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***Selected Paper prepared for presentation at the 2021 Agricultural & Applied Economics Association
Annual Meeting, Austin, TX, August 1 – August 3***

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Abstract: *Air pollution and temperature are both environmental factors that can influence the productivity of labor. Using factory-level data on real-time labor productivity in an industrial setting, we investigate the effects of five common air pollutants and find that elevated concentrations of any of them significantly reduces productivity. Ozone and carbon monoxide are found to have the largest negative effects. We also look for interactive effects between temperature and air pollution on productivity and demonstrate that temperature modifies the marginal effects of several pollutants, even at concentration levels currently deemed safe by the EPA. The effects of ozone, in particular, see large changes in magnitude. Finally, we show that omitting ozone leads to substantial bias in the estimation of the effects of temperature on productivity, suggesting that measures of both temperature and ozone must be accounted for when considering productivity.*

Keyword: Labor productivity, Air pollution, Temperature

JEL Codes: J24, L62, Q53

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I. Introduction

Well before the Environmental Protection Agency began operating in December 1970, public concerns over the impacts of human activity on the environment were increasing. The rise in prominence of public discourse on pollution and environmental conservation has inspired a significant economic literature especially as it pertains to labor productivity. To date, air pollution is known to decrease the harvest rates and fruit packing of agricultural workers (Crocker and Horst, 1981; Graff Zivin and Neidell, 2012; Chang *et al*, 2016), the number of passes in soccer matches (Lichter *et al*, 2017), and the performance of elite cyclist (Gong *et al* 1986), while also increasing the error rates of Major League Baseball umpires (Archsmith *et al*, 2018). Additionally, air pollution reduces the labor supplied by agricultural workers (Fan and Grainger, 2019) and workers who live with individuals who are susceptible to air pollution (Aragon *et al*, 2017). Other environmental factors, like high temperatures, have also been shown to decrease the number of surveys completed by survey takers (LoPalo, 2019) and increase the injury rate of outdoor workers (Dillender 2019). High temperatures also reduce the number of hours worked by workers in industries most affected by high temperatures (Graff Zivin and Neidell, 2014).

The current literature has greatly increased our understanding of how temperature and air pollution affects labor supply, but it has mostly examined the effect of a single pollutant or just temperature alone. But air pollution and temperature are not experienced in a vacuum. Hot days may coincide with poor air quality, and air pollutants may be highly correlated since they are often produced by the same source. Moreover, temperature and air pollutants often affect the same body systems. Cold days and carbon monoxide both decrease respiratory function (Fisher *et al*, 1969; Weaver, 2009; D’Amato *et al* 2018; Kang and Zhang, 2019). Hot days and particulate matter both decrease cognitive performance (Hancock and Vasmatzidis, 2009; Cedeño Laurent *et al*, 2018; Zhang *et al*, 2018). Recognizing the potential for compounding and interactive effects, epidemiologists have examined whether extreme temperatures amplify air pollution’s impact on mortality and have found strong associations (Li *et al*, 2017; Li *et al* 2013; Ren *et al* 2009).

Because extreme temperatures increase the effect of air pollution on mortality, it is also likely that extreme temperatures will increase the effect of air pollution on labor productivity. These interactions may become more important as climate change increases the likelihood of extreme temperatures. We, therefore, seek to estimate the effects of five major ambient air pollutants—carbon monoxide (CO), sulfur dioxide (SO₂), nitrogen dioxide (NO₂), ozone (O₃), and particulate matter smaller than 10 micrometers in diameter

(PM10)—on labor productivity, and then examine whether extreme temperatures increase the effects of each pollutant.

Our analysis is enabled by a unique data set from a Midwestern automotive parts supplier. Each worker at the production facility used tools powered by a centralized, electric compressed air system. The system continuously recorded airflow at the factory level, providing a one-to-one mapping of collective labor productivity. Large window fans ventilated the factory year-round, meaning that workers were subject to contemporaneous changes in outdoor air pollution levels, rather than breathing air filtered by a central heating and cooling system. Because the factory was not a point source for pollution and was located in a city with a population exceeding 500,000, changes in pollution are plausibly exogenous. Since we observe the factory over multiple full years, we likely have sufficient variation in temperature to examine whether pollution effects vary with temperature.¹

Only 3.9% of our sample's pollution observations would exceed current Environmental Protection Agency (EPA) standards, and yet we still find significant negative effects of O₃, CO, NO₂, and PM10 on productivity. More specifically, we find that, relative to the mean, a one standard deviation increase in O₃ and CO decreases productivity by 6.5% and 7.9%, respectively. A similar change for NO₂ and PM10 decreases productivity by 2.9% and 3.4%, respectively. The effect of SO₂, while statistically significant, is comparatively smaller at 0.8%. These results confirm prior research that finds O₃, PM10, and SO₂ decrease productivity, while also expanding the literature by documenting meaningful negative productivity consequences for both CO and NO₂.

Before analyzing the interactions between pollutants and temperature, we step back and ask two important questions related to omitted variable bias. First, are the pollution effects subject to omitted variable bias when we exclude other pollutants? Since point sources often emit multiple pollutants and pollutants are sometimes inputs into the creation of others, it is possible for the omission of one or more pollutants to bias the estimated effect of another. Prior research has tended to focus on a single pollutant, meaning that the results may be subject to omitted variable bias. Our data allows us to examine the extent to which previous estimated effects might be subject to bias. We find that the marginal effects of PM10, O₃, and CO are not meaningfully impacted by the exclusion of the other pollutants in our setting. However,

¹ Other studies analyzing the effects of air pollution on worker productivity have used data collected on seasonal workers: agricultural workers (Graff Zivin and Neidell, 2012), soccer players (Lichter et al, 2017), baseball umpires (Archsmith et al., 2018). The downside to using seasonal worker data is that it may lack substantial variations in temperatures, thus cannot generalize the results to full year effects.

a model only including NO₂ or SO₂ would overstate the marginal effects by 23% and 62%, highlighting the importance of controlling for a robust set of pollutants.

Second, is the effect of temperature on labor productivity subject to omitted variable bias when we exclude all air pollution controls? Without controlling for pollution, we find that an 85 or higher degree day decreases productivity by about 10%, relative to the mean, but when pollution controls are included the effect is approximately quartered. We find that the substantial decrease is almost entirely accounted for by the omission of O₃ from the initial model. A result that is consistent with the fact that O₃ is more prevalent on hot days. Therefore, examinations of the effect of temperature on productivity that omit O₃ are likely subject to substantial bias. As such, the growing literature studying the impact of high temperatures on behavior should also control for O₃.

