PARTICULATE POLLUTION AND THE PRODUCTIVITY OF PEAR PACKERS*

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

January 2014

This draft is preliminary and incomplete. Please do not cite or circulate.

Abstract

We study the effect of air pollution on the productivity of indoor workers. Workers inside a large California factory pack pears into boxes to be shipped to retailers. We find that an increase in fine particulate matter (PM2.5) outdoors leads to a statistically and economically significant drop in packing speeds inside the factory. In contrast, we find little effect of PM2.5 on hours worked or the decision to work, and little effect of pollutants, such as ozone, that do not travel indoors. The effects of PM2.5 arise at levels well below current air quality standards. This effect of outdoor pollution on the productivity of indoor workers suggests a thus-far overlooked consequence of pollution, with important policy implications.

* 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 Schultz 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, research has 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 labor 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% of GDP.[1] Previous evidence on the effect of pollution on the marginal productivity of labor has been limited to the agricultural sector (Graff Zivin and Neidell, 2012), which accounts for a very 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, 2010; Carson et al., 2010; Hanna and Oliva, 2011.

Second, the pollutant we examine, fine particulate matter (PM2.5), has unique properties that make it an especially important pollutant to study in this context. The miniscule size of PM2.5 – 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. While exposure to high levels of PM2.5 causes severe health events, such as heart attacks and hospitalizations for asthma, the degree to which modest exposure to PM2.5 affects more subtle but still economically relevant outcomes, like productivity, is unknown. Minimizing such effects is greatly complicated by the fact that PM2.5 can easily penetrate buildings (Thatcher and Layton, 1995; Ozkaynak et al., 1996; and Vette et al., 2001). The flat indoor-outdoor gradient for fine particulates 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 daily fluctuations in ambient PM2.5 concentrations as measured by a federally administered PM2.5 monitor located near the factory. Those fluctuations are plausibly exogenous; they result from combustion in the hundreds of miles that surround the factory.

Our analysis reveals a statistically significant, negative impact of PM2.5 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 PM2.5 pollution of 10 micrograms per cubic meter reduces the productivity of workers by $0.41 per hour -- approximately 6 percent of the hourly

wage. These effects first arise when PM2.5 exceeds 15 ug/m3 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 PM2.5, suggesting our estimates are not contaminated by sample selection bias.

In order to gauge the potential economy-wide importance of these productivity effects, we apply our coefficient estimate 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 PM2.5 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 significantly understate aggregate benefits from improvements in environmental quality.

The paper proceeds as follows. The subsequent section describes how PM2.5 has been shown to affect health in the laboratory. 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 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 PM10 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 EPA began regulating these particulates (PM2.5), in addition to PM10, in 1997.[4]

The sources of PM2.5 consist of a wide range of both natural and anthropogenic sources. Natural sources include volcanos 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 PM2.5. Given its diminutive size PM2.5 is not visible to the human eye, can remain suspended in the air for extended periods of time, and can travel long distances.

Particularly important for our study, PM2.5 can easily enter buildings, with penetration ranging from 70-100% (Thatcher and Layton, 1995; Ozkaynak et al., 1996; and Vette et al., 2001). This makes PM2.5 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 PM2.5. This is particularly the case in a poorly-insulated factory setting, such as the one we study. Indoor outcome measures can thus be affected by outdoor conditions.

A large body of toxicological and epidemiological evidence suggests that exposure to PM2.5 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 affects, such as changes in blood pressure, irritation in the ear, nose, throat, and lungs, and mild headaches (Pope, 2000; Sorenson et al., 2003; Ghio et al., 2000). These milder effects, which

[3] Particles above 10 micrometers are generally believed to be expelled by coughing or 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.

arise from exposure to lower levels of PM2.5, are generally unobserved by the econometrician – they do not generally 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 PM2.5 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 a sustained, elevated exposure.[5]

These changes in health from PM2.5 exposure can lead to changes in labor market outcomes through two channels. First, sickness related to PM2.5 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 PM2.5 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 PM2.5 exposure may be so mild as to not even register for the impacted individual, such self-reported measures of presenteeism may underestimate 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 PM2.5 on the marginal product of labor, while appropriately accounting for any possible effects of PM2.5 on labor supply.

[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.

