Particulate Pollution and the Productivity of Pear Packers*

Tom Chang¶ Joshua Graff Zivin† Tal Gross‡ Matthew Neidell§

February 2014

Abstract

We study the effect of outdoor air pollution on the productivity of indoor workers at a pear-packing factory. We focus on fine particulate matter ($PM_{2.5}$), a harmful pollutant that easily penetrates indoor settings. We find that an increase in $PM_{2.5}$ outdoors leads to a statistically and economically significant decrease in packing speeds inside the factory, with effects arising at levels well below current air quality standards. In contrast, we find little effect of $PM_{2.5}$ on hours worked or the decision to work, and little effect of pollutants that do not travel indoors, such as ozone. This effect of outdoor pollution on the productivity of indoor workers suggests a thus far overlooked consequence of pollution. Back-of-the-envelope calculations suggest that nationwide reductions in $PM_{2.5}$ from 1999 to 2008 generated $19.5 billion in labor cost savings, which is roughly one-third of the total welfare benefits associated with this change.

* We thank numerous individuals and seminar participants at MIT, UC Santa Barbara, Northwestern University, the University of Connecticut, University of Ottawa, UC San Diego, Georgia State University, Environmental Protection Agency, and the IZA Workshop on Labor Market Effects of Environmental Policies for valuable feedback. Graff Zivin and Neidell gratefully acknowledge financial support from the National Institute of Environmental Health Sciences (1R21ES019670-01). Chang and Gross are grateful for financial support from the George and Obie Shultz Fund. Hyunsoo Chang, Janice Crew, and Jamie Mullins provided superb research assistance.
¶ University of Southern California
† University of California at San Diego and NBER
‡ Columbia University and NBER
§ Columbia University and NBER

1. Introduction

Firms commit sizable resources to a wide range of activities aimed at increasing worker productivity, with U.S. workplace training alone accounting for $62 billion in 2012 (O'Leonard, 2013). Accordingly, researchers have examined the effect of various activities designed to increase employee effort and output, ranging from ergonomics and workspace design to payment contracts and telecommuting (Lazear, 2000; Bloom et al., 2013; Bandiera et al., 2005; Pilcher et al., 2002; Levitt and List, 2011). One area that has received surprisingly little attention by both firms and researchers is pollution within the workplace. Yet, there is ample reason to believe that modest levels of pollution may impair performance through changes in respiratory, cardiovascular, and cognitive function. Moreover, since pollution is largely generated well outside the boundaries of the individual firm, the degree to which firms can internalize pollution-related costs is limited. This underscores the importance of public policy in shaping outcomes in this area.

In this paper, we present the first evidence on the impacts of outdoor pollution on the marginal productivity of indoor workers. This focus is important for two reasons. First, the majority of output among the richest nations is produced in indoor settings, with manufacturing alone accounting for roughly 10–25 percent of GDP.[1] Previous evidence on the effect of pollution on the marginal product of labor has been limited to the agricultural sector (Graff Zivin and Neidell, 2012), which accounts for a small fraction of national income and thus provides limited guidance for policy making in the developed world where the institutional capacity for regulating the environment is strongest.[2]

[1] Estimates are from http://data.worldbank.org/.
[2] There is also a small literature that examines productivity indirectly through a focus on the extensive margin of labor supply. See Ostro, 1983; Hausman et al., 1984; Graff Zivin and Neidell, 2014; Carson et al., 2010; Hanna and Oliva, 2011.

Second, the pollutant we examine, fine particulate matter ($PM_{2.5}$), has unique properties that make it an especially important pollutant to study. The miniscule size of $PM_{2.5}$ – approximately one-thirtieth the width of a human hair – makes it particularly pernicious. It is inhaled deep into the lungs, where it accumulates and impairs respiratory function, and can also enter the bloodstream, where it causes cardiovascular complications. Exposure to high levels of $PM_{2.5}$ causes severe health events, such as heart attacks and hospitalizations for asthma, but the degree to which modest exposure to $PM_{2.5}$ affects more subtle but still economically relevant outcomes, like productivity, is unknown. Minimizing such effects is greatly complicated by the fact that $PM_{2.5}$ can easily penetrate buildings (Thatcher and Layton, 1995; Ozkaynak et al., 1996; and Vette et al., 2001). This implies that, unlike many other pollutants, the most common form of ex-post avoidance behavior – going inside – will be of limited value.

We perform our analysis using a unique panel dataset on the daily productivity of employees in a pear-packing facility in Northern California. The task of packing pears is a tedious one. Each individual piece of fruit is wrapped in paper and then packed tightly to ensure that the required quantity of pears fits the box. Importantly, workers are paid based on their daily productivity, thereby minimizing moral hazard problems associated with imperfectly observed worker effort (Lazear, 2000; Shi, 2010; Bandiera et al. 2005).

Our empirical strategy exploits high-frequency fluctuations in ambient $PM_{2.5}$ concentrations as measured by a federally administered $PM_{2.5}$ monitor located near the factory. Those fluctuations are plausibly exogenous since they do not result from the activity of the factory itself, but rather emanate from sources in the hundreds of miles that surround the factory. In addition, there was a massive wildfire several hundred miles away that led to elevated $PM_{2.5}$ levels during one of the packing seasons in our data. The fire, along with time-varying transportation and economic patterns in the larger cities within the region, generate considerable variation in pollution levels at our study site.

Our analysis reveals a statistically significant, negative impact of $PM_{2.5}$ on the productivity of indoor workers. The negative effect occurs at pollution levels well below current National Ambient Air Quality Standards (NAAQS). An increase in $PM_{2.5}$ pollution of 10 micrograms per cubic meter ($\mu g/m^3$) reduces the productivity of workers by $0.41 per hour, approximately 6 percent of average hourly earnings. These effects first arise when $PM_{2.5}$ exceeds 15 $\mu g/m^3$ and increase thereafter, suggesting a potential threshold effect. These findings are robust to numerous specification checks. Importantly, we find that labor supply does not respond to $PM_{2.5}$, suggesting our estimates are not contaminated by sample selection bias. Furthermore, we also find that outdoor conditions that do not affect the indoor work environment, such as solar radiation and ozone, do not impact worker productivity.

We gauge the potential economy-wide importance of these productivity effects by applying our estimates to all manufacturing workers throughout the U.S., the bulk of whom perform tasks with similar physical demands as those faced by workers in our study. We find that reductions in $PM_{2.5}$ between 1999 and 2008 generated $19.5 billion in labor cost savings. This value represents approximately one-third of the total estimated welfare benefits associated with these air quality improvements as captured by capitalization into housing prices. If these productivity impacts are not capitalized into housing prices, as may well be the case given the novelty of these findings and the localized nature of environmental quality capitalization (Bento et al., 2012, Currie et al., 2013), our results suggest that traditional methods for welfare assessment may substantially understate the benefits from improvements in environmental quality.

The paper proceeds as follows. The subsequent section describes background information on $PM_{2.5}$, including potential mechanisms for a productivity effect. Section 3 describes the data that we use, and Section 4 describes our empirical strategy. Section 5 presents our core results along with a series of robustness checks. Section 6 explores the implications of our empirical results for the US economy. Section 7 concludes.

2. Background on Particulate Matter

Particulate matter (PM) consists of solid and liquid particles in the air that can range considerably in size. The regulation of PM has evolved over time. Total Suspended Particulates (TSPs), which were first regulated in 1971, consists of particles less than 100 micrometers in size. In recognition of the growing evidence that only particles less than 10 micrometers penetrate into the lungs, regulations switched from TSPs to PM_{10} in 1987.[3] Further research demonstrated that the smallest of these particles, those less than 2.5 micrometers, penetrate deep into the lungs and enter the bloodstream. As a result, the Environmental Protection Agency (EPA) began regulating $PM_{2.5}$, in addition to PM_{10}, in 1997.[4]

The sources of $PM_{2.5}$ consist of a wide range of both natural and anthropogenic sources. Natural sources include volcanoes and wildfires, while anthropogenic sources are largely the result of fossil fuel combustion, particularly when gases from power plants, industries, and automobiles interact to form $PM_{2.5}$. Given its diminutive size, $PM_{2.5}$ can remain suspended in the air for extended periods of time and can travel hundreds of miles.

Particularly important for our study, $PM_{2.5}$ can easily enter buildings, with penetration ranging from 70–100 percent (Thatcher and Layton, 1995; Ozkaynak et al., 1996; and Vette et al., 2001). This makes $PM_{2.5}$ hard to avoid. Unlike other pollutants, which either remain outside or rapidly break down once indoors, going inside may do little to reduce one's exposure to $PM_{2.5}$. This is par-

[3] Particles above 10 micrometers are typically expelled by coughing or are trapped in cilia.
[4] Particulates between 2.5 and 10 micrometers are commonly referred to as "coarse particulates," while those less than 2.5 are referred to as "fine particulates." The air quality standard for PM2.5 was strengthened in 2006.

ticularly the case in a poorly insulated, well-ventilated setting, such as the one we study. Indoor pollution measures are thus readily affected by outdoor conditions.

A large body of toxicological and epidemiological evidence suggests that exposure to $PM_{2.5}$ harms health (see EPA, 2004 for a comprehensive review). These risks arise primarily from changes in pulmonary and cardiovascular functioning (Seaton et al., 1995). They may manifest themselves in respiratory episodes, such as asthma attacks, and cardiovascular events, such as heart attacks, that lead to hospitalizations and mortality (Dockery and Pope, 1994; Pope, 2000). They also lead to more subtle effects, such as changes in blood pressure, irritation in the ear, nose, throat, and lungs, and mild headaches (Pope, 2000; Ghio et al., 2000; Auchincloss et al, 2008). These milder effects, which arise from exposure to lower levels of $PM_{2.5}$, are generally unobserved by the econometrician – they typically do not lead to healthcare encounters – and in some cases may be largely unnoticed by the individual experiencing them. Symptoms can arise in as little as a few hours after exposure, particularly for people with existing cardiovascular and respiratory conditions, but $PM_{2.5}$ can also generate effects several days after a period of elevated exposure. Particles also accumulate in the lungs, so effects may be triggered after several days of elevated exposure.[5]

These changes in health from $PM_{2.5}$ exposure can lead to changes in labor market outcomes through two channels. First, sickness related to $PM_{2.5}$ exposure may lead to absenteeism, either by missing work entirely or by reducing the number of hours worked. Any resulting changes in productivity would therefore be due to changes in labor supply. Second, workers may suffer from reduced on-the-job productivity (i.e., "presenteeism") due to the negative health effects of $PM_{2.5}$ exposure. According to worker self-reports, presenteeism decreases U.S. economic output by $27 billion each year (Davis et al. 2005). Moreover, since the health effects of $PM_{2.5}$ exposure may be so mild as to not even register for the impacted individual, such self-reported measures of presenteeism may un-

[5] Less relevant for our analysis, this accumulation in the lungs may also lead to long-term health effects over several years, such as chronic bronchitis and lung cancer.

derestimate the true on-the-job productivity effects of pollution. Since pear packing, like much assembly line work, is a repetitive task that involves standing on one's feet nearly all day, these subtle changes can plausibly lead to fatigue and related symptoms, thereby lowering the marginal product of labor. The goal of our analysis is to estimate the effect of $PM_{2.5}$ on the marginal product of labor, independent from any possible effects of $PM_{2.5}$ on labor supply.

