Air Pollution and School Absenteeism:

Results from a Natural Experiment

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Abstract

In this paper we examine the effect of air pollution on absenteeism among elementary school children in Utah Valley. We take advantage of a "natural" experiment that occurred when a large local steel mill closed for about 13 months in 1986 and 1987. Because the mill had a very large impact on particulate pollution but little or no effect on carbon monoxide, we are able to disentangle the effect of these two pollutants, using the mill closure and various measures of atmospheric stagnation as instruments. We find that particulate pollution had a strong impact on school absences, but that carbon monoxide did not. Our findings also suggest that OLS estimates significantly underestimate the effect of particulates on school absenteeism. However, our IV estimates of the effect of carbon monoxide are negative and implausible in our preferred IV specifications.

I. Introduction

There is a large and growing literature that links air pollution to human health. A number of health outcomes have been studied, including life expectancy, adult and infant mortality, and hospitalizations. We discuss some of these outcomes in our survey, below. In this study we examine the short run impact of air pollution on school absenteeism for elementary school students. As Currie, et. al. (2009) suggests, there are two reasons why we should be interested in school absenteeism as an outcome. First, student absenteeism likely affects educational attainment of children. Second, school absenteeism is in its own right, as it gives us a chance to observe how air pollution affects the daily activities of children, which is a measure of children's health and morbidity that is more sensitive than the extreme measures of hospitalization or death.

Correlational studies of the effect of ambient air pollution suffer from two potential problems. The first is measurement error--measured values of ambient pollution levels are unlikely to accurately measure the actual exposure of a particular individual, who may live at some distance from the pollution monitoring station, or whose activities may lead to greater or lesser exposure . Furthermore, monitoring is often sporadic or monitors may fail from time to time, making it difficult to know the ambient level of pollutants even at the monitoring site. It is well known that measurement errors lead to attenuation bias, so that estimated effects of air pollution are biased towards zero.

The second common problem is that of confounding missing variables. In studies that identify differences in exposure to pollutants across space, other important factors, such as family income, may be spatially correlated with exposure levels due to residential income segregation, for example. In studies, such as ours, that take advantage of variation in exposure over time, confounding effects, such as the prevalence of influenza during winter months, when pollution levels are also high, may occur. Of particular interest in our study is the correlation between carbon monoxide and fine particle pollutants.

During periods of stagnation, levels of both pollutants increase, making it difficult to separately identify their separate effects.

In this analysis, we take advantage of a powerful natural experiment to design an analysis that allows us to estimate causal effects of air pollution on elementary school absenteeism. During much of the period of our study an important source of air pollutants in Utah Valley was a large, World War II era steel mill. On August 1, 1986, the mill shut down. It reopened 13 months later on September 1, 1987. Furthermore, the valley is subject to frequent temperature inversions during the winter months. During these inversion periods, pollutants are trapped near the valley floor, and levels of pollutants increase dramatically. On the other hand, during non-inversion periods, air pollution levels can be quite low. The result is that we observe substantial variation pollution over time, and that the pattern of pollution is much different during the school year during which the plant was not in operation. Importantly, concentrations of particulate pollution fell dramatically during the shut-down period, while the concentration of carbon monoxide was not much affected by the operation of the mill.

II. Literature Review

There is an extremely large body of literature that examines the effect of ambient air pollution on health. This literature looks at a variety of outcomes, including premature death/reduced life expectancy, hospitalization, and absenteeism. Pope and Dockery (2006) provide a broad review of the literature on fine particle pollution. Pope (1996) reviews some of the early research that looks specifically at Utah Valley.

We review here the literature on how air pollution affects school absenteeism. The first study was one that we undertook over 20 years ago. (Ransom and Pope, 1992). In this study, we examine the same data that we use in the current paper, but focus solely on the PM10 as a measure of pollution. We use a straightforward regression model and find a large and statistically significant effect of PM10 on school attendance. We estimate that an exposure of 50 mg/m3 PM would reduce absenteeism by about 1 percentage point, roughly 20 to 25 percent of the total rate of absenteeism in this sample.

A few other authors have studied the issue since then. Makino (2000) examines two elementary schools in Japan. He finds a significant impact of PM10 on absenteeism, as does Park, et. al. (2000), who examined a single elementary school in Korea. On the other hand, two US studies, Chen, et. al. (2000), who studies 57 schools near Reno, Nevada, and Gilliland, et. al. (2001) find a beneficial effect of PM10 on school attendance, while finding that other pollutants (CO and O_3 in the case of Chen, et. al, and O_3 in the case of Gillilandi, et. al.) have a significant harmful effect. We believe that the beneficial effect of exposure to PM10 in these studies is likely due to confounding of different pollutants, which are strongly correlated. Romieu, et. al. (1992) examine exposure to ozone and find a harmful effect on attendance of children at a preschool in Mexico City, but they do not consider other pollutants as potential confounders.

Currie, et. al. (2009) examine Texas schools during the 1996-2001 period. They estimate jointly the effects of PM10, CO and ozone using a difference-in-differences-in-differences strategy to attempt to address the correlation issue. They find that CO strongly increases absenteeism, but the PM10 has mixed effects.

This confusion of findings emphasizes the need for convincing statistical analysis to address this topic.

III. Data

Absenteeism Data

We examine data on school absenteeism from two independent sources in Utah Valley that cover the school years from 1985-86 through 1990-91. This first consists of district-wide attendance averages for the Provo School District. Provo School District includes all students who live in the boundaries of the city of Provo, Utah. (See the map in Figure 1.) Each school day, teachers or school administrators entered school attendance into a computerized database. The district compiled this information into a weekly summary report of enrollment and attendance for each grade level and each school. Unfortunately, the school did not maintain these reports in a permanent archive. When we requested these data during the summer of 1991, we were unable to obtain reports for all weeks during some of the years of our study. For 1985-86 we have 27 weeks of data, for 1986-87 we have only 17 weeks, and for 1987-88 we have 31 weeks. For the subsequent years we have complete sets of reports, which consist of 38 weeks of data. During the period of our study, total enrollment in elementary schools in the Provo district increased slightly from about 6,700 in May 1985 to about 6,900 in May 1991.

