Varying the specification does not change the substantive conclusion (Appendix Table 3).

Mortality. Finally, we assess the the NBP's impact on mortality. This assessment is important because in most analyses of air pollution, mortality accounts for a large share of the benefits. Figure 6 suggests that the market produced a moderate decrease in the overall mortality rates. The market's effect is relatively clear in 2004, 2005, and 2007, though it attenuates in 2006.

The regression models corresponding to this graph show that this decline is statistically significant (Table 6). The emissions market decreased the overall mortality rate by about 5 deaths per 100,000 population. The decline was concentrated among cardiovascular and respiratory deaths. We find that the market had no effect on external deaths. There is insignificant evidence that deaths from other causes declined also, though cardiovascular and respiratory deaths account for most of the decline in deaths.

The most important finding regarding mortality is that most of the market's effect on mortality occurred among the elderly. Table 7 breaks the entire population into four age groups and separately estimates the effect of ozone on the health of each group. We detect no effect on the mortality of persons aged 64 and below, although taken literally, the point estimates imply that the market prevented 1,400 deaths within this group. We also detect no effect of the market on mortality rates of persons aged 65-74, although again the point estimate implies that the market prevented 1,100 deaths. But the clearest impact on mortality, and an impact which we estimate precisely, occurs among people aged 75 and older. The market prevented 3,500 deaths each year in this age group. As with the entire population, the effects on elderly mortality were primarily for respiratory and cardiovascular deaths

The age-group decomposition implies that the market prevented 6,000 deaths.[42] About 60 percent of these were among people aged over 75, and 77 percent were among people aged over 65. By contrast, the overall share of all summer deaths which occur among people aged over 75 is 55%. This comparison suggests that the market had similar effects on the mortality rates of the elderly and non-elderly. However, because baseline mortality rates are relatively high for the elderly, the absolute number of deaths prevented by this market is concentrated among the elderly.

E. Air Quality Model Interactions

Results up to this point also treat the emissions market as having the same impact across all of the Eastern US. This approach substantially simplifies the analysis and interpretation. However, most NO_x emissions reductions occurred among coal-fired power plants in the Ohio River Valley, and emissions from those plants do not fall evenly across the Eastern US.

We now explore one approach to address this heterogeneity—we use an air quality model to predict where the market should have affected pollution, and we then test whether the market affected pollution and health disproportionately in these areas. We use Mendelsohn and Muller's (2008) adaptation of the Climatological Regional Dispersion Model (CRDM, Latimer 1996). This air quality model uses the 2002 National Emissions Inventory as an input to predict ambient pollution concentrations in each county.

This approach is also useful because most atmospheric chemistry models of air quality are calibrated to match mean levels of ozone, but are not tested on whether they correctly predict changes in pollution induced by changes in emissions. Because these chemistry models are the basis of most regulations imposed under the Clean Air Act and because they underpin research on environmental economics (e.g., Bayer, Keohane, and Timmins 2008; Shadbegian, Gray, and Morgan 2007), it is informative to test the accuracy of their predictions.

We apply the model as follows. For each electricity-generating unit and industrial boiler in the data, we use a double-difference estimator to measure how the emissions market affected NO_x emissions. For each county, we calculate ambient pollution concentrations using emissions reported in the 2002 National Emissions Inventory as an input to the air quality model. We then

[42] This total, obtained from aggregating over estimates specific to each age group, is less than one standard error below the estimate of 7,000 deaths obtained by estimating one regression which combines all age groups.

decrease unit-level emissions based on the regression-estimated impact of the emissions market, and recalculate county-level ambient pollution. The difference between county-level predicted pollution with and without the emissions market is CRDM's estimate of the emissions market's impact.

Table 8 tests whether pollution and health changed more in the areas where CRDM predicted larger decreases in ambient air pollution. This table reports both the main triple-difference term, and the interaction of this term with a dummy variable based on CRDM's predictions. The dummy indicates whether a county had more-than-median ozone decrease as predicted by CRDM.

None of the CRDM interaction terms for pollution are statistically significant, though most have the expected negative sign. In Panel A the CRDM interaction is consistently negative, which is consistent with the idea that the air quality model accurately predicts declines in pollution, but the interaction is small and never statistically significant. Overall, CRDM under-predicts the decline in ozone. CRDM predicted a mean ozone decline of less than 1 ppb, while the ozone monitors reveal a decline of about 4 ppb.[43]

Panel B tests whether medication purchases declined more in the parts of the Eastern US where CRDM predicted that ozone levels would fall more. The interaction term again has the expected sign, suggesting that the air quality model was accurately predicting the larger benefits of the market in counties with larger ozone declines. However, these interaction terms are again small and imprecise. Hospitalizations and mortality estimates in Panels C and D display a similar pattern.

Overall, we take this evidence to suggest that the CRDM air quality model may capture roughly correct patterns of the effect of this emissions market on air quality. However, the predicted improvement in ambient air quality was substantially smaller than the actual change, and the county-by-county predictions differ substantially from the actual pattern of air quality improvements .

F. "Harvesting" and Double-Difference Estimates

---

[43] Because we detect no impact of the emissions market on ambient NO_2, $PM_{2.5}$, or PM_{10} levels, we do not report comparisons of ambient levels of these pollutants against CRDM's predictions. The CRDM interaction term in such regressions is almost never statistically significant and varies sign across specifications.

Results up to this point use a triple-difference specification which compares summer against winter. That estimator assumes that all effects of the emissions market occur during summer, which is when the market decreased pollution. However, the market could alter the timing of medication purchases, hospital admissions, and deaths by a relatively short amount of time.

This possibility of displacement is relevant for at least two reasons. First, if the market merely moved elderly deaths – from July of one year to November of the same year, for example – then its effects on life expectancy would be small. A typical benefit-cost analysis would apply the life expectancy of the mean 75 year-old to a prevented death here. But it is possible that the people whose deaths were prevented had much lower life expectancy than the mean person of the same age had. In this case the typical approach could substantially overstate the effects of this market on life expectancy.

Second, displacement could also cause the short run effects estimated by the DDD model to be overstated. To see this, consider that a death moved from July to November will reduce the summer mortality rate and increase the winter mortality rate. This is problematic because the DDD model compares the winter and summer mortality rates, and thus this model could overstate the true short run effect by as much as a factor of two.

To explore these issues, we report differences-in-differences models which examine outcomes for the summer, winter, and full year. These models use two approaches. The first, reported in columns (1)-(4) of Table 9, uses a double difference estimate for calendar years. This estimate does not compare between summer and winter within a year. Column (2) allows the East to have a different trend than the West, while columns (3)-(4) estimate these models for summer and winter separately.

Our main conclusion is that these models lack statistical power to detect long-run changes in health due to this market. In Panel D, for example, column (1) suggests that the market increased mortality rates of the elderly. But column (2) suggests this result is driven by different trends in the East and West, since the sign changes upon allowing for differential trends. These estimates underpin the importance of county-by-year fixed effects in the preceding tables, since they control for such differential trends.

We also report a second differences-in-differences estimator to measure long-run changes in life expectancy. Rather than basing regressions on calendar years, this second set of estimates compares the summer ozone season, May-September, against the following 7 months. In this

second set of estimates, a "year" is defined as the period from May of one calendar year to April of the following calendar year.[44]

This second set of DD estimates, reported in columns (5)-(8) of Table 9, is again consistent with the possibility that NBP merely displaced deaths in the short-run, rather than changing long-run life expectancy. The full year DD are generally not different from zero, although they are imprecise. For medications and hospitalizations, the point estimates in columns (7) and (8) are consistent with short-run displacement—they suggest that the emissions market merely allowed people to delay purchases of medications, or delayed (but did not completely prevent) adverse medical incidence requiring hospitalization. However, these estimates are too imprecise either to rule out or confirm the possibility of short-term displacement.

VII. Aggregate Benefits of the Emissions Market and of Ozone Reduction

The preceding sections measure the reduced form effects of the market on pollution, defenses, and health. We now use these results to undertake two exercises, both of which have useful information for current policy discussions about ozone and for the successors to the market studied here.

A. Instrumental Variables

We use instrumental variables 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 2010). Table 10 first reports a simple association of ozone with medication purchases, and with mortality rates for the elderly. The OLS medication regressions have varying signs and most associations are not statistically significant. These unstable estimates may reflect the feature highlighted in Table 1 that counties with high ozone have different characteristics than counties with low ozone.

Standard instrumental variables estimates use the same sample as OLS and detect no significant effect of ozone on medication purchases. These estimates do detect effects of ozone on mortality, due partly to cardiovascular mortality and partly to "other" causes not listed in Table 10.

[44] Because medication data are available only through calendar year 2007, these estimates are based on the period May 2001 through April 2007.