3. Data

In order to measure the effect of $PM_{2.5}$ on productivity, we require both precise measures of productivity and precise measures of $PM_{2.5}$. This section describes how we construct a dataset with both of those variables.

In most settings, labor productivity, particularly at the individual level, is unobservable to researchers. By focusing on a firm where workers are paid on a piece rate basis, our setting offers a unique opportunity to measure worker productivity on a daily basis. We focus on a large pear-packing factory in northern California. The firm, which has since closed, was the largest pear-packing factory in the area. The firm contracted with pear growers throughout Northern California. Pears would start arriving at the factory early each morning, well before packers arrive. After being cleaned and passing through a manual quality assurance check, the pears are mechanically sorted by size into large, rotating bins. Packers would then individually wrap each pear in tissue paper and arrange the pears in boxes.[6] The boxes would then be sent to retailers around the country.

Packers were expected to work every day that the factory was open and to arrive by 7 AM, at the start of the day shift. In general, packers would work until all pears brought in during the day

[6] The pears need to be individually wrapped in tissue paper, and then arranged in boxes according to specific patterns. While labor intensive, it allowed the factory to ship the pears across the country without damaging the produce.

had been packed. If the workday lasted longer than 8 hours, then the packers would be paid an overtime rate that was 50 percent higher than during regular time.[7]

The factory provided us with payroll records for the 2001, 2002, and 2003 packing seasons. The payroll records contain all information that the firm needed in order to calculate paychecks. In particular, packers were paid via a "piece-or-hourly" system. The packers earned a piece rate for each box they packed. If their piece rate earnings for the day implied an hourly wage below California's minimum wage, then the packers were paid an hourly rate for the day. Importantly, productivity is recorded even for those paid minimum wage, thus providing a comprehensive measure of daily productivity for all workers regardless of where they end up on the wage schedule.[8] The dataset includes measures of regular-time boxes packed, overtime boxes packed, regular-time hours, and overtime hours worked for each packer each day. Those variables compose the bulk of our data.

One complication in measuring productivity is that the workers packed different kinds of packages over time, both within and across days. Most packages were standard, four-fifths bushel boxes, but occasionally workers would pack trays or plastic bags for some retailers. Packers were paid a different piece rate for each package, with payroll records indicating the type of boxes packed and each packer's piece earnings for each type of box. Given the different types of packaging, we use each packer's total piece rate earnings per hour as our standardized measure of productivity. Importantly, the type of box being packed on a given day is uncorrelated with $PM_{2.5}$, so this standardization is unlikely to introduce a bias.[9] For those workers paid minimum wage, we use their implied piece rate wage based on their actual productivity.

[7] Further details on how the factory operated are described by Chang and Gross (2014). Our description here is also based on interviews with the factory's former CEO.
[8] Since workers may have an incentive to shirk when facing a fixed hourly wage, we directly test this assumption using the methodology outlined by Graff Zivin and Neidell (2012). As described below, we find no such evidence of shirking.
[9] We regressed the share of four-fifths boxes packed on a given day on all covariates (described below), and find that a 1 unit increase in $PM_{2.5}$ is associated with a 0.002 decrease in the share of four-fifths boxes, with a *t*-statistic of 0.52. Using a fractional logit model yielded identical results.

Figure 1 plots the variation in productivity as measured by earnings.[10] The first panel plots the productivity across workers by taking the mean earnings per hour for each worker. The second plots the productivity across days by taking the mean earnings of all workers on a given day. Immediately evident is that the variation across workers is as large as the variation across days, suggesting a potentially important role for day-to-day factors, such as pollution, in determining productivity.

This analysis also requires measures of the environmental shocks faced by the packers. The pear-packing factory was located 2.7 miles from a weather and pollution station. This monitor is maintained by the California Air Resources Board, and is used for determining compliance with both state and national air quality standards. Based on the station's records, we compiled data on the area's rain fall, temperature, wind speed, dew point, and solar radiation. From the pollution station, we compiled data on 5 pollutants: fine particulate matter (less than 2.5 micrometers in diameter), coarse particulate matter (between 2.5 and 10 micrometers in diameter), ozone, carbon monoxide, and nitrogen dioxide.

While nearly all environmental data were collected at the hourly level during the time period of our analysis, particulate matter was only measured every 6 days, thus producing a 6-day daily average measure.[11] This measure has three implications for our analysis. First, the grouping of $PM_{2.5}$ measures can lead to a "Moulton effect" (Moulton, 1986), so we cluster standard errors on each 6-day measure of $PM_{2.5}$. Second, this 6-day measure means that our measure of worker exposure is based on time both at work and at home, and both indoors and outside. As previously mentioned, effects from $PM_{2.5}$ may arise both immediately and over several days. Therefore, it is not possible for us to ascertain which source and what timing of exposure over the 6-day period can explain the

[10] We drop from the sample workers who worked fewer than 14 days. We also drop worker-days with implausibly high earnings values, greater than 3 standard deviations above the mean.

[11] PM2.5 was commonly measured every 6 days after its initial regulation in 1997, but is now routinely measured on an hourly basis in light of growing evidence of more immediate effects. The 6-day measurement was accomplished by placing a filtered unit that only allowed PM2.5 to pass, with the accumulated amount after 6 days then measured and divided by 6 to give an average daily measure. The same process was used for PM10.

productivity effects we find. Third, while the factory is reasonably close to the monitor, there may be measurement error in our assignment of exposure to workers during non-work hours. If classical, this measurement error will bias our estimates down. Table 1 presents summary statistics for the data, both at the individual worker level and at the unit of $PM_{2.5}$ measurement.

4. EMPIRICAL STRATEGY

Our goal is to estimate the effect of fine particulate matter on worker productivity. We estimate the following hybrid production function:

$$y_{it} = \beta \times (PM_{2.5})_t + X_t'\gamma + \delta_t + \varepsilon_{it}.$$

The outcome y_{it} is the measure of hourly productivity denominated in hourly earnings for worker i on date t.[12] The covariate $PM_{2.5}$ is a daily average of particulate matter (based on the 6-day measure), and β captures the effect of $PM_{2.5}$ on earnings. The vector X_t consists of daily wind speed, a quadratic function of temperature, dew point, rain, solar radiation, and ozone to account for other environmental factors that may affect productivity.[13] The fixed effects, δ, include day-of-week and year-month indicator variables to account for trends within the week and over time, respectively. Since the error term, ε, likely exhibits auto-correlation between observations based on the same worker or same 6-day $PM_{2.5}$ measurement period, we allow for two-way clustering (Cameron et al., 2011) along those dimensions.

We face two main obstacles in estimating β. First, our goal is to estimate the effect of pollution on the marginal product of labor, so we need to isolate changes in productivity that are not contaminated by changes in labor supply. If hours worked responds to changes in pollution, then any

[12] As noted earlier, for those who fall under the minimum wage portion of the wage schedule, our productivity measure corresponds to the earnings implied by the worker's actual packing rate.
[13] Below, we also include controls for other pollutants as a robustness check.

estimated effects of pollution on productivity could suffer from sample selection bias. In particular, we want to separate the direct effects of pollution from workers decision to work and their shift length. To limit this concern, we focus our analysis on the productivity of workers during the regular-time day shift. Overtime hours are more discretionary and can, in fact, depend directly on productivity during the regular-time shift.[14] While it is still possible that labor supply during the regular shift could respond to pollution (Hanna and Oliva, 2011), the levels of pollution found in this region are remarkably low (with one important exception, described below). Therefore, it is unlikely that pollution led workers to reduce time at work. Importantly, since we follow workers over time and observe hours worked, we explicitly test these assumptions by examining whether $PM_{2.5}$ relates to the probability of working and the number of hours worked.

The second challenge involves endogeneity of pollution. In general, pollution levels are influenced by local business activity, so an increase in pollution could in fact result from higher levels of economic activity. Furthermore, individuals can sort into locations based on the amount of pollution in that area, leading to non-random assignment of pollution. These and other concerns are unlikely to arise in our setting for several reasons. Since $PM_{2.5}$ travels far and remains suspended in the air for extended periods of time, the levels of $PM_{2.5}$ at the factory are largely driven by factors outside the firm, including traffic conditions and business activity in neighboring areas, such as Sacramento and the Bay Area, both of which are more than 100 miles away.[15] In addition, since the demand for the pears comes from retailers around the country, and the supply of pears is from farms throughout the region, factory activity is not likely to be driven by local economic activity. Moreo-

[14] We nonetheless present evidence on overtime outcomes, noting this limitation. The factory also utilized a night shift, which was designed to absorb any unexpected productivity shocks experienced during the regular day shift. We unfortunately do not possess data on the night shift.
[15] Although not specific to our setting, numerous studies document that the majority of air pollution levels are not caused by local sources. See, for example, Ault et al. (2009) and Brook et al. (2007).

ver, our focus on the high-frequency variation in pollution limits concerns regarding residential sorting, which is largely based on average pollution levels.

Figures 2 and 3 provide some empirical evidence regarding the exogeneity of $PM_{2.5}$. Figure 2, which plots $PM_{2.5}$ over time, shows that it varies considerably from one period to the next. Figure 3, which plots $PM_{2.5}$ against temperature, shows that the variation in $PM_{2.5}$ is not correlated with temperature, a potentially important factor in productivity.[16] In fact, $PM_{2.5}$ is not correlated with any of the environmental covariates in our analysis. When we regress $PM_{2.5}$ on all of the environmental covariates, the covariates are neither jointly nor individually statistically significant at even the 10 percent level (not shown). While we cannot rule out the possibility of omitted variables bias, this prima facie evidence, supported by additional evidence below, suggests that this threat is minimized in our setting.