The second data source is for Northridge Elementary School, located in Orem, Utah. Northridge School is in the Alpine School District, which borders the Provo School District. Northridge School was selected for our original study because it is located near the Lindon pollution monitoring station. (The map in Figure 1 shows the location of the school and monitors.) Total enrollment in Northridge Elementary grew rapidly from about 820 in 1985-86 to about 1120 in 1987-88, and then leveled off at approximately 1000 for the subsequent years of our study. This pattern can be explained by the rapid growth of the neighborhood that the school served due to new housing developments in the area, along with boundary adjustments to keep enrollment within the designed capacity of the school.

To collect the information on enrollment and absences each day, we examined the attendance roll books for each class in the school for each year and counted the total number of students enrolled and total number absent each day.

Table 1 summarizes the data on enrollments and absenteeism rates for the data that we analyze. We focus much of our analysis on grades 1-6, so we report information for those numbers separately. In both the Northridge data and the Provo data, it is clear that 1986-87, the year of the mill closure, was a year of unusually low absenteeism. For Northridge, it appears that the rate was about .5 percentage points lower that year. For Provo the difference is somewhat larger, but the raw comparison is less useful since we only have attendance data for about half of the weeks during the year.

Pollution Data

The Utah State Department of Health monitored PM_{10} levels in accordance with the Environmental Protection Agency's reference method (EPA, 1987). Twenty–four-hour samples were collected commencing at midnight. PM_{10} was monitored at three sites in Utah Valley—Lindon, North Provo , and Orem. The locations of these monitors are also noted on the map in Figure 1. Monitoring at the Lindon site began in April 1985, approximately five months before the beginning of our study. Monitoring was conducted every other day for the first six months and daily thereafter. However, occasionally technical problems resulted in missing observations, sometimes for several consecutive days.

Monitoring of PM_{10} at the Provo site began in January 1986, but was conducted only every 6 days until October 1989, when daily monitoring commenced. Monitoring at the Orem site began in October 1988 and was conducted daily from that date. During the 1989-90 school year (July 1 – June 30), all three monitors were in use on a daily basis. Mean PM_{10} levels at the Orem and Lindon sites were very close at 38.5 and 37.4 mg/m3, respectively, and were highly correlated (R=.91.) Mean PM_{10} levels at the Provo site was somewhat lower at 33.4 mg/m3, but were highly correlated with the Lindon site (R=.94). The maximum 24-hour PM_{10} during the 1989-90 school year was 186, 195, and 166 mg/m3 at the Lindon, Orem and North Provo monitors, respectively. These maximums occurred on the same day at Lindon and Provo, but on the preceding day at Orem. This comparison suggests that the Lindon site provides an adequate characterization of PM10 levels across the area of our study, although it may overstate pollution levels in Provo by somewhat more than 10 percent. Because Lindon was the only site that provided daily monitoring over the entire study period, we use data from the Lindon monitor for all of our analysis.

Carbon monoxide (CO) was monitored daily at the North Provo site over the entire period of our sample. We use the daily maximum 8-hour concentrations to characterize the daily level of CO for our study.

For both CO and PM_{10},we use as our measure of exposure the 7-day lagged average of the available recorded concentrations, averaged over the current day and the preceding six days. During periods for which not all days have reported values, we average over the available days. In a few cases, data are not available for any of the seven days, in which case we treat the observation as missing and exclude that day or week from our analysis.

The effect of ozone concentrations on health has also often been studied, including the Gilliland, et. al. (2001), which found the high concentrations of ozone were associated with higher rates of health-related school absences. However, our study is not well-suited to examine the effect of ozone. Because conditions for ozone formation are absent during winter months, ozone has not been monitored in Utah Valley. Furthermore, ozone concentrations were undoubtedly low during the winter temperature inversions that we study here, although ozone and PM are positively correlated during the months when ozone is monitored. Absenteeism is very low during the part of the school year when ozone is monitored (September and early October), so simple regressions typically show that ozone is beneficial with respect to student absenteeism, but we do not further analyze this in the current study.

Weather

We obtained standard daily weather measurements (high and low temperature, precipitation, and snowfall) from the Brigham Young University weather station. An important weather parameter in our analysis is the clearing index, which measure the level of ventilation or air movement in the atmosphere. The clearing index is defined as the mixed layer depth (in hundreds of feet above ground level) times the wind speed (measured in knots). The index is calculated from atmospheric computer models by National Weather Service meteorologists in Salt Lake City. On days with measureable precipitation or if a cold front passage occurs, the clearing index is assigned a value of 1000+. Values of the clearing index below 500 indicate poor ventilation. Values above 1000 indicate excellent ventilation, and these are simply reported as 1000+. In our study, we define a “stagnant” day as any day when the clearing index on that day and the preceding two days was below 200. We use the number of stagnant days during the preceding week as a predictor of the average concentration of pollution for the preceding week.

Utah Valley is a high mountain valley that has a dry, four season climate. During winter months, the valley is subject to the phenomenon of temperature inversions. During temperature inversions the air becomes stagnant, sometimes for several days at a time. Stagnation episodes allow pollutants to collect in the air. As a result of these weather patterns and the operation of the steel mill, Utah Valley has occasionally experienced extremely high levels of particulate pollution. For example, on January 11, 1986, during the first year of our study, the 24-hour concentration of PM_{10} was 365 mg/m^3, which is among the highest ever recorded in the United States during EPA monitoring. (Monitoring of PM_{10} began in most areas in 1987.) On the other hand, other patterns of weather may result in air that is almost pristine.

Table 2 summarizes the weather and pollution data over the period from July 1, 1985 (about 2 months before the start of school in the first year of our study), to July 1, 1991 (about 1 month after the close of school in the last year of this study). For purposes of this table, we define a "School Year" as beginning on July 1 and ending on June 30, although classes are typically only in session between late August or early September and late May or early June. Data from these years exhibit the typical variation in weather for Utah Valley—some years are a bit warmer (86-87 and 89-90), while others are wetter (85-86), or snowier (88-89). Last line of the table presents our measure of the frequency or severity of air stagnation during the year. This variable is the 7-day lagged sum of the "Stagnant Day" indicator. In the context of Utah Valley, it is basically an index of the number and severity of temperature inversion episodes. It is notable that in 1989-90 and 1990-91 the value of this index is very low, and this is reflected also in the noticeably lower concentrations of PM_{10} and CO during those years. On the other hand, 1986-87, the year that the mill was closed, actually experienced the most severe episodes of inversion, by this measure.