Two-sample instrumental variables using the emissions market as an instrument for ambient ozone give similar magnitude as the standard instrumental variables estimator, but with more precision. This could be expected since their sample size is more than ten times as large. Column (1) of Table 10 implies that each 1 ppb increase in ozone causes medication expenditures to increase by half of a percent, although the medication results are not precise. This effect is almost twice as large for respiratory as for cardiovascular medications. Days with high ozone are particularly harmful.

Two-sample instrumental variables estimates of the relationship between ozone and mortality are more precise (Table 10). These point estimates imply that a 1 ppb increase in summer ozone increases the overall mortality rate by 1.2 per 100,000, from a baseline rate of about 335 deaths per 100,000. These estimates are significant at 97% confidence, and are primarily due to respiratory and cardiovascular deaths. Hence, although ozone reductions will not alone cause dramatic changes in life expectancy, they may contribute a reasonable amount to decreases in cardiovascular and respiratory mortality.

B. Benefit-Cost Analysis

These results also let us report a benefit-cost analysis for the entire NO_x Budget Trading Program, with the caveat that we only calculate health benefits. Table 2 implies that this market decreased NO_x emissions by 379,200 tons per summer.[45] The average cost of a NO_x permit during the market was $2080/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, the market required firms to spend some amount less than $788 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 $3.5 billion (=788*4.5).

We can now compare this upper bound of costs against the market's total health benefits. Our mortality estimates imply that the market prevented about 7,000 deaths annually. The monetary value assigned to these deaths depends on the value of a statistical life (VSL). Analysts can apply any VSL to the deaths to obtain an estimate of this market's benefits. In Table 11, we use a combination of two methods to choose a VSL. First, we use the age-adjustment for each age group from Murphy and Topel (2006). Second, we use the upper-bound VSL of $1.93

[45] The market included 1,185 counties.

million (2006 dollars) from Ashenfelter and Greenstone (2004). This combination results implies that the value of the mortality avoided by this market is \$4.3 billion per year, or \$19.1 billion in the period 2003-2007.[46]

Because medication purchases have market prices, we can measure their monetary cost without having to choose a VSL.[47] Table 11 shows that this emissions market let Americans decrease medication expenditures by about \$700 million per year, or \$3.3 billion when summed over the 4.5 years of the market.

We take this finding as evidence that defensive investments are economically important. The NBP's aggregate abatement costs were less than \$3.5 billion, but it lead to a decrease in aggregate expenditures on defensive investments by \$3.3 billion. So even ignoring other benefits, defenses alone are nearly able to justify the market's existence in a benefit-cost test. Nonetheless, these defenses were not complete: ozone had increased mortality rates before this market began. Roughly 90 percent of the health benefits of this market arose because the market decreased mortality rates.

VIII. Conclusions

Optimal air pollution policy decisions are based on an informed comparison of all the costs and benefits associated with reducing exposure to ambient pollutants. This study is the first to provide a complete assessment, derived from real-world data, of the costs and benefits of large market-based environmental intervention, the NOx Budget Trading Program.

Our research design and rich data sets allows us to construct credible measures of the willingness to pay for reductions in ozone air pollution concentrations that accounts for

[46] We thank Murphy and 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 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 their paper calculates 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.

[47] Branded medications generally have low marginal cost and high markups to reflect intellectual property rights. Because drugs prices exceed marginal cost, 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 approach is that firms invest costly resources to develop medications which 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 Finkelstein (2004). Because it is beyond the scope of this paper to measure the magnitude of those research costs relative to the market price of medications, we use the market price of medications as the best-available measure of their social cost, and note that this topic is open for future research.

defensive expenditures, as well as ozone's direct health impacts. To the best of our knowledge this is the first large-scale study to provide such calculations.

The estimates are identified by three distinct sources of temporal and geographical variation in the emissions, medication purchase, and health data. We find that the emissions market lead to sharp reductions in summer ozone concentrations, especially in the number of summer days with harmful ozone levels. These improvements in air quality produced substantial short-run benefits. The monetized value of the reduced medication expenditures corresponds to \$700 million per year, which are nearly as large as an upper bound estimate of abatement costs attributed to the NBP. Further, our results show that the NBP lead to about 7,000 fewer deaths per year, mainly among individuals 75 and older.

This paper focuses exclusively on health benefits and compensatory responses. Although health costs are generally the largest component of benefit-cost analyses of air quality regulations, one limitation of this study is that it overlooks non-health costs which may have their own compensatory responses. For example, small-scale experiments consistently show that ambient ozone depresses agricultural yields. This emissions market may have increased yields for crops in the Eastern US, and may have allowed farmers to choose crops which are more sensitive to ozone.

Similarly, ambient ozone could decrease worker productivity, and workers who suffer from respiratory ailments might avoid outdoor work like agriculture and construction which are particularly exposed. This market may have increased worker productivity, but may also have led some workers to make the compensatory response of changing to outdoor work. We leave these lines of investigation to future work.

Bibliography

Auffhammer, Maximilian, and Ryan Kellogg. Forthcoming. "Clearing the Air? The Effects of Gasoline Content Regulation on Air Quality." American Economic Review..

Bayer, Patrick, Nathaniel Keohane, and Christopher Timmins. 2009. "Migration and Hedonic Valuation: The Case of Air Quality." Journal of Environmental Economics and Management 58(1): 1-14.

Becker, Gary S. 1965. "A Theory of the Allocation of Time." Economic Journal 75: 493-517.

Bell, Michelle L., Aidan McDermott, Scott L. Zeger, Jonathan M. Samet, and Francesca Dominici. 2004. "Ozone and Short-Term Mortality in 95 US Urban Communities, 1987-2000." Journal of the American Medical Association 292(19): 2372-2378.

Blanchard, Charles L. 2001. "Spatial Mapping of VOC and NOx Limitation of Ozone Formation in Six Areas." 94th Annual Conference of the Air and Waste Management Association, Orlando, FL.

Cameron, A. Colin, Jonah B. Gelbach, and Douglas L. Miller. 2008. "Bootstrap-Based Improvements for Inference with Clustered Errors." Review of Economics and Statistics 90(3): 414-427.

Carlson, Curtis, Dallas Burtraw, Maureen Cropper, and Karen L. Palmer. 2000. "Sulfur Dioxide Control by Electric Utilities: What Are the Gains from Trade?" *Journal of Political Economy* 108(6).

Chay, Kenneth Y., and Michael Greenstone. 2003. "The Impact of Air Pollution on Infant Mortality: Evidence From Geographic Variation in Pollution Shocks Induced by a Recession." Quarterly Journal of Economics 118(3).

Chay, Kenneth, Carlos Dobkin, and Michael Greenstone. 2003. "The Clean Air Act of 1970 and Adult Mortality." The Journal of Risk and Uncertainty 27(3): 279-300.

Cropper, Maureen L., and A. Myrick Freeman III. 1991. "Valuing Environmental Health Effects." In Measuring the Demand for Environmental Commodities. Ed. John Branden and Charles Kolstad Amsterdam: North-Holland.

Currie, Janet, and Matthew Neidell. 2005. "Air Pollution and Infant Health: What Can We Learn From California's Recent Experience?" Quarterly Journal of Economics 120(3): 1003-1030.

Dee, Thomas S., and William N. Evans. 2003. "Teen Drinking and Educational Attainment: Evidence from Two-Sample Instrumental Variables Estimates." Journal of Labor Economics 21(1): 178-209.

Deschênes, Olivier, and Enrico Moretti. 2009. "Extreme Weather Events, Mortality, and Migration." Review of Economics and Statistics 91(4): 659-681.

Deschênes, Olivier, and Michael Greenstone. Forthcoming. "Climate Change, Mortality, and Adaptation: Evidence from Annual Fluctuations in Weather in the U.S." American Economic Journal: Applied Economics.

Duan, Naihua, Willard G. Manning Jr., Carl N. Morris, and Joseph P. Newhouse. 1983. "A Comparison of Alternative Models for the Demand for Medical Care." *Journal of Business & Economic Statistics* 1(2): 115-126.

Fanta, Christopher H. 2009. "Asthma." *New England Journal of Medicine* 360(10): 1002-1014.

Finkelstein, Amy. 2004. "Static and Dynamic Effects of Health Policy: Evidence from the Vaccine Industry." Quarterly Journal of Economics 119(2): 527-564.

Fowlie, Meredith. 2009. "Incomplete Environmental Regulation, Imperfect Competition, and Emissions Leakage." American Economic Journal: Economic Policy 1(2).

Fowlie, Meredith. 2010. "Emissions Trading, Electricity Industry Restructuring, and Investment in Pollution Control." American Economic Review 100(3).