3. DATA

In order to measure the effect of PM2.5 on productivity, we require both precise measures of productivity and precise measures of PM2.5. 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, and pears would arrive at the factory each morning. The pears would be cleaned and sorted by machines, and then packers would 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 and to arrive by 7 AM, at the start of the day shift. They would work until all pears had been packed. If the workday lasted longer than 8 hours, then the packers would be paid overtime. Overtime pay meant a piece rate that was 50 percent higher than piece rates during regular time.[7]

The pear-packing 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

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

[7] Further details on how the factory operated are described by Chang and Gross (2013). Our description here is also based on interviews with the factory's former CEO.

day. Importantly, productivity is recorded even for those who are paid an hourly minimum wage for the day, thus providing a comprehensive measure of daily productivity for all workers regardless of where they end up on the wage schedule.[8] The plant 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 retailers. Packers were paid a different piece rate for each product, 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 piece-rate earnings per hour as our standardized measure of productivity. For those workers paid minimum wage, we use their implied piece-rate wage based on their actual productivity. Our standardized measure of productivity assumes that the firm's piece rates approximate the relative effort required to pack each type of box.

Figure 1 plots the variation in productivity as measured by earnings. The first panel plots the productivity across workers by taking the mean earnings 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

[8] Since workers may have an incentive to shirk when facing a fixed hourly wage, we directly test this assumption as a robustness check using the methodology outlined in Graff Zivin and Neidell (2012) and find no such evidence.

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 ug/m3), coarse particulate matter (between 2.5 and 10 ug/m3), ozone, carbon monoxide, and nitrogen dioxide.

While nearly all environmental data were collected at the hourly level, during the time period of our analysis, PM2.5 was only measured every 6 days, thus producing a 6-day daily average measure.[9] This measure has three implications for our analysis. First, the grouping of PM2.5 measures can lead to a "Moulton effect" (Moulton, 1986), so we must cluster standard errors on each 6-day measure of PM2.5. Second, this 6-day measure means that our measure of worker exposure is based on time both at work and home, and both indoors and out. As previously mentioned, effects from PM2.5 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 productivity effects we find. Third, while the factory is reasonably close to the monitor, there may be considerable 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 PM2.5 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:

$$(1) \qquad y_{it} = \beta \times \text{PM2.5}_t + \gamma \times X_t + \delta_t + \varepsilon_{it}$$

[9] 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 day then measured and divided by 6 to give an average daily measure.

where y is the measure of hourly productivity denominated in hourly earnings for worker i on date t.[10] PM2.5 is a daily average of particulate matter (based on the 6-day measure), and β captures the effect of PM2.5 on earnings. The vector X_t consists of wind speed, a quadratic function of temperature, dew point, rain, solar radiation, and ozone[11] to account for other environmental factors that may affect productivity. 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 PM2.5 measurement period, we allow for two-way clustering (Cameron et al., 2011) along those two dimensions.

We face three 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 responded to changes in pollution, then any estimated effects of pollution on productivity could suffer from sample-selection bias. In particular, we want to be able to separate the direct effects of pollution from both the selection of workers who chose to work that day and the impact of shift length on overall worker productivity. To limit this concern, we focus our analysis on the productivity of workers during the regular day shift. Overtime hours, as well as night shift hours, are more discretionary and can, in fact, depend directly on productivity during the regular shift.[12] As such, productivity shocks would have to be large enough to overcome both buffers before affecting regular time, day-shift hours. 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,

[10] As noted earlier, for those that 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.
[11] We account for additional pollutants in our robustness checks.
[12] We nonetheless present evidence on overtime outcomes, noting this limitation. The factory also utilized a "night shift", which was also designed to absorb any unexpected productivity shocks experienced during the regular day shift. We unfortunately do not possess data on the night shift.

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. We also perform a variety of specification checks, described in the results section, to further assess whether any changes in labor supply affect our estimates of the marginal product of labor.

The second empirical challenge is that, during the study period, the area suffered from some of the highest pollution levels it had ever experienced. This was caused by a massive wildfire several hundred miles away, on the border between northern California and Oregon. The fire was called "the Biscuit Fire," and it led to unprecedented PM2.5 levels. While pollution levels are typically quite low in this area, never exceeding air quality standards, the resulting pollution levels during this week-long episode were over 5–7 times higher than usual, as indicated in Figure 2. These high levels are much more likely to have induced sickness that led to changes in labor supply. Furthermore, since much of the public was aware of the dramatic changes in air quality, in part because of local air quality alerts, this could have resulted in substantial behavioral changes that might bias our estimates. To account for this, we omit the time period when the fire occurred. We also model PM2.5 with a series of indicator variables to allow for a non-linear effect of PM2.5. This enables us to not only isolate PM2.5 levels during the fire, but also to explore the dose-response relationship at lower levels of PM2.5.