IV. Identification

In order to overcome the potential problems of measurement error and omitted variables, we need only find an appropriate instrument. To be valid, an instrumental variable must be correlated with air pollution, but uncorrelated with absenteeism. We propose two such variables. The first is provided by the closure of the mill. During the closure, particulate pollution fell, as the mill was a significant source of particulates, as is apparent in Table 2.

It is unlikely that the closing of the mill would have an impact on absenteeism apart from its impact on health through pollution levels. Potentially, those who lost their jobs moved, and this may have changed the composition of the student bodies of the schools that we study. This is very unlikely to have happened. First, although the mill was a large employer, it represented only a small fraction of all employment within Utah Valley. Second, both in Provo and at Northridge, student populations were growing. This was especially true at Northridge during the years immediately before, during, and after the closure. Thus, it is implausible that changes in employment at the mill had much of an impact on who was enrolled at the schools.

The second instrument that we use is based on atmospheric stagnation. We define a stagnant day as one in which the clearing index is below 200, and that the previous two days also had a clearing index of less than 200. We count the number of stagnant days during the current and previous six days. This is our measure of atmospheric stagnation. As we show below, this has a very strong effect on the level of pollution. Basically, our measure of stagnation depends on whether there are winds that ventilate the valley. It is implausible that students would be more prone to absence during periods of low wind speed. It is worth noting that almost all of the temperature inversion episodes occur during the period from late December through early March, and that these winter months may also be periods of unusually high morbidity due to season outbreaks of disease, such as influenza, that may have nothing to do with exposure to pollution.

This experiment actually provides a very simple Wald-type estimator of the effect of the PM10 on absenteeism by comparing the change in pollution when the mill was closed –it fell by 11.9, on average-to the change in absenteeism—it fell by .692 percentage points at Northridge. This estimate .692/11.9 = .058, which is on the high end of our IV estimates. (The corresponding estimator for Provo is quite a bit larger, but is less useful because we are missing many weeks of attendance data during the crucial winter during the year the mill was closed.) Since CO concentrations were not really affected by the mill, this estimate of the effect of PM10 is free from confounding with the effect of CO. (Actually, CO concentrations were slightly higher (difference - .114, p=.168) during the year the mill was closed, but this difference is not statistically significant.)

The primary regression model that we estimate is of the following form:

(1) $$R_t = \beta_1 PM_t + \beta_2 PM_{t-1} + \gamma_1 CO_t + \gamma_2 CO_{t-1} + X_t' B + \epsilon_t$$

Where PM_t measures the average daily concentration of PM_{10} during the current and previous six days, and CO_t represents the same 7-day average for the maximum daily 8-hour concentration of CO. The matrix X represents a set of other covariates, which include indicator variables for day of week, month of year, days before and after school holidays, as well as indicators for unusually cold days, unusually hot days, days with heavy snowfall, and measures of rain.

The effects that we are most interested are the sum of β_1 and β_2 and the sum of γ_1 and γ_2. We include lagged variables because we expect that pollution on a given day may lead to absences in subsequent days. The large literature on particulates suggests that they cause morbidity through inflammation. Thus, high levels of particulate will lead to episodes of illness that may persist for some time, or that exposure may lead to more severe illness. In these specifications, we allow for the effect of pollution to persist for two weeks. We allow that CO exposure may have the same lagged effect.

As instruments, we use an indicator that the mill was in operation, the number of stagnant days during the previous week, the interaction of these two variables, the seven-day lag of the number of stagnant days, and the seven-day lag of the interaction. Figure 2 illustrates the relationship between these variables and the level of pollution for the “current week” instruments only. Each graph shows the average pollution level for a given level of the stagnation index. As expected, levels of both PM10 and CO increase with the level of stagnation. However, the impact of the mill’s operation is quite different for the two pollutants. There is little apparent difference between the levels of CO when the mill is open for the same level of stagnation. On the other hand, the concentration of PM10 increased much more rapidly with stagnation when the mill was in operation.

To further illustrate this, we estimate a regression with the 7-day average pollution exposure on the left hand side and the instruments on the right hand side. The results are reported in Table 3. The results show that the severity of stagnation has a very significant impact on the level of both CO and PM_{10}, but that mill operation impacts mostly the level of particulates. Together, the variables explain almost 65 percent of the variation in particulates and slightly less than 40 percent of the variation in CO.

VI. Estimation

OLS Results

We estimate equation (1) by both OLS and by IV. Table 4 reports the OLS estimates for Northridge, and Table 5 reports the corresponding estimates for Provo. We estimate six versions of the model—PM and CO alone, with and without covariates, then with PM and CO both included, with and without covariates. Column II of Table 4 estimates that an increase in the weekly average of PM10 by 100 mg/m3, (a fairly extreme level), would lead to an increase in the absence rate of about 2.2 points. This is close to the estimate reported in Ransom and Pope (1992) of about 2.1, using the same data but a slightly different model. Estimates for CO alone (Columns III and IV) suggest a very large and statistically significant impact of CO exposure on absenteeism. The model with covariates, reported in IV, indicates that at the current EPA ambient standard of 8 ppm, the absence rate would be more than 4 points higher compared to an alternative where there was no exposure to CO!

Columns V and VI report the results when both CO and PM are included in the model. The estimates for PM hardly change when CO is added to the model. However, the estimated effect of CO falls dramatically. In the “with covariates” model in VI, the estimated sum of the lagged effects is positive but it is about 80 percent smaller, and it is not statistically significant . (The reported standard errors and hypotheses tests are based on robust estimates of the variance-covariance, but are not corrected for serial correlation, which is likely present in these data.)

Table 5 reports the corresponding estimates for Provo School District. The results are qualitatively similar to those for Northridge. However, the estimated effects of PM are generally smaller, and the estimated effects of CO are generally larger. Also, the estimated effects of PM are fall substantially when CO is added, as in column (VI) compared to column (II).