Fowlie, Meredith, Christopher Knittel, and Catherine Wolfram. 2009. "Sacred Cars? Optimal Regulation of Stationary and Non-stationary Pollution Sources." Working Paper, UC Berkeley.

Fowlie, Meredith, Stephen Holland, and Erin Mansur. 2011. "What do Emissions Markets Deliver and to Whom? Evidence from Southern California's NOx Trading Program." Working Paper, UC Berkeley.

Freeman, A. Myrick. 2003. The Measurement of Environmental and Resources Values: Theory and Methods. RFF Press.

Glaeser, Edward L. 1998. "Are Cities Dying?" 12(2): 139-160.

Graff-Zivin, Joshua, and Matthew Neidell. 2009. "Days of Haze: Information Disclosure and Intertemporal Avoidance Behavior." Journal of Environmental Economics and Management 58(2).

Graff-Zivin, Joshua, Matthew Neidell, and Wolfram Schlenker. 2011. "Water Quality Violations and Avoidance Behavior: Evidence from Bottled Water Consumption." NBER Working Paper No. 16695.

Grossman, Michael. 1972. "On the Concept of Health Capital and the Demand for Health." Journal of Political Economy 80(2): 223-255.

Hernández-Cadena, Leticia, Fernando Holguin, Albino Barraza-Villarreal, Blanca E. Del Río-Navarro, Juan J. Sienra-Monge, and Isabelle Romieu. 1999. "Increased Levels of Outdoor Air Pollutants Are Associated With Reduced Bronchodilation in Children With Asthma." Chest136(6): 1529-1536.

Henderson, J Vernon. 1996. "Effects of Air Quality Regulation." American Economic Revuew 86(4): 789-813.

Hoffman, James M. Nilay D. Shah, Lee C. Vermeulen, Glen T. Schumock, Penny Grim, Robert J. Hunkler, and Karrie M. Hontz. 2007. "Projecting Future Drug Expenditures – 2007." American Journal of Health-System Pharmacy 64(3): 298-314.

Jerrett, Michael, Richard T. Burnett, C. Arden Pope III, Kazuhike Ito, George Thurston, Daniel Krewski, Yuanli Shi, Eugenia Calle, and Michael Thun. 2009. "Long-Term Ozone Exposure and Mortality." New England Journal of Medicine 360: 1085-95.

Latimer, Douglas. 1996. "Particulate Matter Source-Rceceptor Relationships Between all Point and Area Sources in the United States and PSD Class I Area Receptors." USEPA, OAQPS.

Lippman, Morton. 2009. Environmental Toxicants: Human Exposures and Their Health Effects. Third Edition. Hoboken, NJ: John Wiley & Sons.

Martin, Katherine C, Paul L. Joskow, and Denny A. Ellerman. 2007. "Time and location differentiated NOx control in competitive electricity markets using cap-and-trade mechanisms." CEEPR Working Paper.

Moretti, Enricco, and Matthew Neidell. Forthcoming. "Pollution, Health, and Avoidance Behavior: Evidence from the Ports of Los Angeles." Journal of Human Resources.

Muller, Nicholas Z, and Robert Mendelsohn. 2009. "Efficient Pollution Regulation: Getting the Prices Right." *American Economic Review* 99(5): 1714-1739.

Neidell, Matthew. 2009. "Information, Avoidance Behavior, and Health: The Effect of Ozone on Asthma Hospitalizations." Journal of Human Resources 44(2).

NHLBI. 2007. Expert Panel Report 3: Guidelines for the Diagnosis and Management of Asthma. Washington, DC: NHLBI.

NRC. 2008. Estimating Risk Reduction and Economic Benefits from Controlling Ozone Air Pollution. National Research Council.

OTC. 1998. Pollution Control Strategies in the Northeast and Mid-Atlantic States To Clean Up Ground Level Ozone: Progress to Date and Look Towards the Future. Mimeo, OTC.

Pew 2000.

PDR. 2003. Red Book: Pharmacy's Fundamental Reference. Thomson PDR.

PDR. 2006. Red Book: Pharmacy's Fundamental Reference. Thomson PDR.

Pickering LK, Baker CJ, Kimberlin DW, Long SS. 2003. Eds., Red Book: 2009 Report of the Committee on Infectious Diseases. 28th ed. Elk Grove Village, IL: American Academy of Pediatrics.

Pope, C. Arden, Majid Ezzati, and Douglas W. Dockery. 2009. "Fine-Particulate Air Pollution and Life Expectancy in the United States." New England Journal of Medicine 360: 376-86.

Thompson Healthcare, Inc. 2007. MarketScan Research Databases User Guide and Database Dictionary. Commercial Claims and Encounters Medicare Supplemental and COB. Data Year 2006 Edition. Ann Arbor, Michigan: Thomson Healthcare Inc.

Schmalensee, Richard, Paul L. Joskow, A. Denney Ellerman, Juan Pablo Montero, and Elizabeth M. Bailey. 1998. "An Interim Evaluation of Sulfur Dioxide Emissions Trading." Journal of Economic Perspectives 12(3): 53-68.

Shadbegian, Ronald J., Wayne Gray, and Cynthia Morgan. 2007. Benefits and Costs from Sulfur Dioxide Trading: A Distributional Analysis. In Visgilio, Gerald R., and Diana M. Whitelaw. Eds., Acid in the Environment. Springer.

USEPA. 1998. "Regulatory impact analysis for the NOx SIP Call, FIP, and Section 126 Petitions. Volume 2: Health and Welfare Benefits." EPA-452/R-98-003B. Washington, DC.

USEPA. 2000. "Guidance on Air Quality Designations for the 8-Hour Ozone NAAQS." Memorandum, March 28.

USEPA. 2005. Evaluating Ozone Control Programs in the Eastern United States: Focus on the NO_x Budget Trading Program, 2004. Washington, DC: USEPA.

USEPA. 2008. National Air Quality Status and Trends Through 2007. Research Triangle Park, North Carolina: USEPA.

USEPA. 2009a. The NO_x Budget Trading Program: 2008 Emission, Compliance, and Market Data. Washington, DC: USEPA.

USEPA. 2009b. The NO_x Budget Trading Program: 2008 Highlights. Washington, DC: USEPA.

Weiss, Kevin B., and Sean D. Sullivan. 2001. "The Health Economics of Asthma and Rhinits. I. Assessing the Economic Impact." *Current Reviews of Allergy and Clinical Immunology* 107(1): 3-8

WHO. 2003. Health Aspects of Air Pollution With Particulate Matter, Ozone, and Nitrogen Dioxide. Bonn, Germany: WHO.