We also find suggestive evidence that temperature modifies the effects of some pollutants. With the exception of SO₂, the marginal effects of each pollutant are modified by temperature, but the aggregate effects are usually statistically insignificant within the range of temperatures and air quality experienced in our data. Our results suggest that more work probing the relationship between air pollution and temperatures on productivity is needed. In particular, settings with more extreme temperatures and worse air quality would provide greater variation to examine these interactions.

The remainder of our paper is structured as follows, Section II discusses our productivity, pollution, and environmental data. Section III discusses our econometric framework and address endogeneity concerns. Section IV discusses our results, and Section V concludes.

II. Data

We use unique data on labor productivity from a unionized, Midwestern factory that supplied parts for a large domestic automotive company. Additionally, we use measures of environmental conditions from the National Oceanic and Atmospheric Administration's National Weather Service and measures of air pollution from the Division of Air Pollution Control of the state's Environmental Protection Agency (EPA). The subsequent subsections will discuss these three data sources in more detail.

II.A. Labor Productivity Data

Our data on productivity comes from a 1.7 million square foot factory which primarily manufactured parts for automotive door frames and latch assemblies. The operation employed approximately 1,800 workers. A centralized, electric compressed air system powered all the production equipment in the factory and

recorded the aggregate airflow leaving the system at any given moment in time. Production engineers overseeing this factory's operation reported that factory level output and aggregate airflow moved in step, meaning that increases in measured airflow correspond directly with increases in factory-level productivity. Given this one-to-one mapping, we use the airflow readings as our measure of factory-level productivity.

Figure 1 is a representative daily airflow chart from the compressed air system. A stylus, moving in sync with the airflow and air pressure, made two continuous traces around the chart. Each mark represents a measurement at a particular point in time. The blue trace, which is not used in our analysis, measures the system's air pressure in pounds per square inch. The heavier red trace captures the airflow volume measured in hundreds of cubic feet per minute (cfm). It is this airflow volume that we use to measure factory-level productivity.²

Restarting the air compression system was a lengthy process, and therefore, it was rarely turned off. As a result, airflow volume readings rarely fall to zero. Machine breakdowns and shortages of key maintenance personnel did occur periodically, but during interviews managers noted that there was no obvious pattern or regularity to these events. Management also remarked that persistent air flow readings below 3,000 cfm would indicate an issue with the production process. While these events rarely occur during our sample period, we omit any airflow readings below 3,000 cfm as a precaution.

The firm provided daily airflow charts covering roughly a six-year period to researchers to study various aspects of labor utilization for the company (Dunn 1990). The data were collected by digitally recording the airflow volume measure at approximately 15-minute intervals from a random sample of the daily charts provided. To match the frequency of the weather and air quality data, as well as to deal with potential serial-correlation concerns, the productivity data was averaged over each hour. Altogether, 26,142 hourly air flow observations from 1983 to 1989 were obtained from these charts.³ Durbin-Watson tests find no serial correlation at the day, week, or month level; however, at the hourly level, the test is inconclusive. To further examine this issue, we conduct a Breusch-Godfrey test and find evidence of the potential serial correlation at the hour level. Therefore, we account for this by adjusting our standard errors using Newey-West with a lag of 6.⁴

² Airflow is the amount of air that is being moved through the factory to power the equipment.

³ The provided daily charts cover 1,761 calendar workdays, while our sample covers 1,090 days.

⁴ We also tested lags of 2, 8, 12, 24, 48, 168, and 352 and found qualitatively similar results.

The factory utilized three eight-hour shifts.⁵ The first and last 30 minutes of every shift served as a transition period so that there were no workflow disruptions during the day. Before the shift premium, most workers made roughly \$17 per hour during the 1987-1989 union contract.⁶ The factory ran in parallel as often as possible, rather than being configured as a direct assembly line. Workers were stationed in clusters with each cluster producing a different part that was then stockpiled for the subsequent step. At the time, the factory was *not* practicing just-in-time production, so a certain amount of inventory buffered each successive phase of production. As a result, no individual or small group of workers could act as bottlenecks, slowing the speed of production. The factory employed a rolling meal break schedule around normal mealtimes to attempt to mitigate the reduction in the number of active workers over mealtimes.

Each shift consisted of the same number of workers performing the same tasks with the same equipment. We do not observe the number of employees that worked each shift in our data, but we are confident that absenteeism was minimal and within acceptable bounds for two reasons (Dunn 1990; Senney and Dunn 2019). First, chronic absenteeism was one of the few valid reasons for automatic termination allowed for in the union contract. Second, the union contract contained “Additional Help (Replacement)” clauses which permitted management to obtain temporary replacement workers to fill in for absent workers if it was deemed necessary to avoid material disruptions to production standards. Interviews with management and union officials at the time confirm that managers attempted to employ the plant’s workforce evenly across the three shifts.

Workers bid for shift assignments according to seniority, but we do not believe this played an important role in shift productivity. At the time of the data collection, the worker with the least amount of tenure had been at the factory for eleven years. Moreover, managers self-reported viewing all workers as sufficiently trained and experienced enough to be interchangeable. Management and union officials also confirmed that turnover (both voluntary and involuntary) was rare, largely due to union termination rules and pay that was superior to other local alternatives.⁷ Furthermore, the results of a worker survey suggested that there was a diversity of tenure across the shifts—some senior workers without dependents actually preferred irregular work schedules due to the pay increase (Dunn 1990). Thus, the overall potential

⁵ First shift was 7:30 am-4:00 pm, second shift was 3:30 pm-12:00 am and third shift was 11:30 pm- 8:00 am.

⁶ According to the union contract, an incentive component was added to the base hourly wage if the shift’s production met at least 150 percent of a predetermined target production level. These two components formed the total hourly pay for production workers, Shift differentials (5 percent premium for second shift and 10 percent for third shift) were then added on top of this total hourly pay.

⁷ For reference, the highest paid worker in the plant earned almost double what the median worker in the MSA made in 1980, and 79% more than the median worker in 1990.

productivity of the workers across the shifts was stable over the period of examination. Finally, management reported that they tried to keep overtime and weekend work at negligible levels because of the extra premiums that were involved. The data confirms that management was generally successful.