Notably, a massive wildfire (the "Biscuit Fire") several hundred miles away on the border between northern California and Oregon dramatically increased $PM_{2.5}$ levels across the region during the study period. The fire started on July 12–15, 2002, as a result of a series of lightning storms, and was not fully contained until December 31, 2002. While pollution levels in our study area were largely unaffected by the fire, there was a brief period when emissions from the fire traveled near the factory and increased pollution levels considerably. As a result, air quality at our study site exceeded national ambient air quality standards for a two-week period in August of 2002, as shown in Figure 2.

While the fire provides an exogenous source of variation in $PM_{2.5}$, one concern is that it could have led to behavioral responses that affected worker productivity. If some workers altered the time they allocate to labor in response to higher pollution levels, estimated effects on the inten-

[16] We also interviewed the former CEO of the factory and asked how the factory handled environmental shocks. He told us that the factory would occasionally pause work during heat waves, but not for pollution-related incidents. In fact, he was entirely unaware of a potential relationship between pollution and worker productivity.

sive margin of productivity could be contaminated by changes in the composition of labor. Fortunately, our analysis of labor supply responses, as described above, allows us to directly address this concern.[17] We also note that during the two-week period when national air quality standards were violated, air quality alerts were issued to raise public awareness about potential health risks. Given the gravity of these alerts, worker anxiety and distractions could have contributed to productivity impacts on the intensive margin that are not purely the result of elevated pollution levels, so that the alerts themselves may have affected productivity. For that reason, we present estimates that both include and exclude the time period when fire-related alerts were issued. Furthermore, we model $PM_{2.5}$ with a series of indicator variables to allow for a non-linear effect of $PM_{2.5}$. This enables us to not only isolate $PM_{2.5}$ levels during the alert period, but also to explore the dose-response relationship at lower levels of $PM_{2.5}$.

5. Empirical Results

A. Labor Supply Responses

We begin our analysis by assessing whether labor supply responds to $PM_{2.5}$. Table 2 provides estimates of our regression equation using an indicator variable for working or hours worked conditional on working as the dependent variable. We begin with our linear-in-$PM_{2.5}$ model, both with and without those weeks in which there was at least one air quality alert as a result of the Biscuit Fire, and then estimate the nonlinear model both with and without the fire-related alert.

Focusing on the probability worked, the first column demonstrates that each 1-unit increase in $PM_{2.5}$ has no effect (0.00) on the likelihood of working. Excluding the two weeks with air quality alerts resulting from the Biscuit Fire (column 3) raises this estimate to 0.001 though it remains statis-

[17] Similarly, to the extent that the elevated $PM_{2.5}$ levels induced sickness, we would detect this in our measures of days and hours worked.

tically insignificant. Columns 3 and 4 present the results for the nonlinear model and here again we find no significant impact of pollution on turning up at work.

The last four columns in Table 2 focus on hours worked conditional on working, for the same model specifications as before. Column 5 shows that a 1-unit increase in $PM_{2.5}$ leads to a statistically insignificant decrease of 0.002 hours worked. Excluding alert weeks (column 6) flips the sign but, again, the effect is both small and statistically insignificant. When we allow $PM_{2.5}$ to enter nonlinearly (columns 7 and 8), we continue to find no evidence that hours worked responds to $PM_{2.5}$. This lack of impact on the extensive margin, even during alert periods associated with the Biscuit Fire, implies that our estimates of the impact of $PM_{2.5}$ on labor productivity will not be biased by changes in labor force composition.

B. Marginal Product of Labor

As a first pass at establishing the relationship between productivity and $PM_{2.5}$, Figure 4 plots $PM_{2.5}$ versus earnings. The figure uses data aggregated to the level of the firm and the 6-day $PM_{2.5}$ measurement period, which is our effective level of variation in $PM_{2.5}$.[18] The figure plots unadjusted sample means for the 6-day periods, and includes a linear prediction. Even with no controls, the raw data suggest a negative relationship: as $PM_{2.5}$ levels rise, workers produce less.

Estimates of our regression equation are shown in Table 3, which make up the core findings of our analysis. As with labor supply, we present results from four specifications, focusing on earnings both in levels and in logs. Turning to levels, we find that $PM_{2.5}$ has a statistically significant, negative effect on earnings per hour. Each additional unit of $PM_{2.5}$ decreases hourly earnings by \$0.041. When we exclude weeks with air quality alerts because of the fire, our estimate is no longer statistically significant at conventional levels, but it remains of comparable magnitude. Thus, while $PM_{2.5}$

[18] For ease of exposition, we exclude the Biscuit Fire from this plot.

levels during the alerts improve the precision of our estimates, they do not appear to be biasing them; additional estimates below support this claim. This, in turn, implies that any behavioral responses that might have resulted from the fire-related alerts did not affect worker productivity, strengthening our claim that the fire during this period provides a useful source of identifying variation in $PM_{2.5}$ for our analysis.

The next two columns in Table 3 allow $PM_{2.5}$ to have a non-linear effect on productivity. This also allows us to isolate the effect of air quality alerts stemming from the fire, which only occurred when $PM_{2.5}$ levels were greater than 25 $\mu g/m^3$. We find that $PM_{2.5}$ levels between 15–20 $\mu g/m^3$ decreases earnings by \$0.53 per hour, though this effect is not statistically significant at conventional levels. When $PM_{2.5}$ reaches 20–25 $\mu g/m^3$, the effect increases to \$1.03 per hour and becomes statistically significant. Importantly, this level of $PM_{2.5}$ is well below the current air quality standard of 35 $\mu g/m^3$. The effect further increases to \$1.88 per hour when $PM_{2.5}$ exceeds 25 and remains statistically significant. Excluding the two weeks with air quality alerts yields virtually identical results, suggesting again that our results are not driven solely by alert-induced effects.

These results provide clear evidence of a dose-response relationship between $PM_{2.5}$ and productivity, with a possible threshold at 15–20 $\mu g/m^3$. To further illustrate this, Figure 5 plots the linear and nonlinear estimates. The nonlinear estimates suggest a possible threshold around 15 $\mu g/m^3$ with a roughly linear effect beyond the threshold. While we cannot be certain of a threshold at this point – measurement error may bias the estimates towards zero – we note that this pattern is roughly consistent with evidence on the $PM_{2.5}$-mortality relationship, which suggests a possible threshold effect at around 20 $\mu g/m^3$ (Smith et al., 2000).[19]

The next set of columns present estimates using the logarithm of earnings as our measure of productivity. As with the estimates based on productivity in levels, we find a very similar pattern

[19] It seems quite plausible that a lower threshold exists for productivity, since it is a significantly less harmful outcome.

across the four specifications. When we convert the estimates using levels into percent by dividing by the mean hourly earnings of $6.93 in our sample, the estimates suggest a roughly 0.6 percent effect from a 1 unit change in $PM_{2.5}$. Using the logarithm of earnings, we obtain an estimate of 0.8 percent. Compared to the nonlinear-in-$PM_{2.5}$ model, the implied percent effect for the 3 highest $PM_{2.5}$ bins are 0.08, 0.15, and 0.27, respectively, which is also quite close to the estimates from the log model of 0.08, 0.15, and 0.35. Hence our results do not appear to be driven by the functional form of the dependent variable.

The coefficients on the other covariates in Table 3 also reveal a pattern of results that reinforce the plausibility of our econometric model.[20] Environmental conditions vary in the degree to which they influence the indoor work environment, and thus productivity should vary accordingly. Ozone, which is a highly volatile pollutant, rapidly breaks down indoors as it interacts with other surfaces. Likewise, solar radiation, a measure of available sunlight, is also unlikely to affect indoor conditions given the presence of opaque roofing and walls at the factory. Consistent with this, we find that the coefficients on ozone and solar radiation are both small and statistically insignificant.

On the other hand, outside temperature directly affects working conditions inside the factory, which is not air conditioned, so it may be related to productivity. Consistent with this, we find that the coefficient on the first-order term for temperature is positive, although not statistically significant at conventional levels, and the quadratic term is negative and statistically significant. Based on these estimates, we find an inflection point at roughly 72 degrees Fahrenheit. This is consistent with a large body of ergonomic evidence that finds that task performance exhibits an inverted U-shaped relationship with temperature at a similar inflection point (Hancock et al., 2007).

[20] Many of these variables are also likely to be exogenous for similar reasons as $PM_{2.5}$, allowing us to interpret the coefficients as causal (Lu and White, 2014).

C. Robustness Checks

One concern with interpreting our estimate for $PM_{2.5}$ as a causal effect on factory production is that $PM_{2.5}$ could be influencing factory productivity indirectly by affecting outdoor workers who harvest the fruit. If harvest production declines with $PM_{2.5}$, this could reduce the queue of pears available for factory workers to pack, thereby lowering their productivity indirectly. While we have no way of directly testing this since we do not have measures of the pear queue, there are three reasons this is unlikely to hinder inference.

First, the pears that arrive at the factory are harvested all around the region.[21] Given the tremendous spatial variation in $PM_{2.5}$, levels at the farms are likely to exhibit low correlation with $PM_{2.5}$ at the factory. Second, the factory's operational procedures limit the potential effect of harvest productivity on pear-packer productivity. Since the harvesters start earlier in the day than the packers, the queue is unlikely to be empty, thereby shielding the packers from negative shocks in harvest productivity. Furthermore, the workers on the overtime and night shifts handle any pears left over by the regular shift, so shocks in harvest productivity will be absorbed by these later shifts, and not the regular-time day shift on which we focus. Third, we can also use our estimate for ozone to directly test for this indirect channel. Ozone is likely to affect harvest productivity (Graff Zivin and Neidell, 2012), but it does not penetrate indoors, so it should not affect packer productivity. A significant effect of ozone on factory productivity would therefore suggest indirect effects due to losses in harvest productivity. The lack of a significant effect of ozone, shown in Table 3, however, suggests that this is not the case. This suggests that our results for $PM_{2.5}$ are indeed being driven by direct effects on the productivity of workers inside the factory rather than external factors that might be disrupting the queue of fruit to be processed.

[21] The factory packed pears from Contra Costa, El Dorado, Lake, Mendocino, Sacramento, San Joaquin, Solano, Yolo counties. Together these counties cover 12,187 square miles and span 6 air basins.

Table 4 presents a series of additional robustness checks. Column 1 repeats the baseline results for the linear-in-$PM_{2.5}$ models with alert weeks stemming from the fire included. Since daily variation in $PM_{2.5}$ may be driven by other environmental conditions that may also affect productivity, it is essential that we control for those other environmental conditions adequately; the next 3 columns explore this. Column 2 completely excludes all of the meteorology variables, while column 3 controls for temperature more flexibly by including a series of indicator variables, and column 4 adds three additional pollutants to the model (nitrogen dioxide, carbon monoxide, and coarse PM).[22] The effect of $PM_{2.5}$ on productivity remains similar in magnitude across all three models, suggesting environmental confounding is limited in our setting.