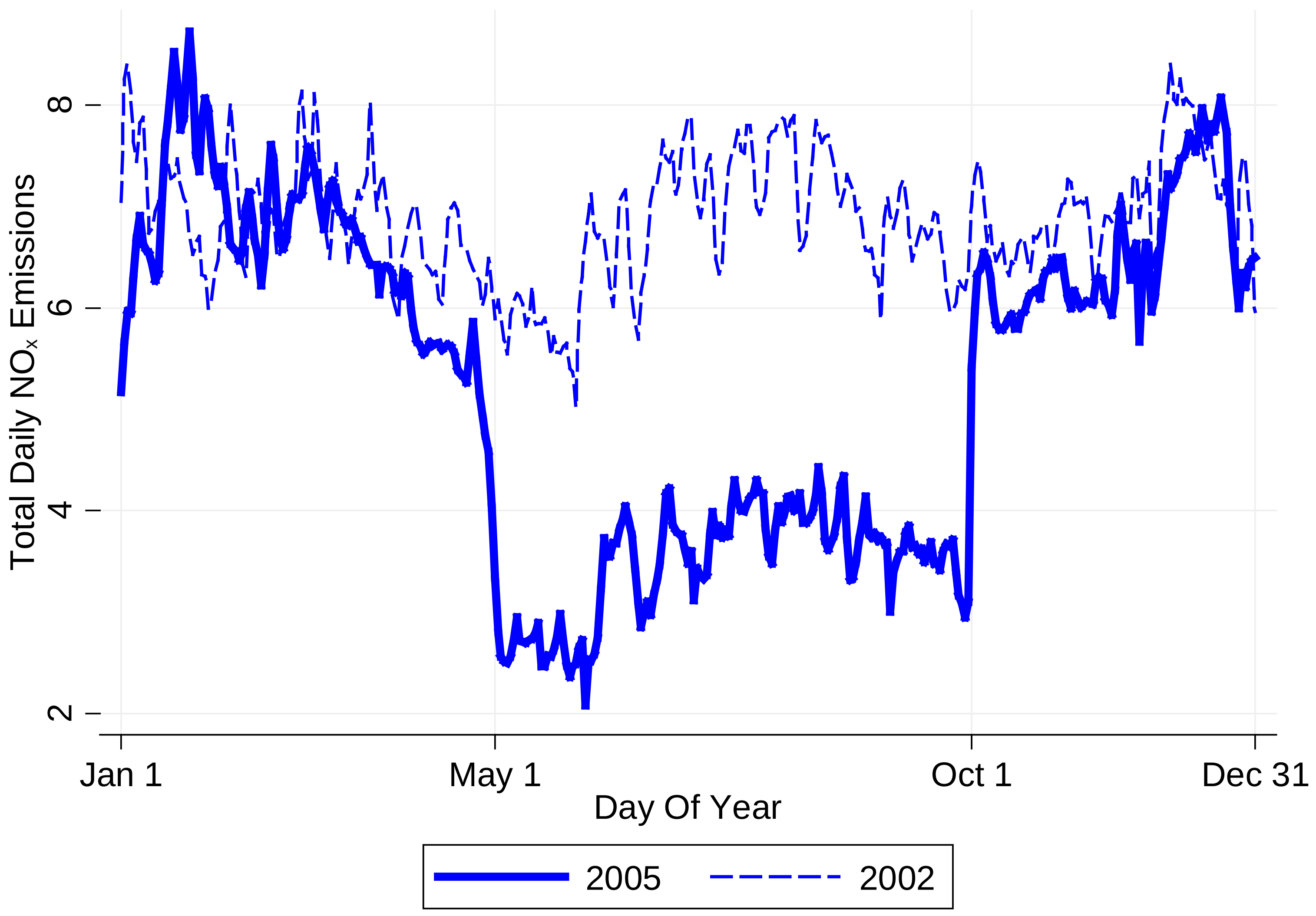


Figure 1. Total Daily NO_x Emissions in Eastern U.S.
Note: Graph depicts fitted NOx residuals for Wednesday after partialling out day-of-week indicators. Y-axis measured in thousands of tons.

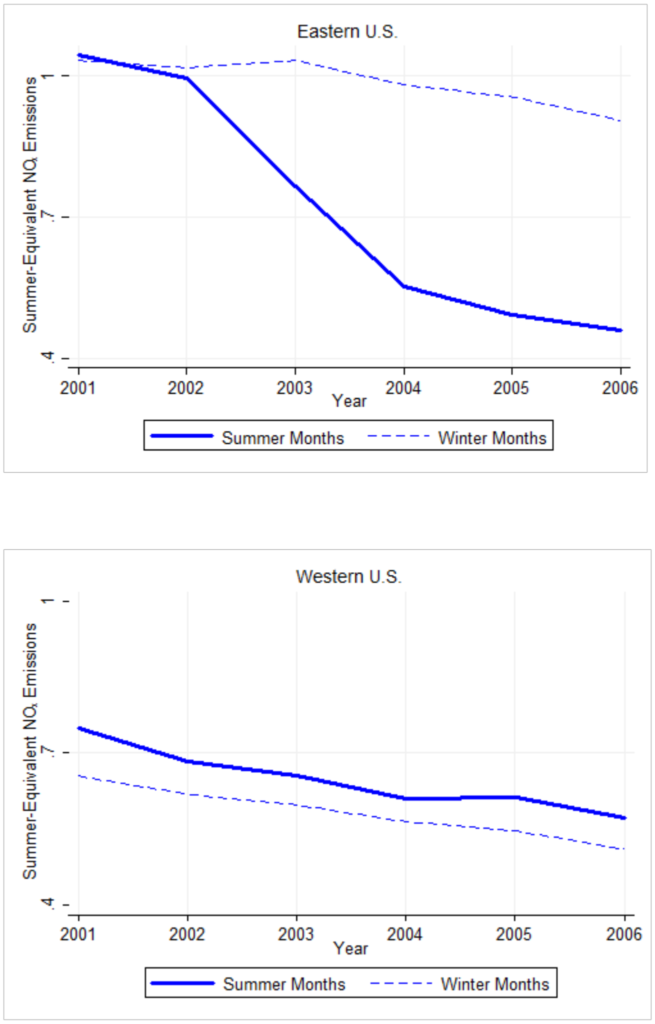
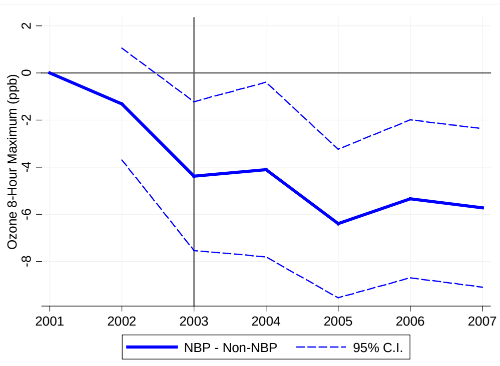
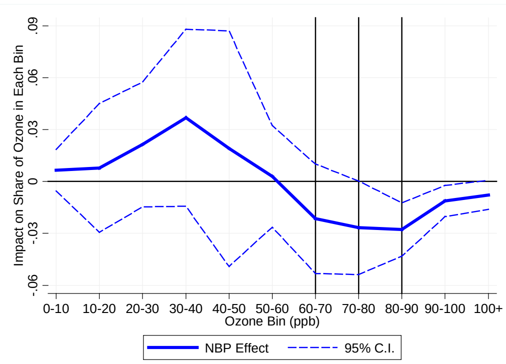


Figure 2. Seasonal NOx Emissions, 2001-2006

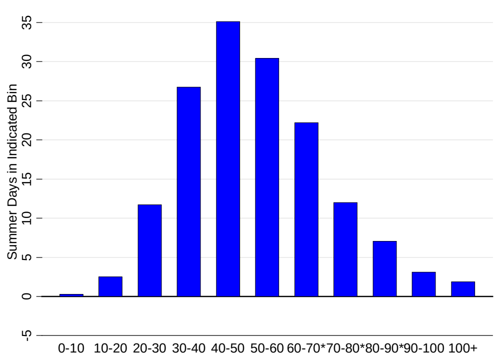
Notes: y-axis is in millions of tons. Summer-equivalent multiplies the winter total by 5/7.



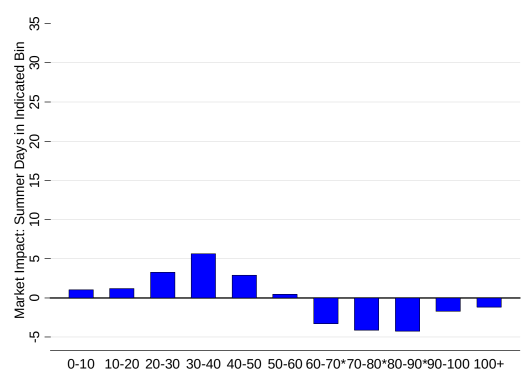
Panel A. Event Study for Mean Ozone



Panel B. Market Impact on Share of Days in Each Ozone Bin



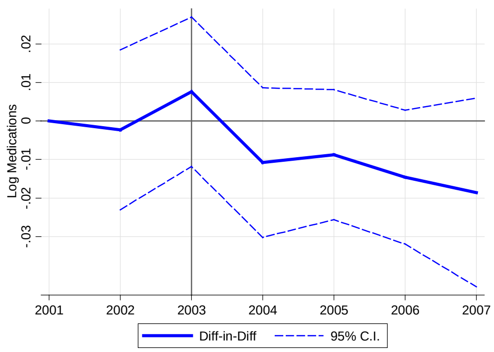
Panel C. Summer Days in Each Ozone Bin, Eastern US, 2001-2002



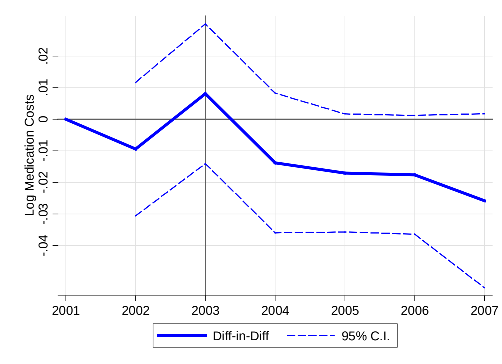
Panel D. Market Impact on Summer Days in Each Ozone Bin

Figure 3. Market Impact on Ambient Ozone Pollution

Notes: Ozone is measured as the maximum 8-hour mean of hourly values within in each day, which is the statistic used in EPA nonattainment designations. Vertical lines in Panel B and asterisks (*) in Panel C represent EPA nonattainment standards in ppb: 85 (1997 standard), 75 (2008 standard), and 60-70 (2010 proposed standard).