II.B. Pollution and Weather Data

Weather conditions affect the transmission and spread of pollutants, so it is necessary to have data on contemporaneous weather conditions. We use weather data from the city and county level provided by the National Weather Service. The pollution data comes from the state EPA. These data offer measures of multiple pollutants and the weather conditions at numerous monitoring sites throughout the county. The factory is near to over fifteen monitoring stations, with seven stations located within 15 miles to the north and east of the factory. Not every monitoring station records all the pollutants every day; therefore, for each pollutant, we use the observation from the closest monitoring station. To address systematic differences in the monitoring stations, we include station fixed effects in our analysis. Overall, a mean of 6.6 and a median of 6 monitoring stations recorded a value for a pollutant on any given day, and 92% of the days in our sample had least 5 stations reporting.

Using multiple monitoring stations might give rise to questions of spatial uniformity. Following the example of Graff Zivin and Neidell (2012), we regress the measured pollution level from the nearest monitoring station against the next closest reporting station. Across all five of our pollution measures, the smallest R^2 obtained was 0.78. Additionally, we examine differences between the first and second closest reporting stations. Across all five of our pollutants, the means of the differences are not significant from zero at the 5% level. This suggests that any measurement error potentially introduced by our method of assigning pollution should be rather small and immaterial.

We focus our investigation on NO_2 , SO_2 , CO, O_3 , and PM10 because these pollutants represent the major ambient air pollutants that EPA measured in the 1980s and they all have well documented adverse health consequences⁸. Specifically, they affect a number of bodily systems and organs, both in acute and chronic exposure, in the short- and long-term. (Chen *et al*, 2007; Kampa and Castanas, 2008; Mohai *et al*, 2011). The current National Ambient Air Quality Standards of the five pollutants are 35 parts per million (ppm) for CO over one hour, 100 parts per billion (ppb) for NO_2 over one hour, 75 ppb for SO_2 over one

⁸More detailed descriptions of each pollutant are provided by the EPA:

<https://www.epa.gov/sites/production/files/2015-10/documents/ace3_criteria_air_pollutants.pdf>

hour, 0.07 ppm for O₃ over 8 hours, and 150 micrograms per meters cubic for PM10 over 24 hours.⁹ It is important to note that only 3.9% of the days in our sample experience substandard air quality that would have exceeded current health standards. Given that a majority of the sample is well within current regulatory standards, the effects of pollution on productivity are the result of pollution levels currently deemed safe by the EPA. To verify the pollution effects were not driven by outliers we re-ran our model with a fixed effect for days exceeding EPA standards, our results were nearly identical.

II.C. Summary Statistics

Table 1 shows summary statistics for productivity, temperature, economic, and pollution variables. The hourly weather variables (i.e., temperature, humidity) show a good variety of conditions consistent with our data covering all four seasons across 6 years. The economic condition variables (i.e., unemployment rate, Federal Funds rate) align with expectations for a manufacturing heavy Midwestern county in the 1980s.

While 20,000 cfm was the maximum airflow of the system, management considered 18,000 cfm to be the full utilization rate for the factory operating at peak efficiency. Consistent with the previous literature on shift work, we find that productivity monotonically decreases across the shifts (Carrier and Monk, 2000; Iskra-Golec *et al.* 2016, Senney and Dunn, 2019) with first shift being the most productive and third shift being the least. As can be seen from Figure 2, the first and second shifts are generally more productive at the beginning of their shifts and their productivity declines over time, whereas the third shift's productivity begins low, and increases towards the end of their shift. The shift hour average productivity differences are statistically significant at 1 percent level, except for 7th hour of the second and third. This result is consistent with the fact that each worker cluster had an incentive component that was added to the base hourly wage if the shift's production met a predetermined daily production target. First and second shift workers exerted more earlier in their shift to reach their target, while third shift workers waited until later in their shift to exert more to hit their target.

In line with this MSA being a non-coastal temperate climate, 90 percent of the sample experienced average hourly temperature between 20 and 80 degrees Fahrenheit while less than 0.7 percent of the sample had temperature below 0 or above 90 degrees. Figure 3 displays how the pollutants and factory productivity vary throughout the day. The pollutants clearly exhibit different patterns and trends throughout the day meaning that the different shifts were subject to different pollution levels. For example, O₃, which is

⁹ For reference consult: <<https://www.epa.gov/criteria-air-pollutants/naaqs-table>>

produced naturally by complex interactions between sunlight, NO₂, and volatile organic chemicals in the atmosphere—peaks during the early afternoon.¹⁰ Both CO and NO₂ are slightly elevated during pre- and post-work rush hours because they are outputs of fuel combustion. SO₂, which is primarily produced by burning fossil fuels in power plants, is elevated during the early to mid-morning. PM10—which is a result of traffic, combustion, domestic fuel burning, natural dust, and salt—levels are relatively stable throughout the course of the day.

Figure 4 demonstrates the seasonality of certain pollutants. O₃ has the clearest seasonal effect because seasonal changes cause temperatures to increase and days to lengthen, directly contributing to its natural production. CO and SO₂ both display relatively stable monthly medians over time. NO₂ is on a general increasing trend over time, but it experienced a large secular decline in early 1988. PM10 spiked in the middle of 1984 then started to decrease during the mid-1980s before increasing during the last few years of the decade.

III. An Econometric Framework

We estimate the relationship between contemporaneous pollution and productivity by estimating the following equation using ordinary least squares:

$$\log(\text{air flow}_t) = \sum_{i=1}^5 (P_{it}\beta_{1i} + P_{it}^2\beta_{2i}) + X_t\gamma + \varepsilon_t \quad (1),$$

where air flow_t is the contemporaneously recorded airflow at time t ; P_{it} represents the level of pollutant i at time t ; X_t is a vector of controls (discussed more below); and ε_t represents the unobservables.

Our specification differs from prior analyses in two important ways. First, we examine the factory rather than person-level productivity. Thus, absenteeism is not directly captured by an indicator but rather by declines in productivity. Whether pollution affects plant-level productivity directly through decreases in worker productivity or indirectly by causing workers to miss more often is not important for understanding the effects of pollution on aggregate productivity. From a policy standpoint, however, the margin matters a great deal. If contemporaneous pollution decreases productivity primarily by decreasing worker productivity, improvements in plant-level air quality could have substantial effects on productivity. If the effect were primarily operating through absenteeism, improvements in ambient air quality would have larger productivity effects by decreasing absenteeism.

¹⁰ As industrial and automotive activity increases throughout the morning, concentrations of NO₂ and volatile organic chemicals also rise. This coincides with when the sunlight is at its most intense; thus, O₃ concentrations typically will reach its daily maximum around the early afternoon (Allen, 2002).