The third challenge involves omitted variable bias from confounders associated with both worker productivity and pollution. In general, pollution levels are correlated with local business activity, so an increase in pollution could in fact result from higher levels of economic activity. Focusing our analysis on the high-frequency variation in pollution circumvents this concern. PM2.5 is formed directly from various emitting sources, and is also the result of complex interactions between emissions. Since PM2.5 travels far and remains suspended in the air for extended periods of

time, the variation in PM2.5 at the factory is largely driven by factors outside the firm. In addition, since the demand for the factory's services is generated by areas all throughout the U.S., and the supply of pears is from farms throughout the region, factory activity is not likely to driven by local economic activity. Figures 2 and 3 provide some evidence regarding the exogeneity of PM2.5. Figure 2, which plots PM2.5 over time, shows that it varies considerably from one period to the next. Figure 3, which plots PM2.5 against temperature, shows that the variation in PM2.5 is not driven by temperature, a potentially important factor in productivity.[13] In fact, PM2.5 is not correlated with any of the environmental covariates in our analysis – when we regress PM2.5 on all of the environmental covariates, the covariates are neither jointly nor individually statistically significant at even the 10-percent level. While we cannot rule out the possibility of omitted variable bias, this prima facie evidence, supported by further evidence below, suggests that this threat is minimized in our setting.

5. EMPIRICAL RESULTS

A. Testing labor supply responses

We begin our analysis by assessing whether labor supply responds to PM2.5. Table 2 provides estimates of equation (1) using probability worked or hours worked (conditional on working) as the dependent variable. We begin with our linear-in-PM2.5 model, both with and without the Biscuit Fire included, and then proceed to the nonlinear model.

Focusing on the probability worked, the first column demonstrates that each 1-unit increase in PM2.5 has no effect (0.00) on the likelihood of working. Excluding the fire (column 3) raises this estimate to 0.002 though it remains statistically insignificant. Columns 2 and 4 present the results

[13] 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 he was entirely unaware of the existence a connection between fine PM2.5 or ozone levels and worker productivity.

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 PM2.5 leads to a statistically insignificant decrease of 0.003 hours worked. Excluding the fire (column 7) flips the sign but, again, the effect is both small and statistically insignificant. When we allow PM2.5 to enter non-linearly (columns 6 and 8), we continue to find no evidence that hours worked responds to PM2.5. The lack of impacts on the extensive margin, even at the higher levels of pollution associated with the biscuit fire, implies that our estimates of the impacts of PM2.5 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 PM2.5, Figure 4 plots PM2.5 versus earnings, with a linear prediction from regressing earnings on PM2.5 included. This figure uses data aggregated to the level of the firm and the 6-day PM2.5 measurement, which is our effective level of variation in PM2.5.[14] It is also a raw scatter plot that does not adjust for any potential confounding factors. Even with no controls, the raw data suggest a negative relationship: workers earn less each hour as PM2.5 rises.

Estimates of equation (1) are shown in Table 3, which make up the core findings of our analysis. As with labor supply, we present results from four specifications, and we focus on both earnings in levels and in logs. Turning to levels, we find that PM2.5 has a statistically significant, negative effect on earnings per hour. Each additional unit of PM2.5 decreases hourly earnings by

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

$0.041. When we exclude the fire our estimate is no longer statistically significant at conventional levels, but it remains of comparable magnitude.

The next two columns in Table 3 allow PM2.5 to have a non-linear effect on productivity. This also allows us to isolate the effect of the Biscuit Fire, which was the only time period in our sample in which PM2.5 was greater than 25 ug/m3. We find that PM2.5 levels between 15–20 decreases earnings by $0.49 per hour, though this effect is not statistically significant at conventional levels. When PM2.5 reaches 20–25 the effect increases to $1.13 per hour and becomes statistically significant. Importantly, this level of PM2.5 is well below current air-quality standards of 35. The effect further increases to $1.90 per hour when PM2.5 exceeds 25 and remains statistically significant. Excluding the fire yields virtually identical results, suggesting that our results are not driven solely by the fire.