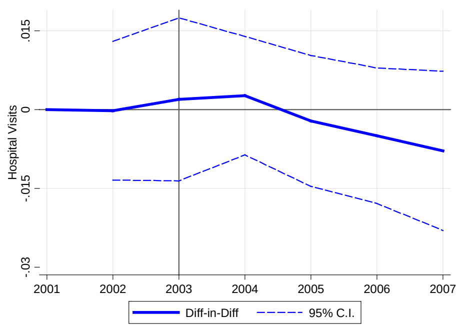


Panel A. Log Medications

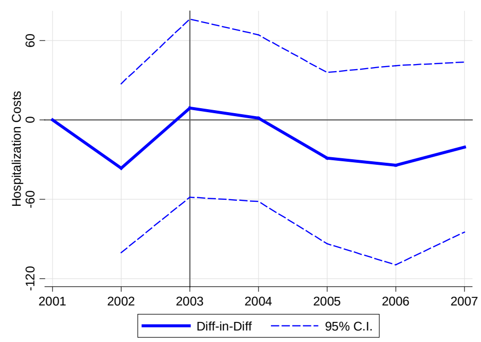


Panel B. Log Medication Costs

Figure 4. Impact of Emissions Market on Medication Purchases



Panel A. Hospital Visit Rate



Panel B. Hospital Costs

Figure 5. Impact of Emissions Market on Hospital Admissions

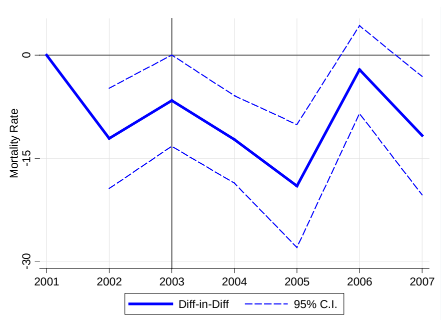


Figure 6. Impact of Emissions Market on Mortality Rates

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)	79	1.62	(3.31)	79	1.45	(4.27)	[0.467]
SO_2 Emissions	2,539	1.50	(6.52)	79	2.74	(6.11)	79	1.76	(4.52)	[0.002]
CO_2 Emissions	2,539	384	(1,299)	79	1,269	(1,933)	79	999	(2,092)	[0.026]
Ambient Pollution										
Ozone 8-Hour Value (ppb)	158	48.01	(9.39)	79	41.10	(6.01)	79	54.91	(6.71)	[0.000]
Ozone Days ≥65 (ppb)	158	23.34	(22.94)	79	10.77	(9.43)	79	35.92	(25.45)	[0.000]
NO_2 (ppb)	103	10.51	(5.14)	33	7.67	(3.75)	34	11.67	(4.43)	[0.000]
CO (ppm)	124	0.45	(0.26)	34	0.46	(0.23)	33	0.45	(0.21)	[0.497]
$PM_{2.5}$ ($\mu g/m^3$)	256	13.45	(4.29)	41	10.49	(3.00)	43	11.75	(4.71)	[0.000]
PM_{10} ($\mu g/m^3$)	17	29.04	(7.68)	3	25.31	(3.94)	4	31.80	(5.93)	[0.000]
SO_2 (ppb)	144	3.28	(2.23)	31	1.88	(1.47)	31	2.87	(1.94)	[0.000]
Weather										
Temperature (ºF)	2,539	70.59	(5.79)	79	73.97	(7.53)	79	71.55	(5.64)	[0.000]
Precipitation (100")	2,539	11.46	(5.37)	79	13.45	(8.84)	79	7.41	(6.13)	[0.000]
Dew Point Temp. (ºF)	2,539	58.31	(7.58)	79	62.39	(8.50)	79	54.30	(9.42)	[0.000]
Medication Costs ($ Per Person)										
All	2,435	338.53	(302.10)	79	267.08	(84.95)	79	277.24	(102.97)	[0.074]
Respiratory	2,435	20.28	(56.12)	79	14.93	(6.80)	79	17.41	(7.64)	[0.000]
Cardiovascular	2,435	67.56	(72.72)	79	52.18	(21.45)	79	51.83	(25.25)	[0.807]
Hospitalizations ($ Per Person)										
All	2,435	502.62	(2120.44)	79	493.00	(603.13)	79	459.67	(574.41)	[0.347]
Respiratory	2,435	23.72	(243.00)	79	17.68	(44.22)	79	16.37	(31.01)	[0.567]
Cardiovascular	2,435	100.76	(777.85)	79	89.19	(252.93)	79	72.35	(144.29)	[0.174]
Mortality (Deaths Per 100,000 People)										
All	2,539	334.57	(152.65)	79	332.55	(102.34)	79	316.95	(98.42)	[0.010]
Respiratory	2,539	30.04	(23.77)	79	28.21	(11.62)	79	27.59	(9.75)	[0.337]
Cardiovascular	2,539	119.75	(64.36)	79	117.17	(39.42)	79	108.51	(38.16)	[0.000]

All costs in real 2006 dollars. 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.

Table 2--Effect of Emissions Market on Emitted Pollution

	(1)	(2)	(3)	(4)
NO_x	-0.343***	-0.343***	-0.311***	-0.320***
	(0.078)	(0.078)	(0.077)	(0.078)
Effect / Mean	-0.398	-0.398	-0.361	-0.371
SO_2	-0.087**	-0.087**	-0.031	-0.048
	(0.043)	(0.043)	(0.049)	(0.049)
Effect / Mean	-0.034	-0.034	-0.012	-0.019
CO_2	-11.506*	-11.506*	7.750	-9.834
	(6.887)	(6.888)	(8.523)	(9.987)
Effect / Mean	-0.026	-0.026	0.018	-0.022
Summer*Post	x			
Summer	x			
Summer*East	x	x	x	x
Summer-by-Year FE		x	x	x
Basic Weather Controls			x	
Detailed Weather Controls				x
County-by-Year FE	x	x	x	x

Note: each observation represents a county-year-season. Response variable measured in thousands of tons. Covariance matrix allows arbitrary autocorrelation within each MSA. Asterisks denote p-value < 0.10 (*), <0.05 (**), <0.01 (***).

Table 3--Effect of Emissions Market on Ambient Pollution

	(1)	(2)	(3)	(4)
Ozone 8-Hour Value	-3.145***	-3.147***	-4.388***	-4.284***
	(0.648)	(0.652)	(0.796)	(0.882)
Effect / Mean	-0.061	-0.061	-0.085	-0.083
Ozone Days ≥ 65	-8.948***	-8.946***	-10.015***	-13.309***
	(2.162)	(2.172)	(2.062)	(3.729)
Effect / Mean	-0.268	-0.268	-0.300	-0.398
NO_2	-0.159	-0.162	-0.109	-0.668
	(0.397)	(0.399)	(0.432)	(0.522)
Effect / Mean	-0.011	-0.011	-0.008	-0.046
CO	0.002	0.002	0.015	0.012
	(0.027)	(0.027)	(0.027)	(0.033)
Effect / Mean	0.005	0.005	0.029	0.023
$PM_{2.5}$	-0.535*	-0.541*	-0.403	-0.409
	(0.310)	(0.308)	(0.304)	(0.357)
Effect / Mean	-0.032	-0.032	-0.024	-0.024
PM_{10}	1.632	1.600	1.307	-3.856*
	(2.157)	(2.207)	(2.179)	(1.888)
Effect / Mean	0.047	0.046	0.037	-0.110
SO_2	0.152	0.154	0.207	0.083
	(0.178)	(0.179)	(0.191)	(0.266)
Effect / Mean	0.033	0.033	0.045	0.018
Summer*Post	x			
Summer	x			
Summer*East	x	x	x	x
Summer-by-Year FE		x	x	x
Basic Weather Controls			x	
Detailed Weather Controls				x
County-by-Year FE	x	x	x	x

Note: each observation represents a county-year-season. Regressions are GLS weighted by number of underlying pollution readings. Mean is for 2001-2002 summers in Eastern US. Covariance matrix allows arbitrary autocorrelation within each MSA. Asterisks denote p-value < 0.10 (*), <0.05 (**), <0.01 (***).

Table 4--Effect of Emissions Market on Log Medication Costs

	(1)	(2)	(3)	(4)
All Medications	-0.018*	-0.018*	-0.018*	-0.016**
	(0.010)	(0.010)	(0.010)	(0.008)
Respiratory	-0.033*	-0.032*	-0.037**	-0.025*
	(0.017)	(0.017)	(0.017)	(0.014)
Cardiovascular	-0.015	-0.015	-0.015	-0.016**
	(0.010)	(0.010)	(0.010)	(0.007)
Gastrointestinal	-0.009	-0.009	-0.009	-0.011
	(0.010)	(0.010)	(0.010)	(0.010)
FE:				
Summer*Post	x			
Summer	x			
Summer*East	x	x	x	x
Summer-by-Year FE		x	x	x
Basic Weather Controls			x	
Detailed Weather Controls				x
County-by-Year FE	x	x	x	x

Note: each observation represents a county-year-season. Regressions are GLS with weight equal to MarketScan population in a given county-year-season. Covariance matrix allows arbitrary autocorrelation within MSAs. Asterisks denote p-value < 0.10 (*), <0.05 (**), <0.01 (***).