Second, we examine the effects of multiple pollutants. When a worker inhales, they are breathing in a mix of pollutants rather than just one, and it is logical to assume that excluding a pollutant may lead to bias in the effect of another. While not a complete list, by combining the five major pollutants we are able to examine whether omitting pollutants is a source of omitted variable bias because pollutants are often correlated. For example, O_3 is formed by a combination of volatile organic compounds and NO_2 .¹¹ Because the pollutants we examine are measured in differing units (parts per billion versus parts per million) and have different mean levels, we ease interpretation by standardizing the pollutants to have a mean of zero and standard deviation of one; see Aiken *et al.* (1991) for more details on standardization.

With the vector X_t we control for factors correlated with airflow, pollutants, or both. We include indicators for pollution measurement site, shift effects, local weather (*i.e.*, temperature, wind speed and direction, humidity), local and national economic conditions, as well as year, month, day of the week, and hour of the day fixed effects. As discussed in our introduction, a main goal of this paper is to examine whether air temperature exacerbates the effects of air pollution on productivity. We explore this possible synergy by estimating the following equation:

$$\log(\text{air flow}_t) = \sum_{b=1}^n \sum_{i=1}^5 (P_{it}\beta_{1i} + P_{it}T_{bt}\beta_{2i} + P_{it}^2\beta_{3i} + P_{it}^2T_{bt}\beta_{4i}) + X_t\gamma + \varepsilon_t \quad (2)$$

That is, we interact the linear and quadratic pollutant terms with indicators for the air temperature being in a certain range (*e.g.*, temperature greater than 85 degrees Fahrenheit). To check the robustness of our estimates we used a number of temperature indicators. Specifically, we check decile, quintile, and ad hoc temperature bins for the daily mean, daily maximum, daily minimum, and contemporaneous temperature. Our estimated results are robust to all specifications, so we present the maximum shift temperature control in the results section.¹²

III.B. Endogeneity Concerns

As pointed out by Graff Ziven and Neidell (2012) and Graff Ziven and Neidell (2013), there are three potential sources of endogeneity that threaten causal interpretation in the air quality literature: (1) changes in capital, (2) demand induced pollution changes, and (3) mitigation behavior by workers that may alter their pollution and temperature exposure. In this subsection, we discuss each concern, identifying the strengths and weaknesses of our data.

¹¹ For more info see: <https://www.epa.gov/ozone-pollution-and-your-patients-health/what-ozone>.

¹² All specifications can be provided upon request.

Changes in capital are not a concern for our paper. For the entire data period there were no changes to the management structure, equipment, or tools used by the employees. As discussed in the data section, there was relatively little turnover in the factory, suggesting little change in human capital as well. To control for any potential changes in human capital that do exist (aging and changes in demographic composition) we use year fixed effects.

Demand induced pollution changes are not a concern for our paper. The demand for the factory's components was derived directly from expectations of future national demand for the finished product (cars and trucks), implying that local economic activity does not affect the factory's production. The factory, at the time, was a wholly owned, direct subsidiary of the parent automotive company. Moreover, the factory was not a point source for pollution because its tools were electric-powered meaning that any additional pollution created from increased factory production would not directly affect the factory workers. Even if the factory was a point source, previous work shows that regional effects generally outweigh local sources of air pollution (Ault *et al.* 2009; Brook *et al.* 2007). As an extra precaution, we address this concern by controlling for local and macroeconomic factors (described above) and include year and month fixed effects, which address seasonal and annual changes in demand.

Lastly, workers might be engaging in avoidance behavior to mitigate their exposure to pollution and extreme temperatures. As mentioned earlier, the factory was ventilated year-round by large window fans, so while on the factory floor, workers were exposed to contemporaneous pollution with no filtration. Short-run responses by workers require accurate and timely knowledge about daily pollution levels. Only a few of the sampled days would have actually triggered air quality warnings from the EPA using today's more strict safety standards.¹³ Therefore, there is little reason to believe pollution was a major source of absenteeism or caused intentional shirking at the factory. Additionally, chronic absenteeism was one of the few reasons for permissible termination under the union contract. Given that these factory jobs were high wage, came with union benefits, and did not require a college degree, finding comparable alternative employment would have been challenging. Thus, we believe pollution can be seen as plausibly exogenous (after controlling for economic factors) and primarily operates through the intensive margin.

With regard to temperature, workers likely have more means of altering their exposure to ambient air temperature and were more likely to alter their behavior. We can address changes in behavior due to temperature (*e.g.*, absenteeism) by controlling for ambient air temperature flexibly. However, even after

¹³ As a robustness check we ran a specification with an indicator for pollution exceeding current EPA standards. There was no meaningful change in the outcome. These results available upon request.

controlling for ambient temperature our interactions likely do not fully capture the synergies between pollution and cold weather. During hot days workers were exposed to high temperatures because the factory did not have air conditioning, but during the winter the factory was steam heated. Providing ample heating of the factory floor was an explicit item of the governing local union contract. Therefore, our results, while providing good evidence for the synergies between high temperatures and pollution, probably does not allow us to examine synergies at the cold end of the temperature spectrum.¹⁴

Overall, these data provide plausibly exogenous variation in air pollution and high temperatures. This implies that our results capture causal relationships between pollution and productivity in a unique setting. We are also able to provide the first set of estimates of the synergies between pollution and temperature on productivity.

IV. Results

Our analysis begins by discussing results for our baseline linear model. We then introduce non-linearity by including quadratic air pollutant variables. From these results, we check for omitted variable bias by looking at the total effects of pollution, marginal effects of pollution, and the total effect of temperature, which may be correlated with certain pollutants. Finally, we expand upon the potential synergistic effects between pollutants and temperature by including pollutant interactions with a hot temperature indicator to analyze the difference in the effects when the temperature exceeds a given temperature. In all regressions, we control for the site, shift, weather, and economic variables, as well as month, year, and day of the week fixed effects.

IV.A. The Effect of Pollution on Productivity

IV.A.1. Linear Pollutant Model

As the name implies, this model assumes that the total effect of each pollutant on labor productivity is linear (i.e., the marginal effect of each pollutant on productivity is constant). Table 2 presents the regression results for our five pollutants of interest. Column 1 reveals statistically significant, negative coefficients for all five of the pollutant variables. The greatest impacts on productivity come from CO and O₃. This implies that when the CO and O₃ concentration is one standard deviation above their means, productivity at the factory falls by 7.9% and 5.3%, respectively. The negative effects of PM₁₀, NO₂, and SO₂ are also

¹⁴ Current medical research suggests that the effect of temperature on health is U-shape, both cold and hot are potentially harmful. The synergies around productivity and cold is an interesting research question that deserves further work.

statistically significant, but smaller in magnitude. Overall, these findings are consistent with the literature that finds that air pollution negatively affects productivity.