Since we follow workers over time, we add worker fixed effects to our model to control for all time-invariant characteristics of the workers, shown in Column 5. The estimated effect of $PM_{2.5}$ is unaffected by this additional control. Although we argue that worker exposure to $PM_{2.5}$ is exogenous, the fact that our estimates are unchanged by including fixed effects further supports our contention that worker selection is not related to $PM_{2.5}$.

Recall that while worker productivity is measured every day, $PM_{2.5}$ is only measured every 6 days. Although we perform a daily analysis and cluster standard errors on these 6-day periods, we also perform an alternative analysis aggregated to the 6-day period. The results from this analysis, reported in Column 6, show a very similar estimate that remains statistically significant at the 1 percent level.

A complication with payroll at the factory is that earnings per hour are bounded from below by the California minimum wage. When the minimum wage binds, workers may shirk since they no longer receive additional compensation per piece. If $PM_{2.5}$ lowers productivity such that workers are more likely to be in the minimum wage regime, and then shirking further lowers productivity, this

[22] Coarse PM is PM between 2.5 and 10 microns.

will bias our estimates (in absolute value) upward. While shirking should be limited in our setting by the employer's ability to observe individual output and easily terminate workers on short-term contracts, we cannot entirely rule it out. Therefore, to assess the degree to which shirking might be happening, we artificially censor earnings at the minimum wage for all observations where workers fall into the minimum wage regime, and estimate censored regression models (Graff Zivin and Neidell, 2012). If shirking increases with $PM_{2.5}$ when workers earn the minimum wage, estimates from censored models will be unbiased because the precise measure of productivity for workers earning the minimum wage no longer contribute to the point estimate; it only contributes to the probability of earning minimum wage. Since parametric censored regression models may be biased under misspecification, we estimate semi-parametric censored median regressions (Chernozhukov and Hong, 2002). For a point of comparison, we first show estimates from a median regression, in column 7, which at -0.044 is quite close to our baseline estimates. The censored median result of -0.040, shown in column 8, is slightly smaller, though the difference is not statistically significant. This suggests that shirking is unlikely to play a significant role in our analysis.

Workers may also respond to decreased performance by cutting corners when packaging boxes. The firm performs random inspections of boxes as a way of eliminating this concern. If the inspectors find a box is packed inappropriately, then the worker receives a wage penalty for the day. Such violations occurred in approximately 5 percent of the worker day observations. We estimate our regression equation using the probability of a penalty on a given day as the dependent variable. Shown in column 8, we find that $PM_{2.5}$ is not significantly related to the probability of a penalty.

Next, we turn to overtime hours. For the bulk of our analysis, we focused on the regular shift when labor supply is more likely to be fixed. For completeness, we also measure the relationship between $PM_{2.5}$ and overtime (OT) outcomes, recognizing that OT hours are more likely to be endogenous. A day with high $PM_{2.5}$ may lower productivity, and the firm may compensate by increasing the demand for OT hours, particularly when contracts with retailers specify fixed delivery dates and quantities. Alternatively, if a day with high $PM_{2.5}$ increases worker fatigue, workers may be less willing to supply the additional hours and/or firms may be less likely to request them. Similarly, higher $PM_{2.5}$, particularly during the alert periods due to the Biscuit Fire, may increase the time allocated to family members who need assistance because of health problems or activity rescheduling, and thus drive down the supply of OT hours through increases in the opportunity cost of time. Shown in column 10, we find that OT hours decrease as $PM_{2.5}$ increases: a 1 $\mu g/m^3$ increase in $PM_{2.5}$ decreases OT hours worked by -0.023 hours. Since OT hours is sensitive to $PM_{2.5}$, any effects on OT productivity is potentially biased by sample selection.

To explore whether selection into overtime induces bias in overtime productivity estimates, we examine the effect of $PM_{2.5}$ on regular-time productivity solely for those who work any overtime. If there is selection bias into OT, the effect of $PM_{2.5}$ on regular-time productivity should differ for those who work OT versus those who do not. Shown in column 11, we find that the effect of $PM_{2.5}$ on regular time productivity for those who work OT is identical to the overall estimate, suggesting that any selection into OT is in fact not inducing bias for estimates of the effect of $PM_{2.5}$ on OT productivity.

Given the apparent absence of selection bias into OT, we measure the effects of $PM_{2.5}$ on OT productivity.[23] Column 12 suggests that $PM_{2.5}$ has a significant, negative effect on productivity. OT productivity decreases by -0.099 for each additional unit of $PM_{2.5}$, which is larger than the effect of $PM_{2.5}$ on productivity during regular time. One explanation for this pattern is that increased fatigue at the end of a day limits workers' ability to compensate for the physiological effects of $PM_{2.5}$.

Last, we explore heterogeneity in the effects of $PM_{2.5}$ by estimating quantile regression models for each decile of regular-time worker productivity, focusing on the log of productivity to ac-

[23] Although the overtime piece rate is 1.5 times the regular-time piece rate, we divide overtime earnings by 1.5 to obtain a coefficient that is directly comparable to the regular-time coefficients.

count for different baseline levels of productivity across workers. Plotted in Panel A of Figure 6, which assumes a linear effect for $PM_{2.5}$, we see that the effect on productivity is statistically significant in all deciles. The effect is largest for the lowest productivity decile, slightly increases until roughly the median level of productivity, and remains flat beyond the median. Importantly, this finding suggests that the effect of $PM_{2.5}$ on worker productivity is not driven by a handful of workers who are particularly susceptible to pollution, but rather affects the entire distribution of workers. By contrast, Panel B plots quantile results for ozone, and finds that the effect of ozone on packer productivity is never statistically significant, further supporting our contention that the packers are directly affected by $PM_{2.5}$.

6. IMPLICATIONS

A key innovation in our analysis is the focus on $PM_{2.5}$, which can easily penetrate indoors and thus affect a large fraction of the economy. In light of this, it is useful to place our findings in a larger context. We estimate that a 1 $\mu g/m^3$ change in $PM_{2.5}$ decreases worker productivity by roughly 0.6 percent. As a first step, we assess the productivity effects at a national level from the changes in $PM_{2.5}$ concentrations across the US from 1999 to 2008.[24]

We assume that our estimate of the effect of $PM_{2.5}$ on the marginal product of labor applies to all workers in the US manufacturing sector. Although we cannot directly verify this assumption, we believe it is a reasonable first-order approximation based on the following logic. The physiological effects from $PM_{2.5}$ are similar across populations throughout the US. Since the effects that we estimate are likely to be driven by physiological changes that impair workers' ability to complete physically demanding tasks, occupations with physical requirements similar to pear packing are likely

[24] We focus on the years 1999 and 2008 because, for these two years, we have measures of PM2.5 for all counties in the US. Pollution monitors provide incomplete coverage for the US, so we use estimates inferred from emissions data (Muller, 2013). We thank Nick Muller for generously sharing this data. Data from pollution monitors led to almost identical estimates to the inferred data for counties where monitors were available.

to be similarly affected by $PM_{2.5}$. Hence, our assumption rests on the idea that all workers in manufacturing are, on average, performing tasks that are similar to pear packing in the degree to which they are physically demanding. While the assumption may not hold for some workers in manufacturing, such as supervisors and office workers, it is, on the other hand, likely to apply to many affected but excluded workers in other industries, such as construction workers and most forms of outdoor work.[25]

As shown in Figure 7, there is considerable variation in county-level changes in fine particulate matter pollution over this time period, with a national average decline of 2.79 $\mu g/m^3$. We merge this pollution data with county-level mean manufacturing earnings from the Bureau of Labor Statistics in 2000. We calculate that the decrease in $PM_{2.5}$ led to an aggregate labor savings of \$19.5 billion. This represents a 2.67 percent increase in manufacturing earnings, which translates to a 0.5 percent increase in economy-wide earnings.

While those numbers are large in absolute terms, it is instructive to compare them to the other welfare benefits associated with reducing $PM_{2.5}$. In addition to affecting mortality and several dimensions of morbidity, pollution also leads to numerous behavioral responses to limit exposure (Harrington and Portney, 1987; Neidell, 2009; Deschenes et al., 2012; Graff Zivin and Neidell, 2013). Given the disparate range of health and behavioral effects that must be considered, the most frequently used method for quantifying the overall welfare benefits of pollution reduction is to use the hedonic price method by studying the effect of $PM_{2.5}$ on housing values. Under the assumption of complete and transparent markets, all of the effects of $PM_{2.5}$ should be capitalized into house prices (Rosen, 1974).

While we are unaware of any studies that link $PM_{2.5}$ and housing values, Bento et al. (2013) have estimated this relationship for PM_{10}, which is closely related to $PM_{2.5}$. Exploiting plausibly ex-

[25] There is also growing evidence that $PM_{2.5}$ affects cognitive performance (Lavy et al., 2012), which implies potential productivity impacts across high-skilled workers as well.

ogenous changes in PM_{10} induced by the Clean Air Act, they find that a 4.7 unit decrease in PM_{10} increases housing values by $43.9 billion. $PM_{2.5}$ is the subset of PM_{10} that is smaller than 2.5 microns[26], with evidence suggesting that roughly 60 percent of PM_{10} concentrations in the US are comprised of $PM_{2.5}$ (Eldred et al., 1997).[27] Applying this number to the estimates from Bento et al. suggests that the changes in $PM_{2.5}$ from 1999–2008 increased housing values by approximately $57.3 billion (in year 2000 dollars).[28]

Thus, if we assume that our estimated labor impacts are capitalized into housing prices, they account for approximately 34 percent of the total benefits associated with reductions in $PM_{2.5}$ pollution. That said, there is reason to believe that these labor impacts may not be fully reflected in housing values. The average American lives 12 miles from their workplace (Santos et al., 2011), and the large spatial variation in pollution implies that pollution exposure faced at work may be quite different from that faced at home. Yet, empirical studies suggest that the impact of pollution on housing values is quite localized. Indeed, Bento et al. (2013) finds that housing values more than 5 miles from a pollution monitor are unaffected by air quality levels. Currie et al. (2013) find a similar result for air toxics, with housing impacts limited to a 0.5 mile radius around an emitting factory. Moreover, this paper is the first to document indoor productivity effects from pollution and thus it seems quite plausible that individuals are unaware of such impacts when they determine their willingness to pay for residential property. As such, it appears likely that much, if not all, of our estimated impacts on labor productivity are overlooked by hedonic valuation approaches. In that case, housing price based estimates understate the total benefits from reducing $PM_{2.5}$ by more than 25 percent.

---

26 Recall that "coarse" particulate matter refers to those particles between 2.5 and 10 microns in diameter, e.g. PM_{10} measures net of $PM_{2.5}$.