Table 5--Effect of Emissions Market on Hospitalization Costs

	(1)	(2)	(3)	(4)
All Emergencies	-0.700	-0.688	-3.082	-6.611
	(17.970)	(17.890)	(17.990)	(19.428)
Respiratory	3.419	3.437	3.316	6.066
	(4.236)	(4.235)	(4.311)	(3.931)
Cardiovascular	-7.515	-7.467	-7.619	-6.579
	(6.840)	(6.853)	(6.891)	(7.771)
Injury	-4.903	-4.958	-5.648	-8.463
	(5.655)	(5.653)	(5.675)	(5.787)
FE:				
Summer*Post	x			
Summer	x			
Summer*East	x	x	x	x
Summer-by-Year FE		x	x	x
Basic Weather Controls			x	
Detailed Weather Controls				x
County-by-Year FE	x	x	x	x

Note: each observation is a county-year-season. Regressions are GLS with weight equal to MarketScan population in a given county-year-season. Covariance matrix allows arbitrary autocorrelation within each MSA. Asterisks denote p-value < 0.10 (*), <0.05 (**), <0.01 (***).

Table 6--Effect of Emissions Market on Mortality Rates

	(1)	(2)	(3)	(4)	(5)
All Deaths	-5.272***	-5.229***	-5.413***	-5.271**	-3.570**
	(1.835)	(1.829)	(1.987)	(2.154)	(1.801)
Respiratory	-0.896**	-0.884**	-0.753*	-1.171**	-0.836*
	(0.396)	(0.396)	(0.404)	(0.485)	(0.455)
Cardiovascular	-1.726*	-1.706*	-1.988**	-1.959**	-1.355
	(0.886)	(0.884)	(0.981)	(0.984)	(0.901)
Neoplasm	-0.342	-0.339	-0.475	-0.408	-0.179
	(0.534)	(0.534)	(0.546)	(0.560)	(0.490)
External	0.181	0.182	0.039	0.259	0.088
	(0.410)	(0.410)	(0.410)	(0.442)	(0.386)
All Other	-2.309**	-2.300**	-2.197**	-1.733	-1.200
	(1.094)	(1.090)	(1.103)	(1.128)	(0.847)
FE:					
Summer*Post	x				
Summer	x				
Summer*East	x	x	x	x	x
Summer-by-Year FE		x	x	x	x
Basic Weather Controls			x		
Detailed Weather Controls				x	x
County-by-Year FE	x	x	x	x	x
First Year of Data	2001	2001	2001	2001	2000

Note: Response variable is deaths per 100,000 population. Specification is same as previous tables. "All Other" all causes other than respiratory, cardiovascular, and neoplasm. Asterisks denote p-value < 0.10 (*), <0.05 (**), <0.01 (***).

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

Cause of Death	All (1)	Respiratory (2)	Cardiovascular (3)	Neoplasm (4)	External (5)	All Other (6)
Age 0 (Infants)						
Summer*Post*NBP	-4.436	-1.250	0.111	0.232	0.030	-3.530
	(9.972)	(1.215)	(1.170)	(0.500)	(1.862)	(9.686)
Response Var Mean	263.31	5.12	5.59	1.50	15.47	251.10
Implied 2005 Deaths	-78	-22	2	4	1	-62
Ages 1-64						
Summer*Post*NBP	-1.112	-0.167	0.016	-0.085	0.398	-0.875
	(1.327)	(0.174)	(0.369)	(0.353)	(0.417)	(1.051)
Response Var Mean	97.66	4.14	21.30	25.87	24.12	46.35
Implied 2005 Deaths	-1,295	-194	19	-99	463	-1,019
Ages 65-74						
Summer*Post*NBP	-12.801	-1.624	-7.587	-1.293	0.254	-2.296
	(7.960)	(2.456)	(5.398)	(5.188)	(1.332)	(3.823)
Response Var Mean	794.47	79.93	240.75	292.71	27.83	181.08
Implied 2005 Deaths	-1,135	-144	-789	-115	23	-204
Ages 75+						
Summer*Post*NBP	-42.582**	-12.536**	-18.588*	-2.665	-1.162	-8.794
	(19.285)	(5.792)	(10.260)	(7.005)	(2.889)	(10.207)
Response Var Mean	2,768.33	290.89	1,131.84	551.91	74.50	793.70
Implied 2005 Deaths	-3,460	-946	-1,703	-304	-73	-506
Observations	30,468	30,468	30,468	30,468	30,468	30,456
Clusters	284	284	284	284	284	284

Note: Response variable is deaths per 100,000 population. 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). "All Other" all causes other than respiratory, cardiovascular, and neoplasm. Asterisks denote p-value < 0.10 (*), <0.05 (**), <0.01 (***).

Table 8--Air Quality Model Interactions

	(1)	(2)	(3)	(4)
Panel A: Ambient Pollution				
Ozone	-2.965***	-2.969***	-3.948***	-3.841***
	(1.024)	(1.027)	(1.166)	(1.058)
CRDM Interaction	-0.425	-0.422	-1.045	-1.031
	(2.153)	(2.159)	(2.239)	(1.534)
Panel B: Log Medication Costs				
All	-0.017*	-0.017*	-0.017*	-0.015*
	(0.010)	(0.010)	(0.010)	(0.008)
CRDM Interaction	-0.003	-0.003	-0.002	-0.003
	(0.004)	(0.004)	(0.004)	(0.004)
Panel C: Hospitalization Costs				
All	4.719	4.767	1.680	-0.782
	(19.100)	(19.010)	(19.092)	(20.719)
CRDM Interaction	-25.154*	-25.321*	-21.228	-21.746
	(13.910)	(13.879)	(13.446)	(13.380)
Panel D: Mortality				
All Causes	-4.756***	-4.711***	-4.921**	-4.871**
	(1.769)	(1.764)	(1.940)	(2.190)
CRDM Interaction	-1.189	-1.194	-1.117	-0.849
	(2.587)	(2.588)	(2.611)	(2.475)
FE:				
Summer*Post	x			
Summer	x			
Summer*East	x	x	x	x
Summer-by-Year FE		x	x	x
Basic Weather Controls			x	
Detailed Weather Controls				x
County-by-Year FE	x	x	x	x

Note: each observation represents a county-year-season. Each table entry represents the coefficient on Post*Summer*East in a separate regression. CRDM Interaction represents the interaction of Post*Summer*East with a dummy indicating that the air quality model predicts a county to have more-than-median decrease in ozone pollution. A negative CRDM coefficient indicates that CRDM correctly predicts that the emissions market decreased the response variable. Covariance matrix allows arbitrary autocorrelation within each MSA. Asterisks denote p-value < 0.10 (*), <0.05 (**), <0.01 (***).

Table 9--Differences in Differences Health Estimates

	Calendar Year				May-April Year			
Specification	DD	Differential Trend	Summer DD	Winter DD	May-April DD	May-April Differential Trend DD	May-Sept DD	Oct-Apr DD
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Log Medication Costs								
	0.009	0.010	-0.007	-0.005	0.0315*	0.0527	-0.0071	0.037
	(0.0188)	(0.0232)	(0.0198)	(0.0216)	(0.0181)	(0.0383)	(0.0191)	(0.0239)
Panel B: Hospitalization Costs								
	-63.5105*	-87.3530**	-0.038	-0.0713*	-0.0111	0.0387	-0.0372	0.0377
	(35.8376)	(42.0786)	(0.0438)	(0.0426)	(0.0368)	(0.0603)	(0.0425)	(0.0484)
Panel C: Mortality								
	-0.741	-2.067	-2.200	0.948	-2.981	18.987**	-3.618*	-1.214
	(5.271)	(5.429)	(2.711)	(1.990)	(3.864)	(8.779)	(2.036)	(2.753)
Panel D: Mortality Age 75+								
	69.688**	-36.887	4.472	40.981**	-17.091	17.286	9.448	119.542
	(34.211)	(63.039)	(13.741)	(16.822)	(14.170)	(17.279)	(24.205)	(83.289)
FE:								
East*Year		x	x	x		x	x	x
East*Year*Post			x	x			x	x
Basic Weather Controls			x				x	
Detailed Weather Controls				x				x
County FE	x	x	x	x	x	x	x	x
Year FE	x	x	x	x	x	x	x	x

Note: Each observation is a county-year. Covariance matrix allows arbitrary autocorrelation within each MSA. Columns (5) through (8) include only May 2001 - April 2007. Standard errors in parentheses, p-values in brackets. Asterisks denote p-value < 0.10 (*), <0.05 (**), <0.01 (***).