IV.A.2. Quadratic Pollutant Model

This model specification includes both linear and quadratic pollutant terms. This gives the model greater flexibility than the baseline model because the marginal effect of changes in pollution on productivity is allowed to change with respect to initial pollutant concentration levels. The regression output for the quadratic model is displayed in Column 2 of Table 2. In line with our linear results, the greatest impacts on productivity come from CO and O₃, which have net effects of -7.9 and -6.5 percent for one standard deviation increases, respectively. The negative net effects of PM10, NO₂, and SO₂ are also statistically significant.

Previous research often presents results in terms of the marginal effect of pollution on productivity. Because we have demeaned and standardized our pollutant measurements, the estimated linear coefficients are the pollutant's marginal effect on productivity at the mean pollutant concentration level. Because these marginal effects now vary by pollution concentration, they are best comprehended in graphical form. Figure 5 displays the visualization of the marginal effects at various levels of pollutants. While the marginal effects are uniformly negative, we see statistically significant differences in the marginal effect for CO, O₃ and PM10. We find that an increase in O₃ and PM10 would have a larger effect on productivity when initial concentrations are low, and that the effect decreases when current initial concentrations are high. For CO, we find that at low initial concentrations, an increase will lead to a smaller effect than when initial concentrations are high. These results suggest that the marginal effect of pollution is not necessarily constant, as is assumed in the linear regression model.

Additionally, we take the quadratic regression results and back out predictions of the total effect of pollution for large ranges of pollutant concentrations. We then take this domain of predictions and compare them to the predicted total effect at the mean pollution level to calculate the predicted percent change in airflow due to deviations in pollution from the mean. These predicted percent changes are presented in Figure 6. All the percent changes are equal to zero when the z-score of pollution is zero because the predicted productivity at the mean is being compared to itself. As pollution increases from its mean, we see that the percent change in predicted productivity is negative, indicating that labor productivity falls as concentrations of any pollutant increase from the mean concentration level. As pollution decreases from the mean, the predicted productivity change is positive, indicating that labor productivity rises as

concentrations of any pollutant decrease from the mean concentration level. Interestingly, all of these variations appear fairly linear over the normal pollution levels that were present in our data. We test for differences between the total effects predicted by the quadratic and linear results in the next section.

IV.A.3. Does Excluding Pollutants Lead to Omitted Variable Bias?

The atmospheric relationships between air pollutants and other environmental factors are very complex, and data on air pollution concentrations can be limited. Previous papers often collect pollution data for only one or two pollutants. Therefore, the potential exists for model specifications to suffer from omitted variable bias. We believe that our data, which includes the five major ambient pollutants, and our quadratic model specification allow us to test for potential omitted variable bias on two fronts; omitting pollutants that are actually present in the real world and omitting non-linear effects of air pollutants.

IV.A.3.1. Omitting pollutants

It is possible for multiple air pollutants to be emitted from the same point source. For example, automobiles are point sources for both PM10 and CO. It is natural to wonder whether pollutant concentration levels are highly correlated, and if so, does this create the possibility of omitted variable bias in studies whose data is limited to only a couple of pollutants. We find the answer to the first question to be no, while the answer to the second is less straight forward. Consider the correlation coefficients matrix presented in Table 3. In absolute terms, no two pollutants in our data have a correlation coefficient greater than 0.2, signifying that these five pollutants are weakly correlated, at best. This suggests that if previous work did not have access to data on a specific pollutant, we would not expect it to significantly bias the effects of the pollutant variables they did have. But what if only one pollutant is included, and the rest are omitted?

Table 4 presents the coefficients from the linear model if only one pollutant is included (Column 2 to 6) and the full linear model (Column 1). By omitting the other pollutants, the effects of SO₂, NO₂, and CO would be overestimated while O₃ and PM10 would be underestimated. The difference for O₃, CO, and PM10 is less than 8 percent while it is about 23 percent for NO₂ and 62 percent for SO₂.¹⁵ However, the differences in the estimated coefficients are only statistically significant for NO₂ and SO₂. To further illustrate this finding, we also present Figure 7, which compares the estimated marginal effects of solo and multiple pollutant models, and Figure 8, which does the same for the estimated total effects. Figure 7 shows that omitting all other pollutants may lead to biases in the marginal effect of SO₂, NO₂, and O₃. This bias

¹⁵ The results are similar for the quadratic model.

appears to be most prevalent at low levels of O_3 and high levels of NO_2 . The bias also appears across the entire range of SO_2 . These biases in the marginal effects do not, however, appear to extend to the total effects shown in Figure 8 except for extremely low levels of O_3 and high levels of SO_2 and NO_2 . It, therefore, appears unlikely that omitting pollutants from the regression will have large impacts on the predicted total effects of a lone pollutant that is included in the model. While the total effect of solo pollutants appears largely unchanged, we feel strongly that having data on multiple pollutants is important when analyzing pollution related problems. This prevents potential biases in the marginal effects of any included pollutants.

It is also possible that if pollutants are highly correlated with environmental variables, like temperature, then the omission of the correlated pollutant from the regression model could bias the effects of the environmental variable. It is widely known that O_3 concentration levels are highly correlated with temperature (Coates *et al* 2016). In our data, we find a correlation coefficient of 0.57 between the two variables. Therefore, by omitting O_3 , it is possible that the effects of temperature on productivity could be biased. Figure 9 confirms this by showing that when O_3 is omitted, the negative effects of high temperature are severely overestimated. Omitting the other individual pollutants does not have similarly large effect. Thus, analysts that examine the relationship between temperature and productivity need to also control for O_3 .

IV.A.3.2 Omitting Quadratic Pollutants

It is possible that excluding quadratic terms may also lead to omitted variable bias. This would be true if the marginal effect of the pollutant was not constant. While we have previously shown that CO , O_3 , and PM_{10} have significant quadratic coefficients, marginal effects are only statistically different between the linear and quadratic model for O_3 and PM_{10} . Figure 10 displays the marginal effects for both the linear and quadratic model together. The specification bias is largest for O_3 . In both cases, the estimated effects are most different at low concentrations and becomes more similar as the concentration levels of the pollutant increase. However, O_3 also has specification bias at high concentration levels as well.

Additionally, Figure 11 shows the predicted percent change in productivity from the mean for both linear and quadratic models. We see similar results as shown in Figure 10, confirming that the specification bias rising from omitting quadratic terms is most pronounced. Overall, these results show that omitting quadratic pollutant terms may bias marginal effects estimates, especially for low concentrations of O_3 . Predicted total effects, on the other hand, do not seem to be biased by the omission of quadratic pollutant terms. We prefer the quadratic specification because it allows for more flexibility when interacting with a

hot temperature indicator and we, therefore, include quadratic pollutant variables in all future model specifications.