27 This number is calculated by averaging concentrations across study sites and seasons for which elemental data were available as reported in Table 3 of Eldred et al. (1997).

28 We arrive at the estimate of $57.3 billion as follows. We divide the $43.9 billion estimate from Bento et al. (2013) by the 4.7 unit decline in PM_{10} to obtain the value per unit change in PM_{10}. We then multiply it by 0.6 to convert it to a unit change in $PM_{2.5}$. We then multiply by 2.79 to estimate the implied housing change associated with improvements in $PM_{2.5}$ from 1999–2008. Lastly, we adjust for inflation by multiplying by the CPI growth from 1990 to 2000 of 1.32.

7. Conclusion

In this paper, we analyze the relationship between $PM_{2.5}$, a ubiquitous pollutant that penetrates into indoor settings, and individual-level productivity inside a pear packing factory. We find that a 10-unit change in $PM_{2.5}$ significantly decreases worker productivity by roughly 6 percent. Importantly, $PM_{2.5}$ begins to affect productivity at levels well below current US air quality standards. These findings build upon extensive laboratory and epidemiological evidence on the relationship between $PM_{2.5}$ and individual health outcomes by providing the first evidence that outdoor environmental pollution can adversely affect the productivity of indoor workers.

Since these productivity effects also affect firm profits, firms may internalize some of these costs by reducing worker exposure to $PM_{2.5}$. While the installation of sophisticated filtration systems has the potential to remove $PM_{2.5}$ from the air, current technology is limited in its ability to fully remove $PM_{2.5}$, particularly the smallest and most pernicious particulates (Mostofi et al., 2010; Shi et al., 2013). Moreover, since $PM_{2.5}$ accumulates in the body over several days, exposure away from the office, where workers spend the majority of their time, cannot be controlled via investments in these technologies. Reductions of source emissions are also a challenge for the private sector since most occur outside the boundary of the firm, and the multitude of emitters introduces a coordination problem that limits the scope for Coasean bargains to reduce emissions. Thus, productivity-enhancing investments in this context are likely to be more efficient through publicly coordinated reductions in contamination rather than unilateral efforts by firms.

The determination of optimal regulatory standards requires policy makers to balance the costs and benefits of additional regulations. Our results indicate that pollution has an important cost beyond the health effects and quality of life issues typically considered in the calculus of both academics and policymakers. Indeed, applying our estimated effects to all of US manufacturing suggests that the modest decline in $PM_{2.5}$ pollution from 1999 to 2008 generated nearly $20 billion in benefits. In light of growing evidence that $PM_{2.5}$ exposure can affect cognitive performance (Lavy et al., 2012), the aggregate productivity benefits may have, in fact, been substantially larger. The impacts of fine particulate matter pollution on high skilled labor and human capital accumulation are fruitful areas for future research.

8. References

Auchincloss AH, Diez Roux AV, Dvonch JT, Brown PL, Barr RG, Daviglus ML, Goff DC, Kaufman JD, O'Neill MS (2008). "Associations between recent exposure to ambient fine particulate matter and blood pressure in the Multi-ethnic Study of Atherosclerosis (MESA)." Environ Health Perspect. 116(4):486-91.

Ault, Andrew P., Meagan J. Moore, Hiroshi Furutani, and Kimberly A. Prather (2005). "Impact of Emissions from the Los Angeles Port Region on San Diego Air Quality during Regional Transport Events." Environ. Sci. Technol., 43(10): 3500–3506.

Bandiera, Oriana, Iwan Barankay, and Imran Rasul (2005). "Social Preferences and the Response to Incentives: Evidence from Personnel Data." Quarterly Journal of Economics, 120(3): 917-962.

Bento, A., M. Freedman, and C. Lang, "Redistribution, Delegation, and Regulators' Incentives: Evidence from the Clean Air Act," Cornell mimeo.

Bloom, Nicholas, James Liang, John Roberts and Zichung Jenny Ying (2013). "Does working from home work? Evidence from a Chinese experiment." NBER Working Paper 18871

Brook JR, Poirot RL, Dann TF, Lee PK, Lillyman CD, Ip T. (2007). "Assessing Sources of PM2.5 in Cities Influenced by Regional Transport." J Toxicol Environ Health, 70(3-4): 191-9.

Cameron, Colin, Jonah Gelbach, and Douglas Miller (2011). "Robust inference with Multi-Way Clustering." Journal of Business and Economic Statistics, 29(2): 238-249.

Carson, Richard, P Koundouri, & C Nauges (2011). "Arsenic mitigation in Bangladesh: A household labor market approach." American Journal of Agricultural Economics, 93(2): 407-414.

Chang, Tom and Tal Gross (2014) "How Many Pears Would a Pear Packer Pack if a Pear Packer Could Pack Pears at Quasi-Exogenously Varying Piece Rates? An Empirical Evaluation of Intertemporal Labor Supply," Journal of Economic Behavior and Organizations, 99, 1-17.

Chernozhukov, Victor and Han Hong (2002) "Three-Step Censored Quantile Regression and Extramarital Affairs," Journal of the American Statistical Association, 97, 872-882.

Currie, J., L. Davis, M. Greenstone, and R. Walker, "Do Housing Prices Reflect Environmental Health Risks? Evidence from More than 1600 Toxic Plant Openings and Closings," NBER Working Paper No. 18700, January 2013

Davis, Karen, S Collins, M Doty, A Ho, and A Holmgren (2005). "Health and Productivity Among U.S. Workers," Issue Brief (Commonweath Fund), 856:1-10.

Deschenes, Olivier, Michael Greenstone, and Joseph S. Shapiro. *Defensive Investments and the Demand for Air Quality: Evidence from the NOx Budget Program and Ozone Reductions*. No. w18267. National Bureau of Economic Research, 2012.

Dockery DW, and Pope, CA 3rd (1994). "Acute respiratory effects of particulate air pollution." Ann Rev Pub Hlth 15:107-13.

Eldred, Robert A., Thomas A. Cahill, and Robert G. Flocchini. "Composition of PM2. 5 and PM10 Aerosols in the IMPROVE Network." Journal of the Air & Waste Management Association 47, no. 2 (1997): 194-203.

Environmental Protection Agency (2004). Air Quality Criteria for Particulate Matter. National Center for Environmental Assessment. Research Triangle Park, NC.

Froom, P., Y. Caine, I. Shochat, J. Ribak, "Heat stress and helicopter pilot errors." Journal of Occupational and Environmental Medicine 35, 720 (1993).

Ghio, A. J., Kim, C., and Devlin, R. B. (2000). "Concentratedambient air particles induce mild pulmonary inflammation in healthy human volunteers." Am. J. Respir. Crit. Care Med. 162: 981-988.

Graff Zivin, Joshua and Matthew Neidell (2012). "The impact of pollution on worker productivity." American Economic Review, 102, 3652-3673.

Graff Zivin, Joshua and Matthew Neidell (2013) "Environment, Health, and Human Capital" Journal of Economic Literature, 51(3): 689-730.

Graff Zivin, Joshua and Matthew Neidell (2014). "Temperature and the allocation of time: Implications for climate change." Journal of Labor Economics, 32(1): 1-26.

Hancock PA, Ross JM, Szalma JL (2007). "A meta-analysis of performance response under thermal stressors." Hum Factors. 49(5): 851-77.

Hanna, Rema and Paulina Oliva (2011). "The Effect of Pollution on Labor Supply: Evidence from a Natural Experiment in Mexico City." NBER working paper 17302.

Harrington, Winston, and Paul R. Portney. "Valuing the benefits of health and safety regulation." Journal of Urban Economics 22, no. 1 (1987): 101-112.

Hausman, Jerry, Bart Ostro, and David Wise (1984). "Air Pollution and Lost Work." NBER Working Paper 1263.

Lavy, Victor, Avraham Ebenstein, and Sefi Roth (2012). "The Impact of Air Pollution on Cognitive Performance and Human Capital Formation." Mimeo, University of Warwick.

Lazear, Edward (2000). "Performance pay and productivity." American Economic Review, 90(5): 1346-1361.

Levitt, Steven, and John List (2011). "Was There Really a Hawthorne Effect at the Hawthorne Plant? An Analysis of the Original Illumination Experiments." American Economic Journal: Applied Economics, 3(1): 224-38.

Lu, Xun and Halbert White (2014). "Robustness checks and robustness tests in applied economics." Journal of Econometrics, 178(1).

Moulton, Brent R. (1986). "Random Group Effects and the Precision of Regression Estimates," Joumal of Econometrics, 32: 385-397.

Mostofi, Reza, Bei Wang, Fariborz Haghighat, Ali Bahloul, and Lara Jaime. "Performance of mechanical filters and respirators for capturing nanoparticles--limitations and future direction." Industrial health 48, no. 3 (2010): 296-304.

Muller, Nicholas (2013). "Using Index Numbers for Deflation in Environmental Accounting." Environment and Development Economics, forthcoming.

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

O'Leonard, Karen. The Corporate Learning Factbook 2013. Bersin & Associates, 2013.

Ostro, Bart (1983). "The Effects of Air Pollution on Work Lost and Morbidity." Journal of Environmental Economics and Management, 10(4): 371-382.

Ozkaynak, H., Xue, J., Spengler, J., Wallace, L., Pellizzari, E., & Jenkins, P. (1996). "Personal exposure to airborne particles and metals: results from the Particle TEAM study in Riverside, California." Journal of Exposure Analysis and Environmental Epidemiology, 6(1), 57-78

Pilcher JJ, Nadler E, Busch C. (2002). "Effects of hot and cold temperature exposure on performance: a meta-analytic review." Ergonomics 45(10): 682-98.

Pitt, M. M., Rosenzweig, M. R., & Hassan, M. N. (1990). Productivity, health, and inequality in the intrahousehold distribution of food in low-income countries. The American Economic Review, 1139-1156.

Pope, CA 3rd (2000). "Epidemiology of fine particulate air pollution and human health: biologic mechanisms and who's at risk?" Environ Health Perspect. 108(4):713-23.

Rosen, Sherwin. (1974): "Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition," Journal of Political Economy, 82(1).

Santos, Adelia, Nancy McGuckin, Hikari Yukiko Nakamoto, Danielle Gray, and Susan Liss. *Summary of travel trends: 2009 national household travel survey*. No. FHWA-PL-ll-022. 2011.

Seaton, A., MacNee, W., Donaldson, K., and Godden, D. (1995). "Particulate air pollution and acute health effects." Lancet (8943): 176-178.