Table 10--Effect of Ambient Ozone On Medication Purchases and Mortality: Least Squares and Instrumental Variables

	Log Medication Costs				Mortality				
	All	Respiratory	Cardiovascular	Gastrointestinal	All	Respiratory	Cardiovascular	External	All Other
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(5)
OLS (Counties With Ozone)									
8-Hour Ozone	-0.002	-0.001	-0.002	-0.0029*	0.304**	0.038	0.078	0.029	0.127**
	(0.0011)	(0.0012)	(0.0012)	(0.0015)	(0.126)	(0.025)	(0.058)	(0.020)	(0.053)
Days ≥65 ppb	0.000	0.000	0.000	0.000	0.131***	0.018**	0.032*	0.013	0.062***
	(0.0004)	(0.0005)	(0.0003)	(0.0004)	(0.043)	(0.007)	(0.018)	(0.009)	(0.014)
2SLS (Counties With Ozone)									
8-Hour Ozone	0.005	0.014	0.020	0.005	1.567***	0.171	0.609*	0.026	0.754***
	(0.0161)	(0.0197)	(0.0218)	(0.0184)	(0.595)	(0.152)	(0.309)	(0.129)	(0.243)
Days ≥65 ppb	0.002	0.004	0.006	0.002	0.469**	0.051	0.182*	0.008	0.226***
	(0.0047)	(0.0053)	(0.0057)	(0.0053)	(0.192)	(0.045)	(0.103)	(0.038)	(0.073)
Two-Sample IV (All Counties)									
8-Hour Ozone	0.0049	0.0078	0.0051	0.0034	1.187	0.254	0.453	-0.058	0.380
	(0.0036)	(0.0036)	(0.0090)	(0.0053)	(0.5344)	(0.1324)	(0.2350)	(0.0781)	(0.2499)
	[0.181]	[0.387]	[0.335]	[0.254]	[0.027]	[0.056]	[0.055]	[0.459]	[0.129]
Days ≥65 ppb	0.0010	0.0015	0.0007	0.0007	0.418	0.087	0.157	-0.020	0.131
	(0.0050)	(0.0077)	(0.0101)	(0.0032)	(0.2614)	(0.0502)	(0.1096)	(0.0278)	(0.0949)
	[0.840]	[0.841]	[0.947]	[0.824]	[0.111]	[0.085]	[0.153]	[0.475]	[0.167]

Note: Endogenous variable is ozone. IV coefficients are obtained from a Wald estimator. Excluded instrument is Summer*Post*NBP. OLS includes county fixed effects, year fixed effects, and detailed weather control variables. Standard errors in parentheses are estimated by bootstrap clustered by MSA. GLS weights equal the relevant population. P-values in brackets.

Table 11--Aggregate Health Impacts of Emissions Market

	Mortality (# Deaths)	Mortality ($)	Medications ($)	Total ($)
Panel A. NBP Abatement Costs				
Upper Bound Per Year ($ Billion)				$0.8
Upper Bound, 2003-2007 Total ($ Billion)				$3.5
Upper Bound Per Person-Year ($)				$26.4
Panel B. NBP Health Benefits				
Total Per Year ($ Billion)	7,155	$4.3	$0.7	$5.0
Total 2003-2007 ($ Billion)	32,198	$19.1	$3.3	$22.4

Note: All currency in 2006 dollars deflated using BLS CPI for urban consumers. Mortality table entries without dollar signs are number of deaths. 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 $2080/ton and estimated total abatement quantity of 394,000 tons.

Appendix Table 1--Sensitivity Analysis: Emitted and Ambient Pollution

	Emitted Pollution			Ambient Pollution					
	NO_x	SO_2	CO_2	Ozone	NO_2	CO	$PM_{2.5}$	PM_{10}	SO_2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Original	-0.320***	-0.048	-9.834	-4.284***	-0.668	0.012	-0.409	-3.856*	0.083
	(0.078)	(0.049)	(9.987)	(0.882)	(0.522)	(0.033)	(0.357)	(1.888)	(0.266)
Clustered by County	-0.320***	-0.048	-9.834	-4.284***	-0.668	0.012	-0.409	-3.856*	0.083
	(0.093)	(0.054)	(10.056)	(0.681)	(0.560)	(0.038)	(0.423)	(1.961)	(0.280)
Clustered by State	-0.320***	-0.048	-9.834	-4.284***	-0.668	0.012	-0.409	-3.856	0.083
	(0.070)	(0.051)	(8.331)	(0.769)	(0.555)	(0.031)	(0.321)	(2.235)	(0.268)
Clustered by MSA-Season	-0.320***	-0.048	-9.834	-4.284***	-0.668*	0.012	-0.409	-3.856***	0.083
	(0.055)	(0.035)	(7.056)	(0.630)	(0.373)	(0.023)	(0.256)	(1.333)	(0.190)
Weighted by MarketScan Population	-0.553	0.11	-58.959	-4.111**	-0.412	0.029	-0.959	-0.657	0.276
	(0.448)	(0.211)	(127.678)	(1.872)	(0.780)	(0.054)	(0.658)	(1.402)	(0.260)
Weighted by Total County Population	-0.389**	0.092	-75.256	-4.631***	-0.47	0.02	-0.809*	-1.196	0.349
	(0.184)	(0.164)	(77.846)	(1.313)	(0.518)	(0.037)	(0.479)	(1.882)	(0.242)
Summer DD	-0.344***	-0.091	-4.873	-3.112***	-0.611	0.052*	-0.228	-1.994	-0.534**
	(0.065)	(0.073)	(7.832)	(0.421)	(0.640)	(0.030)	(0.419)	(1.502)	(0.232)
Including Year 2000	-0.308***	-0.009	-4.725	-3.273***	-0.528	0.01	-0.057	-2.536	0.208
	(0.078)	(0.052)	(10.889)	(0.740)	(0.434)	(0.037)	(0.325)	(2.197)	(0.208)
Including ME, NH, and VT	-0.298***	-0.005	-4.057	-3.273***	-0.528	0.013	0.003	-1.294	0.208
	(0.077)	(0.050)	(10.628)	(0.740)	(0.434)	(0.037)	(0.317)	(2.662)	(0.208)
Monitors Operating ≥ 30 weeks				-4.601***	-0.618	0.009	-0.371	-1.658	0.114
				(0.774)	(0.473)	(0.032)	(0.373)	(1.916)	(0.240)
State-by-Summer FE	-0.840**	-0.002	-180.196*	-3.125**	-0.136	0.018	-0.752*	-2.549	0.176
	(0.378)	(0.462)	(95.969)	(1.239)	(0.549)	(0.033)	(0.394)	(2.058)	(0.227)
Summer*Post*NBP*Air-Conditioned-Share	-0.748**	0.279	88.965***	4.915	-0.042	-0.101	-2.27	-6.065	1.184*
	(0.294)	(0.172)	(33.494)	(5.246)	(1.883)	(0.067)	(1.686)	(5.639)	(0.662)
Summer*Post*NBP *VOC-Constrained				1.761					
				(1.811)					
Summer*Post*NBP* (High Weekend O_3)				-0.672					
				(1.722)					

Note: unless otherwise noted, each table entry shows the coefficient on Post * NBP from a separate regression. High weekend O_3 indicates that the weekend/weekday ozone ratio exceeds 1.05. Asterisks denote p-value < 0.10 (*), <0.05 (**), <0.01 (***).