IV.B The Effect of Pollution on Productivity Varying with Temperature

Next, we explore the idea that temperature could play a modifying role in air pollution's effects on productivity. The regressions shown in Table 5 include linear and quadratic pollutant variables, as well as interaction terms between linear and quadratic pollutants and an indicator variable for the temperature being greater than 85 degrees (the results are similar if 80 degrees used instead). Columns 1 and 3 reproduce the original linear and quadratic results from Table 2 for convenience. Column 2 adds the hot temperature indicator regressors to the linear model while Column 4 adds them to the quadratic model.

The inclusion of these interactions changes the interpretation of our estimated regression coefficients. The interpretation of the un-interacted linear pollutant coefficients is now the pollutant's marginal effect on worker productivity at mean pollutant concentration levels when the external temperature is below 85 degrees. The un-interacted quadratic pollutant coefficients now tell us one-half the change in the marginal effect of pollution with respect to pollution at temperatures below 85 degrees. The interacted linear coefficient is the difference between the marginal effect of mean pollution at temperatures above and below 85 degrees. Finally, the interacted quadratic coefficient is the difference in the change in the marginal effect of pollution at temperatures above and below 85 degrees.

We begin our analysis of the synergistic effects of temperature and pollution by looking at the results in Column 4 of Table 5. First, note that all of the un-interacted linear pollutant coefficients take a negative sign and are statistically significant. This implies that, at their mean levels, all five air pollutants have negative marginal effects on worker productivity when temperatures are below 85 degrees. Using the un-interacted quadratic coefficients, we can see how these marginal effects change when the pollutant concentrations deviate from their means. These results are best considered by looking at Figure 12, which shows the marginal effects of pollutants at different concentrations when temperatures are below 85 degrees. For any particular Z-score (the initial pollutant concentration), the height of the line is interpreted as the marginal effect of a one standard deviation increase in the pollutant from that Z-score.

Each marginal effect line lies entirely below zero, signifying that productivity decreases as pollutant concentration increases. The degree to which productivity declines depends upon the slope of the marginal effect. When the marginal effect line is downward sloping, as is the case for CO, productivity is declining at an increasing rate. When the marginal effect line is upward sloping, as is the case for SO₂, NO₂,

O₃, and PM10, productivity is declining at a decreasing rate. Interestingly, we find that the slope of the marginal effect lines for many of these pollutants differs when temperatures exceed 85 degrees, as is shown in Figure 13.

For all pollutants except SO₂, we find clear differences in the marginal effect lines for temperatures above and below 85 degrees. The slope of the marginal effects line of CO becomes more negative. The slope of the marginal effects line of O₃ becomes less positive. The slope of the marginal effects line for both NO₂ and PM10 switches from being upward sloping when temperatures are less than 85 degrees to being downward sloping when temperatures are greater than 85. These results suggest that temperature plays a role in determining the marginal effects of various levels of pollution. Figure 14 shows the predicted percent change in productivity across all pollution levels for temperatures above and below 85 degrees.

Over most of the pollution concentration ranges of each pollutant, little difference exists between the total effects of pollutants when the temperature is above or below 85 degrees. Only at extremely low concentration levels of CO or PM10 do we see significant deviations between the two temperature ranges. For both, we see fewer benefits to productivity from lowering pollution when temperatures exceed 85 degrees. We also see that NO₂ concentration is 1.6 standard deviations above its mean causes a significantly larger decline in productivity when temperatures are greater than 85 degrees than when they are below. The pollution with the most readily seen synergistic effects between temperature and pollution is O₃. At temperatures above 85 degrees, an O₃ concentration of 0.8 standard deviations below its mean increases productivity by significantly less than when the temperature is below 85 degrees. When pollution levels rise above the mean, however, the decrease in productivity is less extreme when temperatures exceed 85 degrees. While these results do not appear as clear cut as those revolving around the marginal effects, they are still suggestive of the fact that temperature modifies the productivity effects of certain types of air pollution, especially at low and high concentration levels.

V. Concluding Thoughts

We merge a unique dataset on the labor productivity of automotive workers with a dataset on environmental conditions to assess the impact of five major air pollutants and temperature on productivity. Most previous studies looking at the effects of air pollution on productivity have only considered seasonal workers and one pollutant. Our work, therefore, provides the next step in advancing the generalizability of this literature by examining the effects of more pollutants on the productivity of workers over the course of all four seasons in an industrial setting. Even though the vast majority of observations in our sample have pollution

levels currently deemed safe by the EPA, we find significant negative effects for four out of the five pollutants.

We also provide evidence that models that do not include a robust set of pollutants may suffer from omitted variable bias. We find that when controlling for only one pollutant, and omitting the rest, the marginal effects of SO_2 and NO_2 increase by 23% and 62%. We also find that when we exclude O_3 from our model the negative productivity impacts of an 80 degree day increase by a factor of four. Researchers, therefore, should seek to control for a broader range of environmental variables, in particular when examining the productivity impacts of temperature. Previous work has done much to establish a relationship between labor productivity and temperature and air pollution, but a more fulsome accounting of environmental variables will allow for a better understanding of which environmental variables have the largest impacts, leading to more informed decision making.

Additionally, we find suggestive evidence that temperature can modify the effects of air pollutants on productivity. While the interaction between most of the pollutants and temperature is not particularly large within the range of temperatures and air quality experienced in our data, NO_2 is a noted exception. Specifically, on hot days the productivity decrease associated with a one standard deviation increase in NO_2 , relative to the mean, increases by about 40 percent. This finding suggests that as climate change increases the number of hot days, air pollution will have even larger negative impacts on labor productivity. We, therefore, believe future work exploring this interaction in settings with more extreme temperatures and pollution is important.

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Figures

Figure 1: Recorded Airflow (Red) on May 16, 1985

Figure 2: Labor Productivity by Hour for Each Shift with 95% Confidence Intervals

Note: Labor productivity is measured at the factory level by airflow in 100 cubic feet per minute. The air flow reading is from a centralized, compressed air system that powered all the production equipment at this factory.

Source: The airflow data was obtained from a Midwestern auto parts supplier for the years 1983-1989.

Figure 3: Median and Interquartile Hourly Labor Productivity and Pollution Levels

Note: Labor productivity is measured at the factory level by airflow in 100 cubic feet per minute. The air flow reading is from a centralized, compressed air system that powered all the production equipment at this factory. The pollution abbreviations are carbon monoxide (CO), sulfur dioxide (SO₂), nitrogen dioxide (NO₂), Ozone (O₃), and particulate matter smaller than ten micrograms (PM10).