Instrumental Variables Estimates

Tables 6 and 7 present the corresponding IV estimates. The models were estimated using GMM with a heteroskedasticity/autocorrelation (HAC) robust variance-covariance matrix. In the case of the daily Northridge data, we used a Newey-West kernel with 7 lags. For the weekly Provo data, we use a lag length of 4.[1] These estimated parameters and standard errors are consistent against autocorrelation, which is likely present in these data, as well as heteroskedasticity.

Table 6 reports the estimates based on the Northridge sample. We report the sums of the current and lagged effect, along with a test of the hypothesis that the sum is zero. (Under the null of no effect, this test is distributed as a chi-squared with one degree of freedom.) The estimates for PM alone are reported in columns (I) and (II). These are larger than the corresponding OLS estimates—in the case of the “with covariates” model, about 40 percent larger. This suggests attenuation bias in the OLS estimates. The IV estimates in the CO alone, columns (II) and (IV) show a similar pattern.

[1] We also estimated these models with lag lengths of 10 and 4, for the Northridge sample, and 6 and 2 for the Provo sample. The estimates are not very sensitive to the choice of lag length.

Columns (V) and (VI) report the results for the model that jointly includes PM and CO. The results are surprising. The estimates for PM increase substantially, while the estimates for CO become negative, and quite large in magnitude. For PM, the estimates suggest that a 100 mg/m3 increase in the concentration of particulates would lead to an increase of 4.5 percentage points. Since the annual average concentration across our sample is close to 50 mg/m3, this suggests that about 2.25 of the average 4.5 percent of students absent each day is due to morbidity caused by exposure to particulates. In other words, half of student absenteeism in our sample can be attributed to exposure to fine particles.

On the other hand, the estimates for CO are negative and large in magnitude. Since average annual exposure for our sample was about 2.5 ppm, the estimate found in column VI, (that the sum of lags is bout 1.0), implies that average attendance was increased by roughly 2.5 percentage points because of exposure to CO. This seems unlikely. Although the estimated effects are not estimated with as much precision for CO as those for PM, the hypothesis that the effect of CO is zero (rather than negative) can be easily rejected.

Table 7 presents the corresponding estimates for the Provo sample. The IV estimates for PM are remarkably similar to those from the Northridge sample, and the same pattern exists, including the implausibly large negative effect of CO on absenteeism. However, the CO effects are estimated with much less precision in this case, and the hypothesis of no effect from CO cannot be rejected.

We report the estimates for the full model, including estimated coefficients for all covariates, in Appendix Table 1 (for Northridge) and Appendix Table 2 (for Provo).

We also analyze absenteeism at Northridge for each grade level group, and Table 8 summarizes the results. There is some variation across grades, but for five of the seven grades that we examine, the effect of PM is statistically significant at the 1 percent level. The effect of PM for the younger grades (1-

3) together is quite a bit larger than for the older grades (4-6) together, which suggests that the effect of PM is stronger on younger children. The effect of CO is estimated with much less precision here, but is negative and statistically significant at the 5 percent level for the grades 1-3 group and at the 10 percent level for the grades 4-6 group.

Table 9 presents a similar analysis for the Provo data. The results here are a little more consistent. The effect of PM on absenteeism is large and statistically significant at the 5 percent level for all of the individual grades. The effect on the secondary students, Grades 7-12 is also positive and statistically significant, although it appears to be somewhat smaller than for the primary-aged children. The effect of CO is negative and large in magnitude for all the age groups. It is statistically significantly different from zero at the 10 percent significance level for most grade levels.

VI. Summary and Discussion

We have examined a very promising "natural experiment" that took place in Utah Valley when a large steel mill ceased operations for a single school year, then reopened. This closure had a dramatic effect on particulate pollution in the valley, although it does not appear to have much impact on other types of criteria pollutants, most notably carbon monoxide. If, in fact, only particulates were affected by the operation of the mill, this experiment provides us with a simple Wald-type estimator that can be computed by comparing the change in the level of PM10 to the change in the average percent of students absent. This estimator has a value of about .05. Given that PM10 levels averaged about 45 mg/m3 over the period of our study, this would indicate that particulate pollution caused 2.25 percent of students to be absent on the average day. This is roughly half of the total rate of absenteeism for this time period, suggesting that pollution is a very important source.

One of the main reasons we have reanalyzed these data are concerns about the effect of carbon monoxide on morbidity of children. For example, Currie, et. al. (2009) find a statistically significant effect of CO on the rate of absenteeism for Texas schools. Chen, et. al. also find a significant impact of CO, while finding a beneficial impact from PM. We think this is unlikely, and note that CO and PM, as well as other pollutants, tend to be highly correlated temporally. This makes it difficult to separate the effect of one pollutant from another. Because the experiment we examine has much different effects of PM than on CO, we can, at least in theory, identify separately their causal effects.

Indeed, our IV estimates are much larger for PM. However, our best estimates for CO suggest that it is beneficial to children—reducing absenteeism. This estimated is large, and in some specifications it is not statistically significant. However, in our daily analysis of the Northridge sample, we find that the effect is negative, large in magnitude, and statistically significant. While CO may have little or no impact on absenteeism at the levels that we observed, we do not believe that it has a large beneficial effect. Thus, our results suggest the need for further study of these data.