Appendix Table 2--Sensitivity Analysis: Medications

	Log Medication Costs				
	All	Respiratory	Respiratory: Rescue	Respiratory: Maintenance	Gastrointestinal
	(1)	(2)	(3)	(4)	(5)
Original	-0.016**	-0.025*	-0.051	-0.019	-0.011
	(0.008)	(0.014)	(0.032)	(0.015)	(0.010)
Clustered by County	-0.016**	-0.025**	-0.051*	-0.019	-0.011
	(0.007)	(0.013)	(0.029)	(0.014)	(0.010)
Clustered by State	-0.016*	-0.025	-0.051*	-0.019	-0.011
	(0.009)	(0.015)	(0.026)	(0.016)	(0.007)
Clustered by MSA-Season	-0.016***	-0.025**	-0.051**	-0.019*	-0.011
	(0.006)	(0.010)	(0.023)	(0.010)	(0.007)
Including ME, NH, and VT	-0.016**	-0.025*	-0.051	-0.019	-0.011
	(0.008)	(0.014)	(0.032)	(0.014)	(0.010)
Rx (Not Costs)	-0.014*	-0.018	-0.035*	-0.009	-0.017**
	(0.007)	(0.012)	(0.019)	(0.013)	(0.008)
Panel of People	-0.010	-0.021	-0.073	-0.014	0.003
	(0.008)	(0.017)	(0.059)	(0.018)	(0.017)
Levels (Not Logs)	-13.612***	-1.078*	-0.103	-0.885*	-1.648***
	(4.384)	(0.580)	(0.076)	(0.501)	(0.595)
	-0.013*	-0.023	-0.013*	-0.067	-0.020*
Purchase-Specific Costs	(0.008)	(0.014)	(0.007)	(0.051)	(0.011)
Counties with Ozone Data	-0.017	-0.035*	-0.069	-0.031	-0.007
	(0.014)	(0.020)	(0.055)	(0.020)	(0.017)
Private Costs	-0.009	-0.013	-0.051	-0.019	-0.014
	(0.014)	(0.018)	(0.032)	(0.015)	(0.014)
State-by-Summer FE	-0.018**	-0.029**	-0.05	-0.023*	-0.014
	(0.008)	(0.013)	(0.031)	(0.013)	(0.010)
Summer*Post*NBP* Air-Conditioned-Share	0.018	0.075***	0.013	0.079***	0.008
	(0.018)	(0.027)	(0.093)	(0.025)	(0.015)

Note: each table entry shows the coefficient on Summer*Post*NBP from a separate regression. May-to-April DD includes data from May 2001 to April 2006, where year fixed effects identify the the period from May 1 of one calendar year through April 30 of the following calendar year. Regression specifications are same as in main tables. Asterisks denote p-value < 0.10 (*), <0.05 (**), <0.01 (***).

Appendix Table 3--Sensitivity Analysis: Hospitalizations

	Hospitalization Costs				
	All	Respiratory	Cardiovascular	Neoplasm	External
	(1)	(2)	(3)	(4)	(5)
Original	-6.611	6.066	-6.579	-2.741	-8.463
	(19.428)	(3.931)	(7.771)	(6.051)	(5.787)
Clustered by County	-6.611	6.066	-6.579	-2.741	-8.463
	(19.226)	(4.220)	(8.017)	(5.608)	(6.004)
Clustered by State	-0.016*	-0.025	-0.051*	-0.019	-0.011
	(0.009)	(0.015)	(0.026)	(0.016)	(0.007)
Clustered by MSA-Season	-6.611	6.066**	-6.579	-2.741	-8.463**
	(13.738)	(2.781)	(5.495)	(4.277)	(4.093)
Including ME, NH, and VT	-6.198	6.042	-6.318	-2.784	-8.517
	(19.489)	(3.931)	(7.789)	(6.148)	(5.743)
Hospitalizations (Not Costs)	-0.003	0.002	-0.001	-0.001	0.000
	(0.004)	(0.001)	(0.001)	(0.001)	(0.001)
Panel of People	2.987	0.567	1.874	-3.562	0.727
	(11.035)	(1.939)	(6.550)	(2.175)	(2.866)
Logs (not levels)	-0.006	0.251*	-0.135	-0.074	-0.148
	(0.040)	(0.136)	(0.132)	(0.180)	(0.120)
Counties with Ozone Data	-88.440***	-1.689	-29.826**	-3.364	-16.593**
	(27.883)	(8.168)	(14.342)	(8.725)	(7.307)
Private Costs	-1.114	-0.105	-0.218	-0.045	-0.237
	(0.712)	(0.125)	(0.282)	(0.133)	(0.176)
State-by-Summer FE	-8.207	8.412**	-7.727	-5.297	-7.805
	(20.306)	(4.053)	(8.242)	(6.013)	(6.093)
Post*Summer*T*Air-Conditioned-Share	16.358	-0.724	15.483	1.523	4.427
	(44.946)	(7.892)	(14.766)	(8.208)	(7.245)

Appendix Table 4--Sensitivity Analysis--Mortality

	All	Respiratory	Cardiovascular	Neoplasm	External	All Other
	(1)	(2)	(3)	(4)	(5)	(6)
Original	-5.271**	-1.171**	-1.959**	-0.408	0.259	-1.733
	(2.154)	(0.485)	(0.984)	(0.560)	(0.442)	(1.128)
Clustered by County	-5.271***	-1.171***	-1.959**	-0.408	0.259	-1.733*
	(1.913)	(0.423)	(0.923)	(0.631)	(0.387)	(1.045)
Clustered by State	-5.271*	-1.171**	-1.959*	-0.408	0.259	-1.733
	(2.633)	(0.569)	(1.162)	(0.488)	(0.494)	(1.194)
Clustered by State-Season	-5.271***	-1.171***	-1.959**	-0.408	0.259	-1.733**
	(1.850)	(0.400)	(0.816)	(0.343)	(0.347)	(0.839)
Including ME, NH, and VT	-5.171**	-1.153**	-1.881*	-0.385	0.221	-1.752
	(2.143)	(0.477)	(0.976)	(0.563)	(0.439)	(1.115)
Logs	-0.009*	-0.018	-0.009	-0.001	0.004	-0.009
	(0.005)	(0.015)	(0.007)	(0.007)	(0.017)	(0.010)
Counties with Ozone Data	-7.256*	-0.792	-2.821	-0.15	-0.119	-3.492**
	(3.986)	(1.010)	(2.103)	(1.352)	(0.845)	(1.410)
State-by-Summer FE	-3.553**	-0.599	-1.369	-0.338	0.35	-1.247
	(1.739)	(0.468)	(0.866)	(0.551)	(0.416)	(0.953)
Post*Summer*T*Air-Conditioned-Share	10.876	5.749***	4.964	-1.071	-0.787	1.235
	(10.075)	(1.903)	(4.369)	(1.439)	(0.985)	(3.967)

Note: each table entry shows the coefficient on Summer*Post*NBP from a separate regression. Asterisks denote p-value < 0.10 (*), <0.05 (**), <0.01 (***).

Appendix Table 5--Event Study Regressions

	Emitted NOx	Ambient 8-Hour Ozone	Ambient NO_2	Ambient CO	Ambient $PM_{2.5}$	Ambient SO_2	Log Medication Costs	Hospitzliation Costs	Mortality	Elderly Mortality
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Summer * . . .										
NBP * Year=2000	0.039	-1.561	0.401	0.058	0.216	0.192				
	(0.063)	(1.169)	(0.730)	(0.056)	(0.622)	(0.600)				
NBP * Year=2002	-0.219***	-4.154**	-1.128	0.018	-0.857	-1.018	-0.010	-0.086	-12.104***	-87.762***
	(0.068)	(1.627)	(0.716)	(0.060)	(0.795)	(0.621)	(0.011)	(0.092)	(3.726)	(33.161)
NBP * Year=2003	-0.305***	-3.218	-0.894	0.047	-0.599	0.361	0.009	-0.019	-6.612*	-52.841
	(0.080)	(1.989)	(1.016)	(0.079)	(0.740)	(0.528)	(0.011)	(0.080)	(3.390)	(35.144)
NBP * Year=2004	-0.310***	-6.101***	-1.515**	-0.030	0.206	-0.101	-0.014	-0.047	-12.252***	-111.699***
	(0.098)	(1.536)	(0.701)	(0.057)	(0.579)	(0.496)	(0.011)	(0.069)	(3.250)	(34.693)
NBP * Year=2005	-0.353***	-5.396***	-1.627**	-0.014	-1.954***	0.126	-0.017*	-0.028	-19.047***	-164.781***
	(0.089)	(1.763)	(0.697)	(0.052)	(0.656)	(0.647)	(0.009)	(0.075)	(4.568)	(37.031)
NBP * Year=2006	-0.248**	-5.811***	1.146	0.144**	0.927	1.260**	-0.016*	-0.051	-2.092	-9.943
	(0.100)	(1.671)	(0.851)	(0.070)	(0.576)	(0.569)	(0.009)	(0.087)	(3.264)	(29.394)
NBP * Year=2007	0.405**	-2.602	-3.927***	-0.209*	-3.645**	-0.406	-0.027*	-0.054	-11.701***	-49.646
	(0.187)	(5.669)	(1.064)	(0.106)	(1.526)	(1.364)	(0.014)	(0.074)	(4.396)	(37.838)
Observations	35,546	2,212	1,442	910	3,584	1,246	32,677	28,836	35,546	35,546
Clusters	281	93	65	44	151	61	281	281	281	281

Note: Each regression is GLS weighted by number of underlying raw observations for each county-year. Covariance matrix allows arbitrary autocorrelation within each MSA cell. Medication and Emergency Department data are per 1000 persons.