Shi, Lan (2010). "Incentive Effect of Piece Rate Contracts: Evidence from Two Small Field Experiments." The B.E. Journal of Economic Analysis & Policy, 10(1) (Topics).

Shi, Bingbing, Lars E. Ekberg, and Sarka Langer. "Intermediate air filters for general ventilation applications: An experimental evaluation of various filtration efficiency expressions." *Aerosol* Science and Technology 47, no. 5 (2013): 488-498.

Smith, R. L.; Spitzner, D.; Kim, Y.; Fuentes, M. (2000) Threshold dependence of mortality effects for fine and coarse particles in Phoenix, Arizona. J. Air Waste Manage. Assoc. 50: 1367-1379.

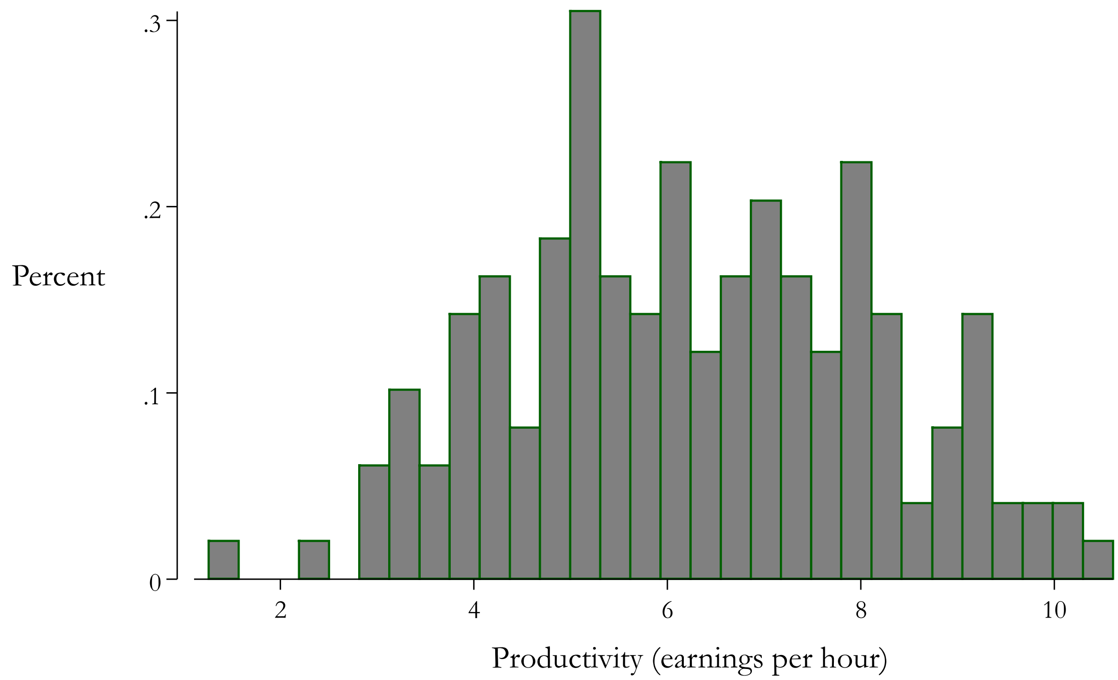
Thatcher, T. L., & Layton, D. W. (1995). "Deposition, resuspension, and penetration of particles within a residence." Atmospheric Environment, 29(13), 1487-1497.

Thomas, Duncan & Strauss, John, 1997. "Health and wages: Evidence on men and women in urban Brazil," Journal of Econometrics, 77(1):159-185.

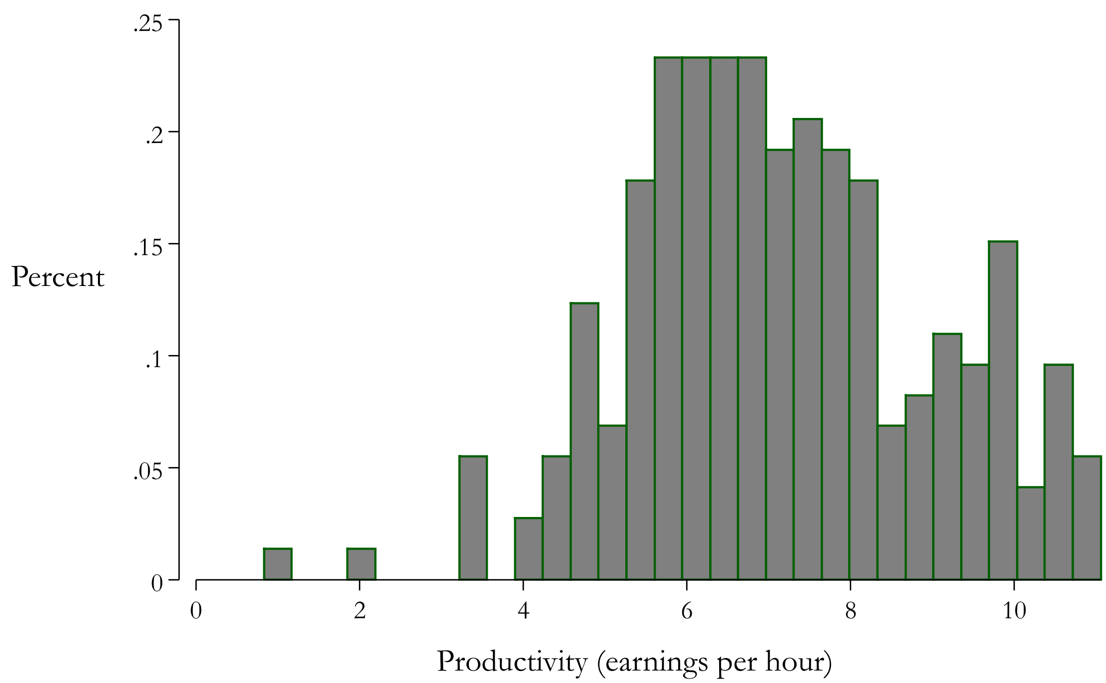
Vette, A. F., Rea, A. W., Lawless, P. A., Rodes, C. E., Evans, G., Highsmith, V. R., & Sheldon, L. (2001). "Characterization of indoor-outdoor aerosol concentration relationships during the Fresno PM exposure studies." Aerosol Science & Technology, 34(1), 118-126.

Figure 1. Variation in Productivity Across Workers and Across Days

A. Histogram across workers

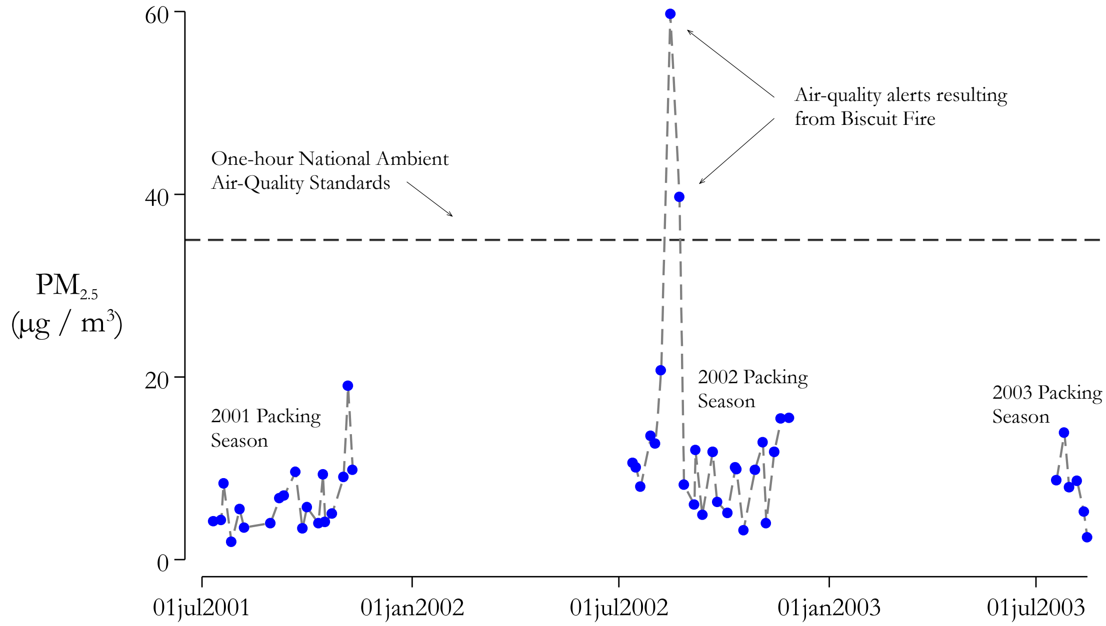


B. Histogram across days



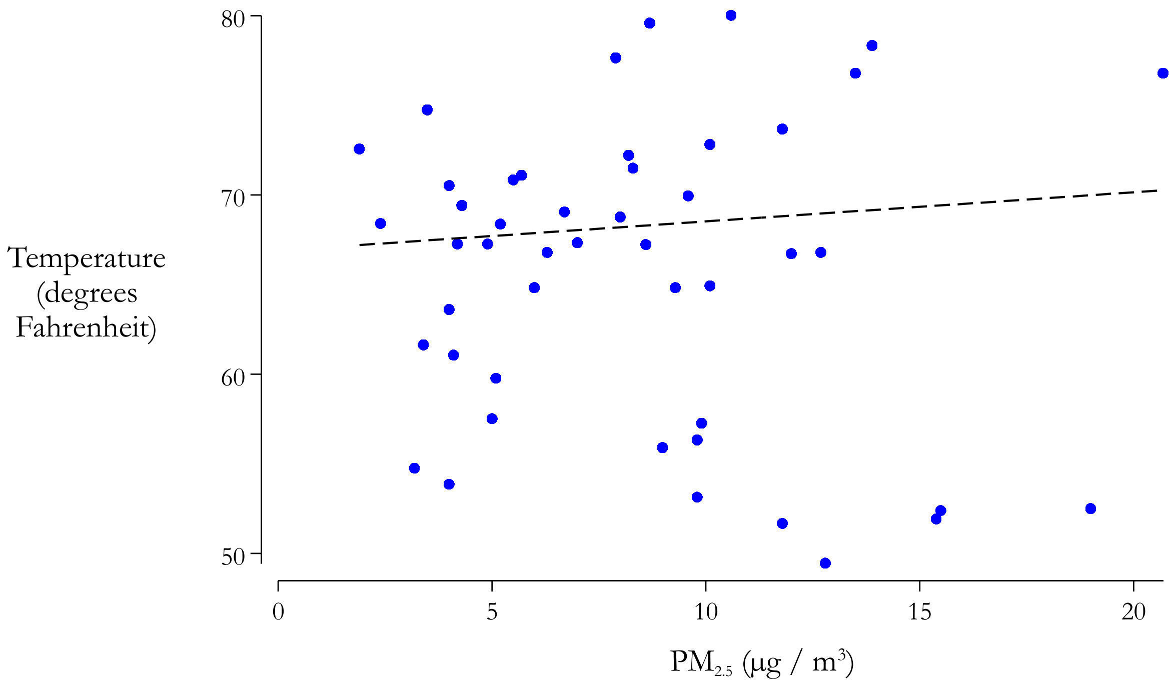
Note: This figure presents the variation in earnings across workers (Panel A) by taking each worker's mean earnings across all time periods, and across days (Panel B) by taking each day's mean earnings across all workers.