In contrast to the labor supply results, these results provide clear evidence of a dose-response relationship between PM2.5 and productivity, with a possible threshold at 15–20 units. To further illustrate this, Figure 5 plots the linear and nonlinear estimates. The nonlinear estimates suggest a possible threshold around 15 μg/m3 with a roughly linear effect beyond the threshold. While we cannot be certain of a threshold at this point – measurement error could be driving our results down – we note that this pattern is roughly consistent with evidence on the PM2.5-mortality relationship, which finds evidence of a threshold effect around 20 ug/m3 (Smith et al., 2000). It seems quite plausible that a lower threshold exists for productivity, since it is a significantly less harmful outcome.

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 qualitative pattern across the four specifications. We also find quite similar quantitative results, as well. When we convert the estimates using levels into percent by dividing by the mean hourly earnings of $6.83

in our sample, the estimates suggest a roughly 0.6 percent effect from a 1 unit change in PM2.5. Using earnings in logs, we obtain an estimate of 0.8 percent. Compared to the nonlinear-in-PM2.5 model, the implied percent effect for the 3 highest PM2.5 bins are 7.3, 16.5, and 27.8, respectively, which is also quite close to the estimates from the log model of 7.5, 17.9, and 36.8. Hence our results do not appear to be driven by functional form choices regarding 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.[15] 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, 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 70 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 comparable inflection point (Hancock et al., 2007).

C. Robustness checks

One concern with interpreting our estimate for PM2.5 as a causal effect on factory production is that PM2.5 could be affecting factory productivity indirectly by affecting outdoor

[15] Note that many of these variables are also exogenous for the same reason as PM2.5, allowing for interpretation of coefficients as causal (Lu and White, 2014).

workers who harvest the fruit. If harvest production declines with PM2.5, 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. One, the pears that arrive at the factory are harvested all around the region. Given the tremendous spatial variation in PM2.5, PM2.5 levels at the farms are likely to exhibit low correlation with PM2.5 at the factory. Two, since the harvesters start earlier in the day then the packers, the queue is unlikely to be empty. Furthermore, the workers on the overtime and night shifts handle any pears left over by the regular shift, so changes in harvest productivity is generally absorbed by these later shifts, and not the regular day shift on which we focus.

Third, we can also use our estimate for ozone to test for this indirect channel. Ozone is likely to affect the harvest productivity (Graff Zivin and Neidell, 2012), but it does not penetrate indoors (as mentioned above). Therefore, finding a significant effect of ozone on factory productivity would suggest potential indirect effects due to losses in harvest productivity. The lack of a significant effect of ozone, shown in Table 3, suggests that this is unlikely to be occurring. The insensitivity of firm productivity to the harvest suggests that our results for PM2.5 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.

Table 4 presents a series of additional robustness checks. Column 1 repeats the baseline results for the linear-in-PM2.5 models with the fire included. The next 3 columns further explore the effects of other environmental conditions. Since daily variation in PM2.5 may be driven by other environmental conditions that may also affect productivity, it is essential that we control for those other environmental conditions adequately. 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).[16] The effect of PM2.5 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 workers, shown in Column 5. The estimated effect of PM2.5 is unaffected by this additional control. Although we argue that worker exposure to PM2.5 is exogenous, the fact that our estimates are unchanged by including fixed effects further supports our contention that worker selection is not related to PM2.5.

Recall that while worker productivity is measured every day, PM2.5 is only measured every 6 days. Although we perform a daily analysis and cluster standard errors on these 6-day periods, we can 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 workers are in the minimum wage regime, this may induce shirking since they no longer receive additional compensation per piece.[17] If PM2.5 lowers productivity such that workers are more likely to be in the minimum wage regime, and then shirking further lowers productivity, this will bias our estimates (in absolute value) upward. To assess this, we artificially censor earnings at the minimum wage and estimate censored regression models (Graff Zivin and Neidell, 2012). If shirking increases with PM2.5 when workers earn the minimum wage, estimates from censored models will be unbiased, because the precise measure of productivity for workers to the left of the minimum wage is not observed and does not contribute to the likelihood

[16] Coarse PM is PM between 2.5 and 10 microns.
[17] In practice, we observed relatively little shirking at the factory. See Chang and Gross (2012) for an analysis of labor supply in the factory.

function. 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 -0.043 is quite close to OLS estimates. The censored median result of -0.034, shown in column 7, is slightly smaller, though the difference is not statistically significant, suggesting 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 entire day. We estimate equation (1) using the probability of a penalty on a given day as the dependent variable. Shown in column 8, we find that PM2.5 is not significantly related to the probability of a penalty.