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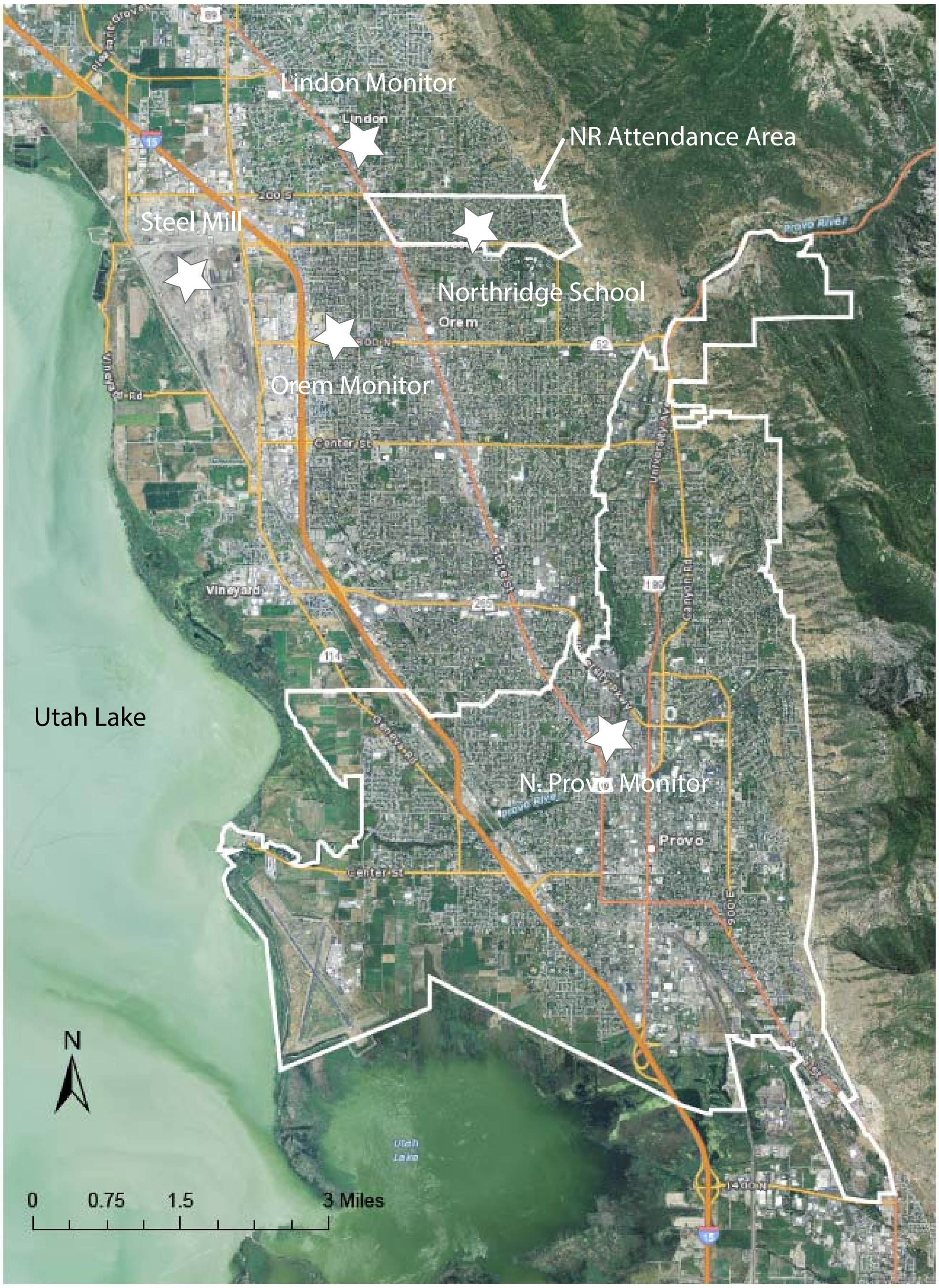
Figure 1: Map of Study Area



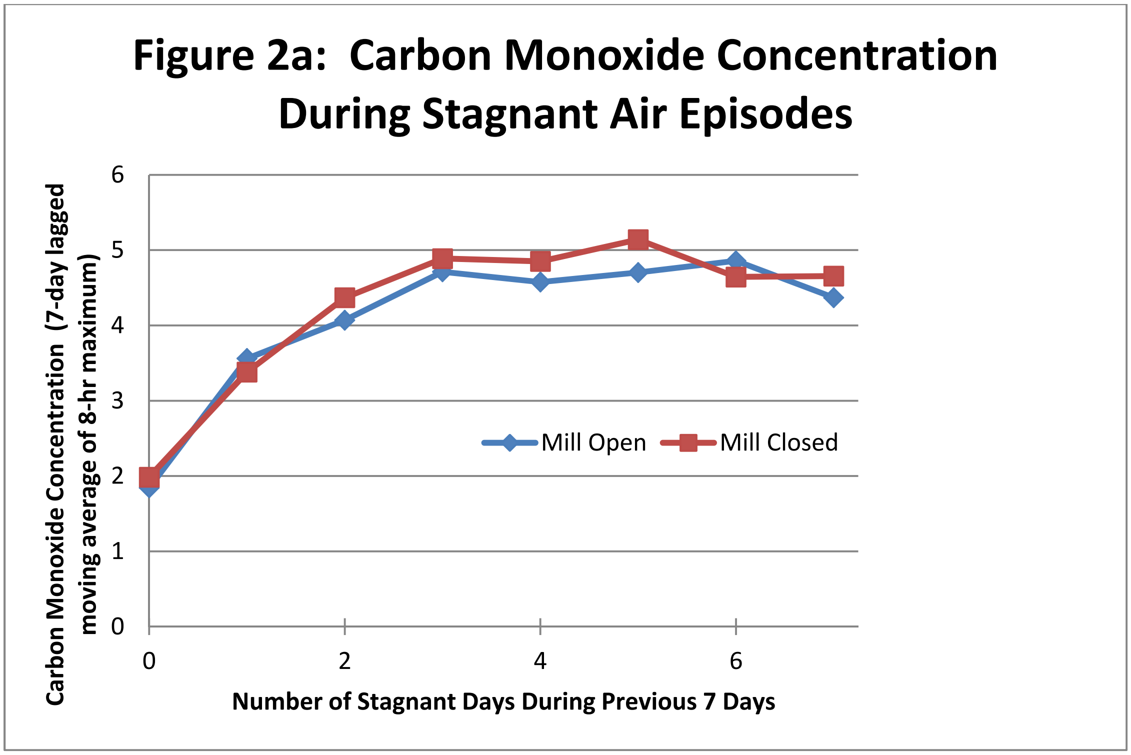


Figure 2a: Carbon Monoxide Concentration During Stagnant Air Episodes
Carbon Monoxide Concentration (7-day lagged moving average of 8-hr maximum)
0
1
2
3
4
5
6
0
2
4
6
Number of Stagnant Days During Previous 7 Days
Mill Open
Mill Closed