Figure 2. $PM_{2.5}$ Levels by Date



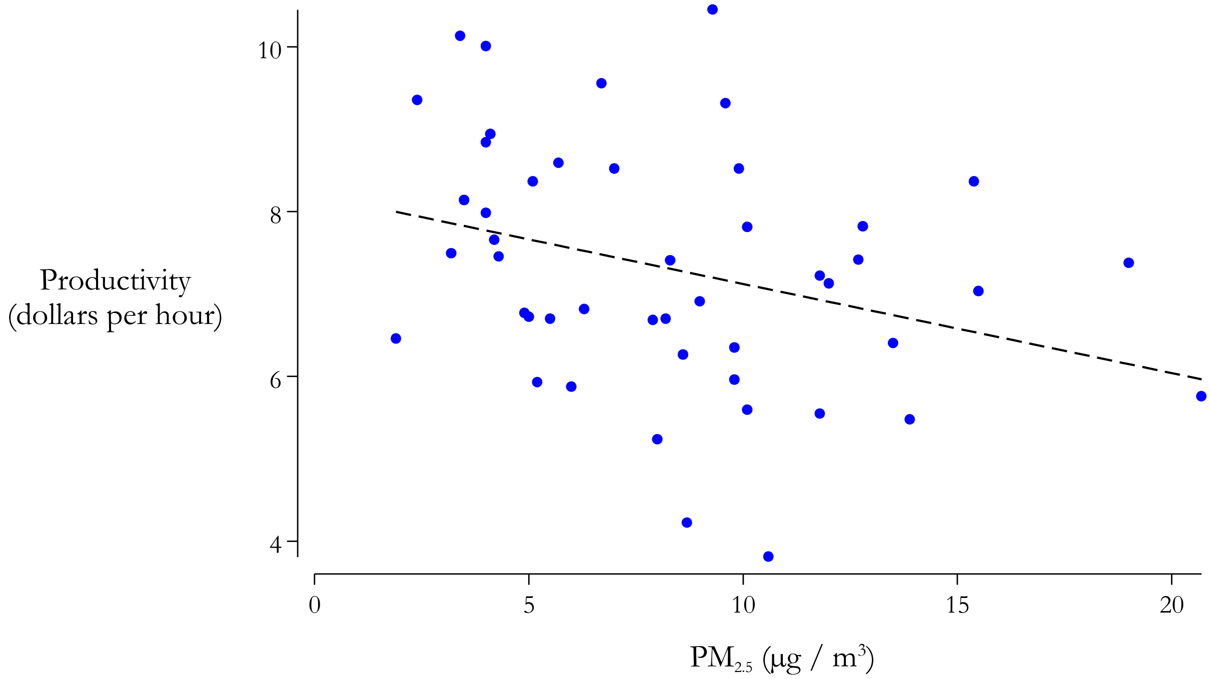
Note: This figure presents $PM_{2.5}$ levels for six-day PM measurement intervals for the 2001, 2002, and 2003 packing seasons. The dotted line corresponds to the one-hour National Ambient Air Quality Standards for $PM_{2.5}$ of 35 $\mu g/m^3$.

Figure 3. The Relationship between $PM_{2.5}$ and Temperature



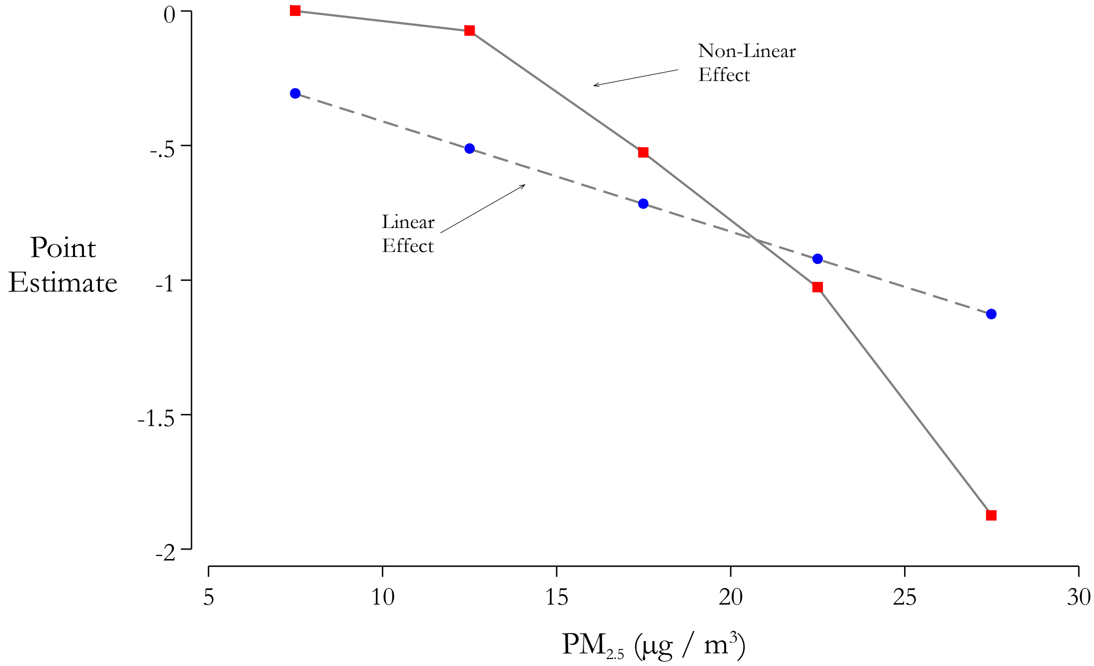
Note: This figure presents $PM_{2.5}$ levels for six-day PM measurement intervals versus the average temperature during those six-day periods. The sample consists of the 2001, 2002, and 2003 packing seasons. We exclude two observations during which the air quality alerts occurred as a result of the Biscuit Fire.

Figure 4. The Relationship between $PM_{2.5}$ and Productivity



Note: This figure presents $PM_{2.5}$ levels for six-day PM measurement intervals versus the average earnings per hour of pear packers during that time period. The sample consists of the 2001, 2002, and 2003 packing seasons. We exclude two observations during which air quality alerts occurred as a result of the Biscuit Fire.

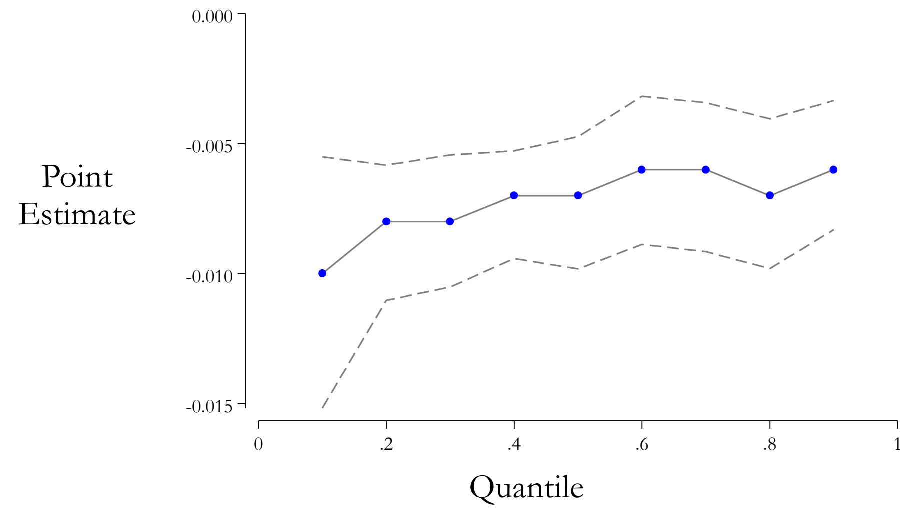
Figure 5. Linear and Non-Linear Effects of $PM_{2.5}$ on Productivity



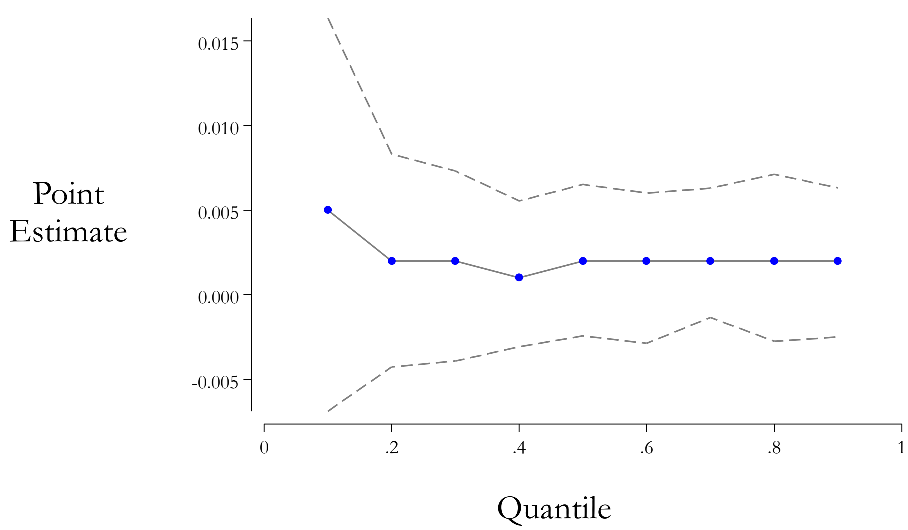
Note: This figure presents the implied effects of $PM_{2.5}$ on productivity based on estimates reported in Table 3, columns 1 (linear) and 3 (nonlinear).