Although we have focused our analysis on the regular shift since labor supply is more likely to be fixed then, we also probe the effect of PM2.5 on overtime (OT) outcomes, recognizing that OT hours are more likely to be endogenous. A day with high PM2.5 may lower productivity, and the firm may compensate by increasing the demand for OT hours. Alternatively, a day with high PM2.5 may reduce OT hours by increasing worker fatigue. Similarly, higher PM2.5, particularly during 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 OT hours through increases in the opportunity cost of time. If OT hours worked is more likely to be affected by PM2.5 than RT hours, then the estimated effects of PM2.5 on OT productivity may be biased due to sample selection. Shown in column 10, we find that OT hours decrease as PM2.5 increases: a 1 unit increase in PM2.5 decreases hours worked by -0.022 hours. Since OT labor supply is sensitive to PM2.5, any effects on OT productivity is potentially biased by sample selection.

We examine whether selection into overtime induces bias in overtime productivity estimates by looking at the effect of PM2.5 on regular shift productivity solely for those who work overtime. If there is selection bias into OT, the effect 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 PM2.5 on RT productivity for those who work OT is identical to the overall estimate, suggesting that any selection into OT is not inducing bias for estimates of the effect of PM2.5 on OT productivity.

Given the absence of selection bias into OT, we measure the effects of PM2.5 on OT productivity. Column 12 suggests that PM2.5 has a significant, negative effect on productivity. OT productivity decreases by -0.098 for each additional unit of PM2.5, which is larger than the effect of PM2.5 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 PM2.5.

Last, we explore heterogeneity in the effects of PM2.5. We estimate quantile regression models for each decile of regular time worker productivity, focusing on the log of productivity to account for different baseline levels of productivity across workers. Plotted in Figure 6a, which assumes a linear effect for PM2.5, we see that the effect on productivity is statistically significant in all deciles, though the effect slightly decreases for below-median workers, and remains flat for other workers. Importantly, this finding suggests that the effect of PM2.5 on worker productivity is not driven by a handful of workers who are particularly susceptible to pollution, but is affecting the entire distribution of workers. For contrast, Figure 6b plots quantile results for ozone, and finds that, as expected, it is never significantly related to indoor productivity, further supporting our contention that the effects of PM2.5 are driven by its direct effects on factory workers rather than indirectly through impacts on the harvest.

6. IMPLICATIONS

A key innovation in our analysis is the focus on PM2.5, which can easily penetrates indoors and thus affect a significant fraction of the economy. In light of this, it is useful to place our finding that a 1-unit change in PM2.5 decreases worker productivity by roughly 0.6 percent in a larger context. As a first step, we assess the productivity effects at a national level from the changes in PM2.5 concentrations across the US from 1999 to 2008.[18] To do so, we assume that our estimate of the effect of PM2.5 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 PM2.5 are widely generalizable throughout the US [CITES]. 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 to be similarly affected by PM2.5. 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 this gross categorization is likely to include many workers where this assumption may not apply, such as supervisors and office workers, it is also likely to exclude many potentially affected workers in other industries, such as construction workers and most forms of outdoor work.[19]

As show 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 ug/m3. After merging this pollution data with county-level measures of manufacturing earnings from the

[18] We focus on the years 1999 and 2008 because these are 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. We note that using pollution monitor data yielded almost identical estimates to the inferred data for the counties where monitors were available.

[19] There is also growing evidence that PM2.5 affects cognitive performance (Lavy et al., 2012), which implies potential productivity impacts across knowledge-based employment as well.

Bureau of Labor Statistics in 2000, we find an aggregate labor savings of $19.5 billion due to the realized improvements in PM2.5. This represents a 2.67 percent increase in manufacturing earnings, which translates to a 0.5 percent increase in economy-wide earnings given the fraction employed in manufacturing.

While those numbers are large in absolute terms, it is also instructive to compare them to the other welfare benefits associated with reducing PM2.5 pollution. Recall that fine particulate matter impacts morbidity and mortality. Behavioral responses to limit exposure to pollution and medical expenditures that ameliorate the negative health effects from exposure are also an essential component of welfare (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 approach for obtaining a comprehensive measure of welfare is through the use of housing values in a hedonic framework, whereby under the assumptions of complete and transparent markets all of these effects are capitalized into house prices (Rosen, 1974).