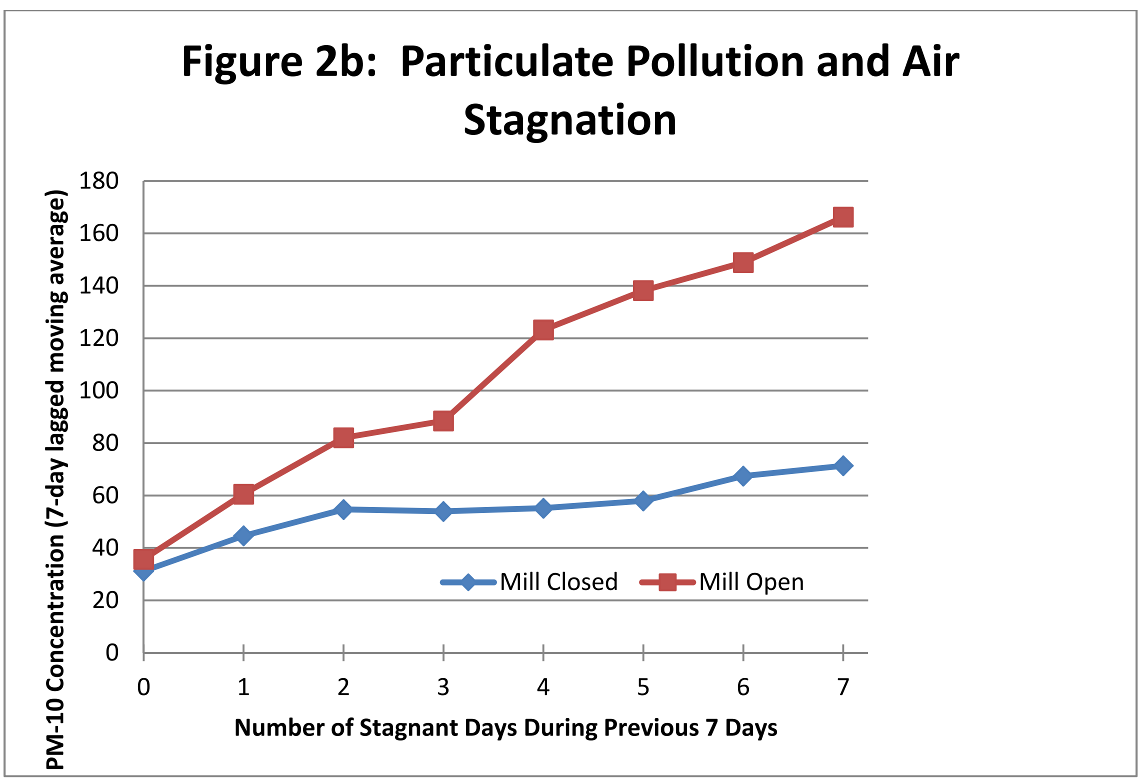


Figure 2b: Particulate Pollution and Air Stagnation
PM-10 Concentration (7-day lagged moving average)
0
20
40
60
80
100
120
140
160
180
0
1
2
3
4
5
6
7
Number of Stagnant Days During Previous 7 Days
Mill Closed
Mill Open

Table 1

Summary Statistics for Absenteeism Data

	School Year					
	1985-86	1986-87	1987-88	1988-89	1989-90	1990-91
Northridge School:						
Average Enrollment (Gr. K-6)	819.53	961.48	1,119.98	987.46	1,041.82	1,038.45
Average Enrollment (Gr. 1-6)	676.94	797.18	935.60	817.94	898.76	882.44
Percent Absent (Total)	4.45	4.08	4.39	4.81	4.76	4.54
Percent Absent (Gr. 1-6)	4.42	3.96	4.38	4.89	4.89	4.57
Provo School District						
Enrollment (Week4) Gr. K-6	6,947	7,079	6,988	7,046	7,004	6,942
Enrollment (Week 4) Gr. 1-6	5,710	5,803	5,872	5,993	5,904	5,928
Enrollment (week 4) Gr. 7-12	4,328	4,501	4,675	4,939	5,233	5,509
Percent Absent Gr. K-6	5.34	4.63	4.76	5.60	5.44	5.71
Percent Absent Gr. 1-6	5.10	4.13	4.70	5.41	5.23	5.55
Percent Absent Gr. 7-12	3.87	4.28	4.50	4.65	5.02	5.52
Weeks of Data Available	27	17	31	38	38	38

Table 2
Summary Statistics for Weather and Pollution Data

	School Year					
Variable	1985-86	1986-87	1987-88	1988-89	1989-90	1990-91
Mean Low Temperature (F)	39.86	40.93	39.34	39.44	40.55	38.28
Minimum Temperature	4	5	-7	-20	9	-16
Mean High Temperature	66.31	65.84	65.60	65.16	67.12	65.48
Maximum Temperature	104	101	99	100	103	104
Mean Precipitation (inches)	0.07	0.05	0.04	0.04	0.05	0.05
Mean Snowfall (inches)	0.14	0.11	0.09	0.26	0.16	0.16
Mean test pmPM_{10} ($\mu g/m^3$)	48.87	36.33	49.51	54.55	38.52	44.69
Days monitored	267	317	327	331	330	325
Mean 7-day average PM_{10}	50.40	37.23	49.43	54.98	38.57	43.48
C0 (max 8-hr avg, ppm)	2.61	2.50	2.68	2.29	2.23	2.27
Days monitored	342	346	239	315	336	291
Mean 7-day average CO	2.60	2.49	2.54	2.24	2.18	2.26
Clearing Index	639.13	615.34	611.32	644.67	717.48	696.07
Stagnant Day (Dummy)	0.08	0.10	0.09	0.10	0.06	0.08
7-Day Sum Stagnant Days	0.60	0.69	0.65	0.67	0.44	0.54

Notes: For purposes of this table, a school year begins on July 1 and ends on June 30, although classes are in session typically only between late August or early September, and the end of May or beginning of June.

Table 3

Regression Estimates of Effect of Stagnation
And Mill Operation on Pollution Levels

	PM_{10}		CO
Mill Open	4.3300**		-0.1270*
	(1.1813)		(0.0708)
Stagnant Days	6.2267**		0.5365**
	(0.6151)		(0.0359)
(Mill Open)×(Stagnant Days)	13.4662**		0.0746*
	(0.6979)		(0.0407)
Intercept	31.8999**		2.1127**
	(1.0653)		(0.0640)
R^2	0.6390		0.3760

Notes: *** indicates statistical significance at the 1% , ** at the 5%, and * at the 10% level.