Source: The airflow data was obtained from a Midwestern auto parts supplier for the years 1983-1989. The air pollution data comes from the State EPA for the same years.

Figure 4: Median and Interquartile Monthly Labor Productivity and Pollution Levels

Note: Labor productivity is measured at the factory level by airflow in 100 cubic feet per minute. The air flow reading is from a centralized, compressed air system that powered all the production equipment at this factory. The pollution abbreviations are carbon monoxide (CO), sulfur dioxide (SO₂), nitrogen dioxide (NO₂), Ozone (O₃), and particulate matter smaller than ten micrograms (PM10).

Source: The airflow data was obtained from a Midwestern auto parts supplier for the years 1983-1989. The air pollution data comes from the State EPA for the same years.

Figure 5: The Marginal Effects of Pollution on Labor Productivity

Note: The pollution abbreviations are carbon monoxide (CO), sulfur dioxide (SO₂), nitrogen dioxide (NO₂), Ozone (O₃), and particulate matter smaller than ten micrograms (PM10).

Source: The airflow data was obtained from a Midwestern auto parts supplier for the years 1983-1989. The air pollution data comes from the State EPA for the same years.

Figure 6: Predicted Percent Change in Labor Productivity Associated with Each Pollutant

Note: The pollution abbreviations are carbon monoxide (CO), sulfur dioxide (SO₂), nitrogen dioxide (NO₂), Ozone (O₃), and particulate matter smaller than ten micrograms (PM10).

Source: The airflow data was obtained from a Midwestern auto parts supplier for the years 1983-1989. The air pollution data comes from the State EPA for the same years.

Figure 7: The Predicted Marginal Effects of Pollution on Labor Productivity Comparing a Model with All Five Pollutants to a Model with Each Pollutant Individually

Note: The pollution abbreviations are carbon monoxide (CO), sulfur dioxide (SO₂), nitrogen dioxide (NO₂), Ozone (O₃), and particulate matter smaller than ten micrograms (PM₁₀).

Source: The airflow data was obtained from a Midwestern auto parts supplier for the years 1983-1989. The air pollution data comes from the State EPA for the same years.

Figure 8: Omitted Variable Bias Shown by Estimated Total Effects in Labor Productivity

Note: The pollution abbreviations are carbon monoxide (CO), sulfur dioxide (SO₂), nitrogen dioxide (NO₂), Ozone (O₃), and particulate matter smaller than ten micrograms (PM10).

Source: The airflow data was obtained from a Midwestern auto parts supplier for the years 1983-1989. The air pollution data comes from the State EPA for the same years.

Figure 9: Predicted Percent Change in Labor Productivity from the Mean

Note: The pollution abbreviations are carbon monoxide (CO), sulfur dioxide (SO₂), nitrogen dioxide (NO₂), Ozone (O₃), and particulate matter smaller than ten micrograms (PM10).

Source: The airflow data was obtained from a Midwestern auto parts supplier for the years 1983-1989. The air pollution data comes from the State EPA for the same years. The temperature data is from the National Oceanic and Atmospheric Administration's National Weather Service

Figure 10: Linear vs. Quadratic Marginal Effects of Pollutant Concentration

Note: The pollution abbreviations are carbon monoxide (CO), sulfur dioxide (SO₂), nitrogen dioxide (NO₂), Ozone (O₃), and particulate matter smaller than ten micrograms (PM₁₀).

Source: The airflow data was obtained from a Midwestern auto parts supplier for the years 1983-1989. The air pollution data comes from the State EPA for the same years.

Figure 11: Linear vs. Quadratic Predicted Percent Change in Labor Productivity from the Mean

Note: The pollution abbreviations are carbon monoxide (CO), sulfur dioxide (SO₂), nitrogen dioxide (NO₂), Ozone (O₃), and particulate matter smaller than ten micrograms (PM10).

Source: The airflow data was obtained from a Midwestern auto parts supplier for the years 1983-1989. The air pollution data comes from the State EPA for the same years.

Figure 12: Marginal Effects of Pollutant Concentrations when Maximum Shift Temperature is Below 85 Degrees

Note: The pollution abbreviations are carbon monoxide (CO), sulfur dioxide (SO₂), nitrogen dioxide (NO₂), Ozone (O₃), and particulate matter smaller than ten micrograms (PM₁₀).

Source: The airflow data was obtained from a Midwestern auto parts supplier for the years 1983-1989. The air pollution data comes from the State EPA for the same years. The temperature data is from the National Oceanic and Atmospheric Administration's National Weather Service

Figure 13: Marginal Effects of Pollutant Concentrations when Maximum Shift Temperature Above and Below 85 Degrees

Note: The pollution abbreviations are carbon monoxide (CO), sulfur dioxide (SO₂), nitrogen dioxide (NO₂), Ozone (O₃), and particulate matter smaller than ten micrograms (PM10).

Source: The airflow data was obtained from a Midwestern auto parts supplier for the years 1983-1989. The air pollution data comes from the State EPA for the same years. The temperature data is from the National Oceanic and Atmospheric Administration's National Weather Service

Figure 14: Predicted Percent Change in Labor Productivity from the Mean when Maximum Shift Temperature is Above and Below 85 Degrees

Note: The pollution abbreviations are carbon monoxide (CO), sulfur dioxide (SO₂), nitrogen dioxide (NO₂), Ozone (O₃), and particulate matter smaller than ten micrograms (PM10).

Source: The airflow data was obtained from a Midwestern auto parts supplier for the years 1983-1989. The air pollution data comes from the State EPA for the same years. The temperature data is from the National Oceanic and Atmospheric Administration's National Weather Service

Tables

Table 1: Descriptive Statistics

	Min	Mean	Median	Max	SD	N
Productivity (100 cfm)	30.05	100.84	98.41	200	30.84	26,142
Productivity Shift 1	30.52	121.13	121.62	200	28.18	8,656
Productivity Shift 2	30.77	100.09	98.74	178	25.49	8,754
Productivity Shift 3	30.05	81.48	76.26	200	24.99	8,732
Temperature (Fahrenheit)	-17	47.44	45	100	19.28	26,142
Humidity	17	64.41	65	100	15.31	26,142
Wind Speed	0	6.85	6	46	5.33	26,142
State level Unemployment Rate	5.20	8.56	8.40	14.00	2.49	26,142
County level Person Income	12,833	15,810	15,942	19,429	2,251	26,142
Federal Funds Rate	5.52	8.24	8.42	16.17	1.38	26,142
Carbon Monoxide (ppm)	0	2.20	2	16	1.67	26,142
Sulfur Dioxide (ppb)	0	11.89	9	198	11.77	26,142
Nitrogen Dioxide (ppb)	0	21.87	21	95	13.85	26,142
Ozone (ppm)	0	14.12	8	166	16.44	26,142
Particulate Matter (g/m³)	0	17.51	10	79	17.04	26,142

Note: The pollution abbreviations are carbon monoxide (CO), sulfur dioxide (SO₂), nitrogen dioxide (NO₂), Ozone (O₃), and particulate matter smaller than ten micrograms (PM10). The county income is measured in nominal dollars.