Figure 6. Quantile Regression Results

A. The Linear Effect of $PM_{2.5}$ By Quantile

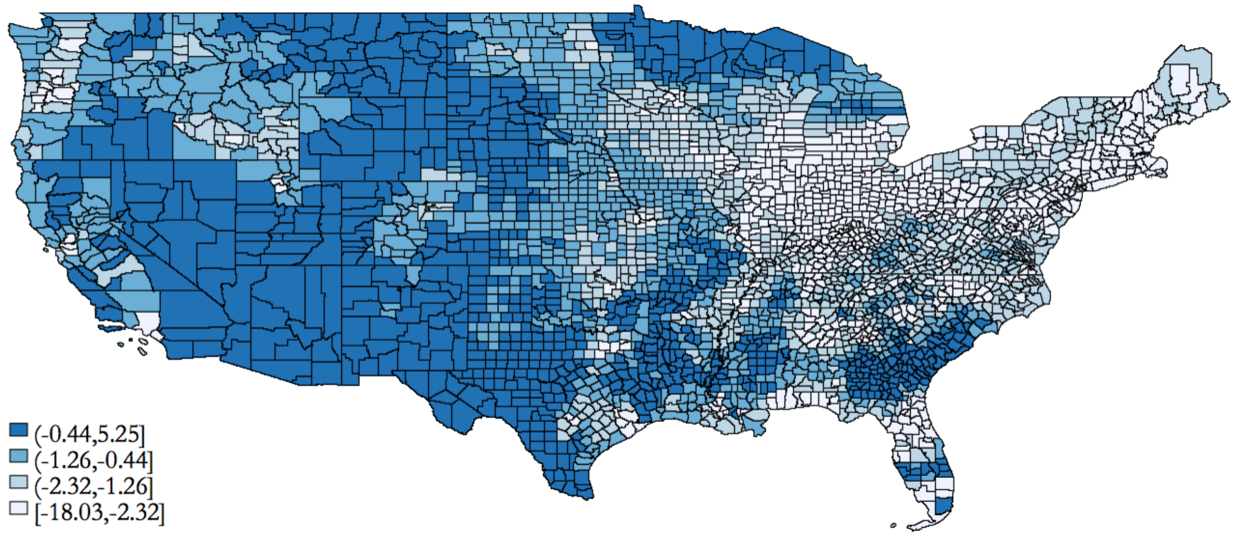


B. The Linear Effect of Ozone By Quantile



Note: This figure presents the quantile estimates for productivity based on a linear control for $PM_{2.5}$ (panel A) or Ozone (panel B).

Figure 7. Variation in Change in $PM_{2.5}$, 1999–2008, By County



Note: This figure presents the variation in county-level changes in $PM_{2.5}$ across the US between 1999 and 2008. All changes are expressed in micrograms per meter cubed as inferred from emissions data. See Muller (2013) for details.

Table 1. Summary Statistics

	Obs.	Mean	Std. Dev.	Min.	Max.
Worked that day	8,222	0.95	0.22	0.00	1.00
Regular-time hours per day	7,242	6.93	1.66	0.25	8.50
Regular-time earnings per hour	7,242	6.99	2.79	0.04	17.18
Worked overtime that day	7,230	0.28	0.45	0.00	1.00
Overtime hours if overtime that day	2,058	1.80	1.49	0.25	9.75
Overtime hours per day	7,242	0.51	1.13	0.00	9.75
Overtime earnings per hour	2,058	11.50	5.37	0.14	41.40
Penalty	5,677	0.05	0.22	0.00	1.00
$PM_{2.5}$ (μg/m3)	49	10.06	9.50	1.90	59.70
Ozone (ppb)	49	31.60	9.77	9.88	55.13
Nitrogen Dioxide (ppb)	49	9.02	3.74	1.88	17.63
Carbon Monoxide (ppm)	49	0.55	0.21	0.18	1.11
Coarse PM (μg/m3)	49	10.19	5.52	1.50	36.40
Dewpoint (°F)	49	9.25	4.15	-4.00	15.00
Rain (in.)	49	0.04	0.20	0.00	1.00
Wind speed (mph)	49	4.06	1.23	1.54	7.68
Solar radiation/1,000 (Wh/m2)	49	0.62	0.18	0.12	0.85
Temperature (°F)	49	74.41	10.22	55.70	92.75

Note: The sample consists of worker-day pear packer payroll records. Coarse PM is defined as PM_{10} – $PM_{2.5}$.

Table 2. Relationship between PM2.5 and labor supply

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var:	Working that day				Hours			
$PM_{2.5}$ (μg/m3)	0.000	0.001			-0.002	0.010		
	(0.000)	(0.001)			(0.005)	(0.027)		
$PM_{2.5}$ 10–15			0.022	0.022			0.080	0.100
			(0.013)	(0.013)			(0.188)	(0.182)
$PM_{2.5}$ 15–20			0.026	0.030			0.089	0.102
			(0.017)	(0.016)			(0.479)	(0.441)
$PM_{2.5}$ 20–25			0.029	0.027			-0.389	-0.252
			(0.023)	(0.020)			(0.261)	(0.239)
$PM_{2.5}$ >25			0.011				-0.291	
			(0.020)				(0.200)	
Ozone (ppb)	0.000	0.000	0.000	0.000	-0.002	-0.004	0.000	-0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.008)	(0.009)	(0.008)	(0.009)
Solar Rad./1,000	0.099	0.116	0.106	0.118	0.769	1.070	0.749	0.986
(Wh/m2)	(0.060)	(0.061)	(0.061)	(0.061)	(1.220)	(1.164)	(1.200)	(1.138)
Temperature (°F)	0.004	0.007	0.006	0.008	0.234	0.222	0.222	0.206
	(0.006)	(0.005)	(0.005)	(0.005)	(0.141)	(0.136)	(0.146)	(0.144)
Temperature	0.000	0.000	0.000	0.000	-0.002	-0.001	-0.001	-0.001
Squared	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Mean of Dep. Var.	0.947	0.949	0.947	0.949	6.934	6.955	6.934	6.955
Includes Alert-Days from Biscuit Fire	Y	N	Y	N	Y	N	Y	N
R^2	0.081	0.079	0.083	0.081	0.352	0.404	0.354	0.405
N	8,222	7,729	8,222	7,729	7,242	6,808	7,242	6,808

Note: Standards errors based on estimates clustered by date of $PM_{2.5}$ assignment and worker in brackets. *,** indicates significant at 5 percent or 1 percent, respectively. The sample consists of worker-day observations over the 2001, 2002, and 2003 pear-packing season. Columns 1 through 4 present marginal effects based on a logit model, and columns 5 through 8 present results from ordinary least squares regressions. All regressions include wind speed, dew point, rain, day of week dummy variables, and year-month dummy variables.

Table 3. Relationship between PM2.5 and productivity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.:		Productivity				Logarithm of Productivity		
$PM_{2.5}$ (μg/m3)	-0.041**	-0.054			-0.008**	-0.007		
	(0.008)	(0.034)			(0.001)	(0.006)		
$PM_{2.5}$ 10–15			-0.074	-0.081			-0.013	-0.013
			(0.247)	(0.247)			(0.040)	(0.040)
$PM_{2.5}$ 15–20			-0.527	-0.494			-0.084	-0.078
			(0.471)	(0.479)			(0.075)	(0.076)
$PM_{2.5}$ 20–25			-1.028**	-1.048**			-0.146*	-0.146*
			(0.325)	(0.331)			(0.059)	(0.061)
$PM_{2.5}$ >25			-1.875**				-0.347*	
			(0.309)				(0.047)	
Ozone (ppb)	0.014	0.017	0.013	0.017	0.004	0.004	0.003	0.004
	(0.015)	(0.016)	(0.018)	(0.016)	(0.003)	(0.003)	(0.003)	(0.003)
Solar Rad./1,000	-0.249	-0.248	-0.170	-0.174	-0.004	0.021	0.020	0.028
(Wh/m2)	(1.293)	(1.309)	(1.298)	(1.309)	(0.245)	(0.244)	(0.245)	(0.246)
Temperature	0.312*	0.305*	0.302	0.289	0.051*	0.049*	0.052*	0.047
(°F)	(0.153)	(0.154)	(0.159)	(0.160)	(0.025)	(0.025)	(0.026)	(0.026)
Temperature	-0.002*	-0.002*	-0.002*	-0.002*	0.000*	0.000*	0.000*	0.000*
Squared	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Mean of Dep. Var.	6.994	6.994	6.955	6.955	1.878	1.878	1.879	1.879
Includes Alert-Days from Biscuit Fire	Y	N	Y	N	Y	N	Y	N
R^2	0.181	0.181	0.171	0.171	0.127	0.127	0.123	0.123
N	7,242	7,242	6,808	6,808	7,242	7,242	6,808	6,808

Note: Standards errors based on estimates clustered by date of $PM_{2.5}$ assignment and worker in brackets. *,** indicates significant at 5 percent or 1 percent, respectively. The sample consists of worker-day observations over the 2001, 2002, and 2003 pear-packing season. All columns present results from ordinary least squares regressions. All regressions include wind speed, dew point, rain, day of week dummy variables, and year-month dummy variables. Productivity is measured as earnings per hour.

Table 4. Robustness checks

	(1) Baseline estimates	(2) Exclude meteorological controls	(3) Control flexibly for temperature	(4) Control for additional pollutants	(5) Add worker fixed effects	(6) Aggregate to 6-day PM-periods
$PM_{2.5}$	-0.041**	-0.036**	-0.039**	-0.040**	-0.039*	-0.046**
(μg/m3)	(0.008)	(0.009)	(0.008)	(0.009)	(0.016)	(0.012)
R^2	0.181	0.172	0.188	0.184	0.445	0.309
N	7,242	7,242	7,242	7,242	7,242	1,810

	(7) Median regression	(8) Censored median regression	(9) Low-quality packing	(10) OT hours	(11) RT productivity when OT exists	(12) OT productivity
$PM_{2.5}$	-0.044**	- 0.040	- 0.001	-0.023*	-0.043*	-0.099**
(μg/m3)	(0.009)	(0.035)	(0.002)	(0.010)	(0.020)	(0.026)
R^2	-	-	0.161	0.174	0.198	0.191
N	7,242	5,084	3,046	7,242	2,058	2,058

Note: Standards errors based on estimates clustered by date of $PM_{2.5}$ assignment and worker in brackets. *,** indicates significant at 5 percent or 1 percent, respectively. The sample consists of worker-day observations over the 2001, 2002, and 2003 pear-packing season. All regressions include data from the entire sample period, including the two weeks in which air quality alerts were issued due to the Biscuit fire. All regressions include ozone, solar radiation, a quadratic in temperature, wind speed, dew point, and rain, except column 2. Column 4 includes nitrogen dioxide, carbon monoxide, and coarse PM. All regressions include day of week dummy variables and year-month dummy variables. In all regressions except for columns 9, 10, and 12 the dependent variable is productivity during the regular-time shift. Productivity is measured as earnings per hour. Column 9 present marginal effects from a logit model. RT indicates regular time, and OT indicates overtime.