Table 4

Effect of Air Pollutants on Percent of Students Absent
Northridge Elementary School Sample (Grades 1-6)

Ordinary Least Squares Estimates

Variable	I	II	III	IV	V	VI
PM_{10}	0.0153	0.0125			0.0166	0.0136
	(0.0025)	(0.0027)			0.0030	0.0030
PM_{10} (lag 7)	0.0138	0.0098			0.0099	0.0082
	(0.0025)	(0.0023)			0.0030	0.0026
Sum	0.0291	0.0221			0.0265	0.0218
Test Sum=0	152.5	56.5100			77.75	46.25
DF (F test)	1, 1060	1, 1027			1, 1007	1, 974
CO			0.1685	0.2625	-0.1458	-0.0635
			0.0638	0.0837	0.0647	0.0823
CO (lag 7)			0.3895	0.2818	0.2616	0.1569
			0.0610	0.0675	0.0644	0.0717
Sum			0.5580	0.5443	0.1158	0.0934
Test Sum=0			110.82	56.51	4.45	0.78
DF (F test)			1,1015	1, 1027	1, 1007	1, 974
Controls	No	Yes	No	Yes	No	Yes
Sample Size	N=1063	N=1063	N=1018	N=1018	N=1012	N=1012

Notes: Controls include indicators for day of week, month of year, weather, and days before and after school holidays. Estimated standard errors are in parenthesis. These are heteroskedasticity robust, but are not corrected for serial correlation.

Table 5

Effect of Air Pollutants on Percent of Students Absent
Provo School District Sample (Grades 1-6)

Ordinary Least Squares Estimates

Variable	I	II	III	IV	V	VI
Pm_{10}	0.0076	0.0049			0.0132	0.0083
	(0.0036)	(0.0046)			(0.0048)	(0.0054)
PM_{10} lag	0.0143	0.0130			0.0036	0.0032
	(0.0042)	(0.0048)			(0.0050)	(0.0060)
Sum Effects	0.0219	0.0179			0.0168	0.0114
Test Sum=0	40.52	14.52			11.45	4.42
DF (F stat)	1, 186	1, 173			1, 180	1, 167
CO			0.0544	0.2237	-0.2251	0.0000
			(0.0875)	(0.1282)	(0.1200)	(0.1389)
CO lag			0.4574	0.4677	0.4158	0.3977
			(0.1073)	(0.1202)	(0.1213)	(0.1558)
Sum			0.5118	0.6914	0.1906	0.3977
Test			45.27	16.12	3.17	3.81
DF (F stat)			1, 182	1, 169	1, 180	1, 167
Controls Included?	No	Yes	No	Yes	No	Yes
Sample Size	189	189	185	185	185	185

Notes: Controls include indicators for month of year and measures of snowy days, rainy days, unusually cold days and unusually hot days, and whether week included, preceded or followed a school holiday. Robust standard errors are in parentheses. Standard errors are not corrected for serial correlation.

Table 6
Effect of Air Pollutants on Percent of Students Absent
Northridge Elementary School Sample (Grades 1-6)

Instrumental Variables Estimates

Variables	I	II	III	IV	V	VI
Pm10	0.0153	0.0199			0.0195	0.0172
	(0.0062)	(0.0062)			(0.0097)	(0.0106)
Pm10 lag	0.0168	0.0114			0.0267	0.0282
	(0.0049)	(0.0048)			(0.0106)	(0.0118)
Sum	0.0321	0.0312			0.0463	0.0454
Test Sum=0 (χ^2, 1)	43.27	22.9			25.98	26.34
p-value	0.000	0.000			0.000	0.000
CO			0.1234	0.1899	-0.1128	-0.1884
			(0.3043)	(0.2761)	(0.3653)	(0.3465)
CO lag			0.6924	0.6087	-0.2769	-0.8991
			(0.2743)	(0.2277)	(0.4147)	(0.5450)
Sum			0.8159	0.7985	-0.3897	-1.0875
Test Sum=0 (χ^2, 1)			32.4	5.72	4.25	6.22
p-value			0.000	0.017	0.039	0.013
J-test	1.99	5.84	6.88	12.25	0.03	0.26
Overidentifying Restrictions	3	3	3	3	1	1
Controls Included?	No	Yes	No	Yes	No	Yes
Sample Size						

Notes: Controls the same as those in Table 4. . HAC standard errors are in parentheses. Estimation by GMM with HAC variance-covariance and bandwidth of 4 lags with Newey-West kernel.

Table 7
Effect of Air Pollutants of Weekly Average Percent of Students Absent
Provo School District Sample (Grades 1-6)

Instrumental Variables Estimates

Variable	I	II	III	IV	V	VI
PM10	0.0117	0.0110			0.0221	0.0149
	(0.0048)	(0.0054)			(0.0111)	(0.0118)
PM lag	0.0190	0.0194			0.0187	0.0322
	(0.0055)	(0.0067)			(0.0252)	(0.0188)
Sum lags	0.0307	0.0304			0.0409	0.0471
Test: Sum lags=0 (χ^2, 1 df)	32.52	18.38			4.33	9.72
p-value	0.000	0.000			0.037	0.002
CO			0.2517	0.4780	-0.3618	-0.2023
			(0.1328)	(0.1826)	(0.4534)	(0.4652)
CO Lagged			0.6355	0.9166	0.0680	-0.6861
			(0.1908)	(0.2686)	(0.8856)	(0.7618)
Sum lags			0.8872	1.3946	-0.2939	-0.8884
Test: Sum lags=0 (χ^2, 1 df)			27.49	16.44	0.38	1.68
p-value			0.000	0.000	0.540	0.1948
Hansen's J	6.06	6.41	4.51	6.95	4.09	5.62
(χ^2, DF)	5	5	5	5	3	3
Controls Included?	No	Yes	No	Yes	No	Yes
Sample Size	189	189	185	185	185	185

Notes: Controls same as those in Table 5. HAC standard errors are in parentheses. Estimation by GMM with HAC variance-covariance and bandwidth of 4 lags.