Source: The airflow data was obtained from a Midwestern auto parts supplier for the years 1983-1989. The air pollution data comes from the State EPA for the same years. The weather data is from the National Oceanic and Atmospheric Administration's National Weather Service. The economic data is from U.S. Bureau of Economic Analysis and Bureau of Labor Statistics.

Table 2: Regression Coefficients

	(1)	(2)
SO₂	-0.0077*** (0.0014)	-0.0080*** (0.0021)
SO₂ squared		0.0000 (0.0002)
NO₂	-0.0275*** (0.0020)	-0.0296*** (0.0019)
NO₂ squared		0.0009 (0.0012)
O₃	-0.0539*** (0.0024)	-0.0753*** (0.0036)
O₃ squared		0.0107*** (0.0016)
CO	-0.0798*** (0.0027)	-0.0763*** (0.0033)
CO squared		-0.0029** (0.0014)
PM10	-0.0305*** (0.0013)	-0.0369*** (0.0027)
PM10 squared		0.0030** (0.0014)
N	26,142	26,142

Note: Pollutants are normalized to have mean zero and standard deviation of one. Labor productivity is measured in 100 cfm. The regression includes controls for pollution site specific fixed effects, shift specific fixed effects, weather, month fixed effect, year fixed effects, day of the week fixed effects, and economic controls.

Source: The airflow data was obtained from a Midwestern auto parts supplier for the years 1983-1989. The air pollution data comes from the State EPA for the same years.

Table 3: Correlation Coefficient Matrix

	SO₂	NO₂	O₃	CO	PM10	Prod.
NO₂	0.20					
O₃	-0.11	-0.15				
CO	-0.11	-0.04	-0.09			
PM10	0.07	0.04	-0.01	-0.03		
Productivity	0.04	-0.17	0.16	-0.04	-0.10	
Air Temperature	-0.10	-0.08	0.57	-0.15	0.06	0.14

Note: The pollution abbreviations are carbon monoxide (CO), sulfur dioxide (SO₂), nitrogen dioxide (NO₂), Ozone (O₃), and particulate matter smaller than ten micrograms (PM10).

Source: The airflow data was obtained from a Midwestern auto parts supplier for the years 1983-1989. The air pollution data comes from the State EPA for the same years. The weather data is from the National Oceanic and Atmospheric Administration's National Weather Service.

Table 4: Coefficients from Omitted Variable Regressions

	(1)	(2)	(3)	(4)	(5)	(6)
SO₂	-0.0077*** (0.0014)	-0.0125*** (0.0016)				
NO₂	-0.0275*** (0.0020)		-0.0337*** (0.0022)			
O₃	-0.0539*** (0.0024)			-0.0503*** (0.0027)		
CO	-0.0798*** (0.0027)				-0.0838*** (0.0027)	
PM10	-0.0305*** (0.0013)					-0.0300*** (0.0016)
N	26,142	26,142	26,142	26,142	26,142	26,142

Note: Pollutants are normalized to have mean zero and standard deviation of one. Labor productivity is measured in 100 cfm. The regression includes controls for pollution site specific fixed effects, shift specific fixed effects, weather, month fixed effect, year fixed effects, day of the week fixed effects, and economic controls.

Source: The airflow data was obtained from a Midwestern auto parts supplier for the years 1983-1989. The air pollution data comes from the State EPA for the same years.

Table 5: Coefficients from Temperature Regression by Maximum Shift Temperature

	(1)	(2)	(3)	(4)
SO₂	-0.0077*** (0.0014)	-0.0084*** (0.0014)	-0.0080*** (0.0021)	-0.0090*** (0.0022)
SO₂ squared			0.0000 (0.0002)	0.0001 (0.0002)
NO₂	-0.0275*** (0.0020)	-0.0272*** (0.0020)	-0.0296*** (0.0019)	-0.0287*** (0.0019)
NO₂ squared			0.0009 (0.0012)	0.0013 (0.0011)
O₃	-0.0539*** (0.0024)	-0.0587*** (0.0027)	-0.0753*** (0.0036)	-0.0821*** (0.0034)
O₃ squared			0.0107*** (0.0016)	0.0164*** (0.0015)
CO	-0.0798*** (0.0027)	-0.0805*** (0.0028)	-0.0763*** (0.0033)	-0.0781*** (0.0035)
CO squared			-0.0029** (0.0014)	-0.0024* (0.0014)
PM10	-0.0305*** (0.0013)	-0.0306*** (0.0014)	-0.0369*** (0.0027)	-0.0383*** (0.0028)
PM10 squared			0.0030** (0.0014)	0.0037** (0.0014)
SO₂ x Temp>85		0.0081 (0.0057)	0.0049	0.0070 (0.0077)
SO₂ squared x Temp>85				-0.0007 (0.0018)
NO₂ x Temp>85		-0.0133* (0.0072)		-0.0150*** (0.0058)
NO₂ squared x Temp>85				-0.0036 (0.0051)
O₃ x Temp>85		0.0246*** (0.0049)		0.0414*** (0.0085)
O₃ squared x Temp>85				-0.0143*** (0.0026)
CO x Temp>85		0.0110 (0.0077)		0.0238*** (0.0069)
CO squared x Temp>85				-0.0190*** (0.0058)

PM10 x Temp>85		0.0000		0.0204*
		(0.0049)		(0.0106)
PM10 squared x Temp>85				-0.0123**
				(0.0049)
N	26,142	26,142	26,142	26,142

Note: Pollutants are normalized to have mean zero and standard deviation of one. Labor productivity is measured in 100 cfm. The regression includes controls for pollution site specific fixed effects, shift specific fixed effects, weather, month fixed effect, year fixed effects, day of the week fixed effects, and economic controls.

Source: The airflow data was obtained from a Midwestern auto parts supplier for the years 1983-1989. The air pollution data comes from the State EPA for the same years.