Table 8
Grade Level Estimates of the Effect of Pollution on Percent Absent
Northridge School
Instrumental Variables Estimates

	Grade Level								
	K	1	2	3	4	5	6	1-3	4-6
PM	-0.0100	0.0396	0.0188	0.0287	0.0021	0.0077	0.0009	0.0272	0.0057
	(0.0096)	(0.0177)	(0.0121)	(0.0143)	(0.0096)	(0.0130)	(0.0098)	(0.0125)	(0.0076)
PM-(lagged 7)	0.0208	0.0497	0.0217	0.0348	0.0120	0.0342	0.0328	0.0303	0.0248
	(0.0156)	(0.0219)	(0.0142)	(0.0196	(0.0128)	(0.0200)	(0.0141)	(0.0149)	(0.0096)
Sum lags	0.0108	0.0893	0.0405	0.0635	0.0141	0.0419	0.0337	0.0576	0.0305
Test Sum = 0 (χ^2, 1df)	0.79	26.57	15.50	23.08	1.55	7.53	9.80	32.26	16.48
p-value	0.37	0.00	0.00	0.00	0.21	0.01	0.00	0.00	0.00
CO	0.6814	-0.8534	0.0704	-0.4039	-0.0370	-0.2712	0.7429	-0.3649	0.0398
	(0.4710)	(0.6363)	(0.5079)	(0.4932)	(0.4273)	(0.5783)	(0.3047)	(0.4610)	(0.2785)
CO-(lagged 1)	-0.4809	-2.1748	-0.5559	-1.1733	0.0680	-1.2209	-1.1424	-0.9916	-0.7488
	(0.7870)	(1.0757)	(0.6862)	(0.9013)	(0.6153)	(0.9694)	(0.6236)	(0.7072)	(0.4641)
Sum lags	0.2005	-3.0282	-0.4855	-1.5772	0.0310	-1.4921	-0.3995	-1.3564	-0.7090
Test Sum = 0 (χ^2, 1df)	0.10	10.86	0.92	5.96	0.00	3.90	0.42	6.88	3.15
p-value	0.75	0.00	0.34	0.15	0.96	0.05	0.52	0.01	0.08

Table 9
Grade Level Estimates of the Effect of Pollution on Percent Absent
Provo School
Instrumental Variables Estimates

	Grade Level							
	K	1	2	3	4	5	6	7-12
PM	0.0437	0.0326	0.0264	0.0255	0.0211	0.0268	-0.0080	0.0125
	(0.0203)	(0.0193)	(0.0238)	(0.0303)	(0.0211)	(0.0309)	(0.0179)	(0.0098)
PM (lagged 1 wk)	0.0233	0.0257	0.0555	0.0633	0.0454	0.0562	0.0532	0.0195
	(0.0293)	(0.0270)	(0.0404)	(0.0463)	(0.0372)	(0.0456)	(0.0331)	(0.0127)
Sum	0.0670	0.0583	0.0819	0.0888	0.0665	0.0830	0.0452	0.0320
Test	10.59	8.04	7.51	6.35	5.72	5.54	3.77	10.45
p-value	0.001	0.005	0.006	0.012	0.017	0.019	0.052	0.001
CO	-1.5360	-0.9617	-0.7578	-0.7900	-0.5840	-0.6556	0.8381	-0.5516
	(0.7617)	(0.7299)	(0.9654)	(1.3257)	(0.8649)	(1.3413)	(0.8610)	(0.4976)
CO (lagged 1 wk)	-0.2101	-0.1848	-1.7596	-2.1435	-1.5157	-2.0170	-1.7028	-0.4256
	(1.1305)	(1.0360)	(1.6398)	(1.9198)	(1.5383)	(1.8732)	(1.3686)	(0.4828)
Sum	-1.7461	-1.1465	-2.5174	-2.9335	-2.0997	-2.6726	-0.8647	-0.9772
Test	3.83	1.51	3.28	3.15	2.74	2.61	0.63	4.76
p-value	0.050	0.219	0.070	0.076	0.098	0.106	0.428	0.029

Appendix Table 1 Northridge Full Model				
Variable	Coeficient	HAC St Err	z	p
PM10	0.0049	0.0408	0.12	0.905
PM10 lag	0.0443	0.0557	0.8	0.426
CO	0.4146	1.9522	0.21	0.832
CO lag	-1.7114	2.8276	-0.61	0.545
Oct	1.3387	0.5349	2.5	0.012
Nov	3.5385	1.7615	2.01	0.045
Dec	3.8007	2.4537	1.55	0.121
Jan	4.0195	1.8672	2.15	0.031
Feb	3.3533	2.0635	1.63	0.104
Mar	2.4129	1.2862	1.88	0.061
Apr	1.7072	0.3527	4.84	0.000
May & Jun	1.3920	0.4210	3.31	0.001
Tuesday	-1.1757	0.1432	-8.21	0.000
Wednesday	-1.5171	0.1836	-8.26	0.000
Thursday	-1.6245	0.2125	-7.65	0.000
Friday	-1.1867	0.1743	-6.81	0.000
Cold	0.6787	1.3123	0.52	0.605
Hot	-0.7679	0.3223	-2.38	0.017
Snow 4+	-0.5031	0.7638	-0.66	0.510
Snow 6+	1.6522	1.1711	1.41	0.158
Precipitation	0.3782	0.4343	0.87	0.384
Before Labor Day	-0.0016	0.5340	0	0.998
After Labor Day	0.0506	0.4249	0.12	0.905
Before UEA	0.6706	0.5130	1.31	0.191
After UEA	0.4232	0.4153	1.02	0.308
Before Thanksgiving	1.6034	1.5082	1.06	0.288
After Thanksgiving	-0.3584	0.6221	-0.58	0.564
Before Christmas	-0.6050	1.1982	-0.5	0.614
After Christmas	-2.7273	2.5130	-1.09	0.278
Before MLK	-0.9861	4.0861	-0.24	0.809
After MLK	-1.0861	5.9582	-0.18	0.855
Before Pres’ Day	-0.9802	2.0995	-0.47	0.641
After Pres' Day	2.3807	1.2725	1.87	0.061
Before Easter	1.1847	0.8808	1.34	0.179
After Easter	0.5544	0.6560	0.85	0.398
Before Memorial Day	1.9002	0.8529	2.23	0.026
After Mem Day	0.9829	0.5536	1.78	0.076
Constant	4.4628	1.0836	4.12	0.000