While we are unaware of any studies that link PM2.5 and housing values, Bento et al. (2013) have estimated this relationship for the closely related pollutant of PM10. Exploiting plausibly exogenous changes induced by the Clean Air Act, they find that a 4.7 unit decrease in PM10 increases housing values by $43.9 billion. PM2.5 is the subset of PM10 that is less than 2.5 microns, and evidence suggests that roughly 60 percent of PM10 concentrations in the US are comprised of PM2.5 (Eldred et al., 1997).[20] Applying this number to the estimates from Bento et al. suggests that the changes in PM2.5 from 1999-2008 increased housing values by approximately $57.3 billion (in $2000).[21]

[20] 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.

[21] We arrive at the estimate of $57.3 billion as follows. The $43.9 billion estimate from Bento et al. (2013) is divided by the 4.7 unit decline in PM10 to obtain the value per unit change in PM10. We then multiply it by 0.6 to convert to a unit change in PM2.5. We then multiply by 2.79 to get implied housing change associated with improvements in PM2.5 from 1999-2008. Last, we adjust for inflation by multiplying by the CPI growth from 1990 to 2000 of 1.32.

Thus, if we assume that our estimated labor impacts are capitalized into housing prices, they account for approximately 34% of the total benefits associated with reductions in PM2.5 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 this case, housing prices understate the total benefits from reducing PM2.5 by more than 25 percent.

7. CONCLUSION

In this paper, we analyze the relationship between PM2.5, a ubiquitous pollutant that penetrates into indoor settings, and individual-level productivity at a large California factory. We find that a 10-unit change in PM2.5 significantly decreases worker productivity by roughly 6 percent. Importantly, PM2.5 begins to affect productivity at levels well below current U.S. air quality standards. These findings build upon extensive laboratory and epidemiological evidence on the relationship between PM2.5 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 impact firm profit, firms may, in theory, internalize some of these costs by reducing worker exposure to PM2.5. While the installation of sophisticated filtration systems has the potential to remove PM2.5 from the air, current technology is limited in its ability to fully remove PM2.5, particularly the smallest and most pernicious particulates (CITE). Moreover, since PM2.5 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, for a variety of reasons, productivity-enhancing investments in this context are likely to be significantly 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 U.S. manufacturing suggests that the modest decline in PM2.5 pollution from 1999 to 2008 generated nearly $20 billion in benefits. In light of growing evidence that PM2.5 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

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

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 (2013) "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 Inter-temporal Labor Supply," mimeo.

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.

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).

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.

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

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

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).

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. (1995). "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.

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.

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).

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.

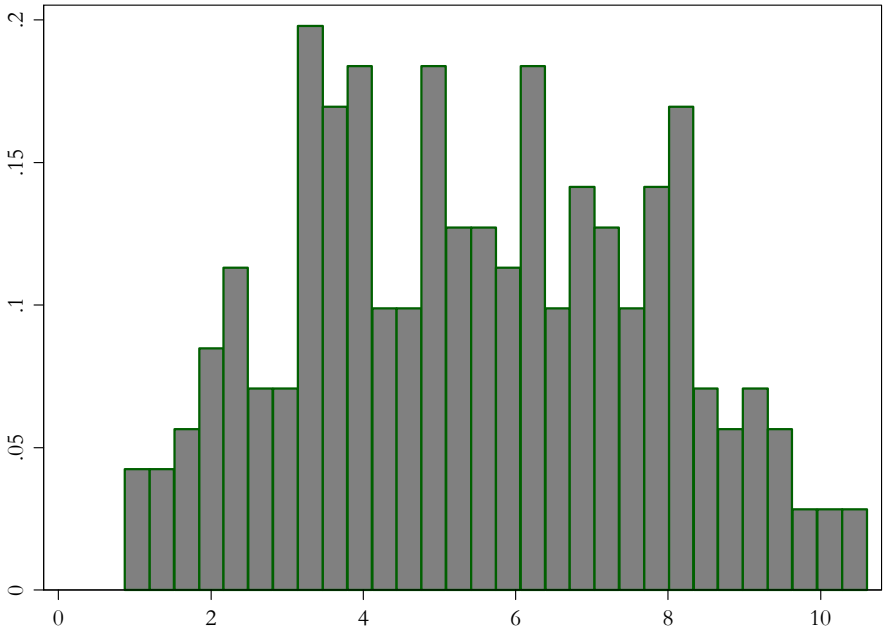
Thatcher, T. L., & Layton, D. W. (1995). "Deposition, resuspension, and penetration of particles within a residence." Atmospheric Environment, 29(13), 1487-1497.

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

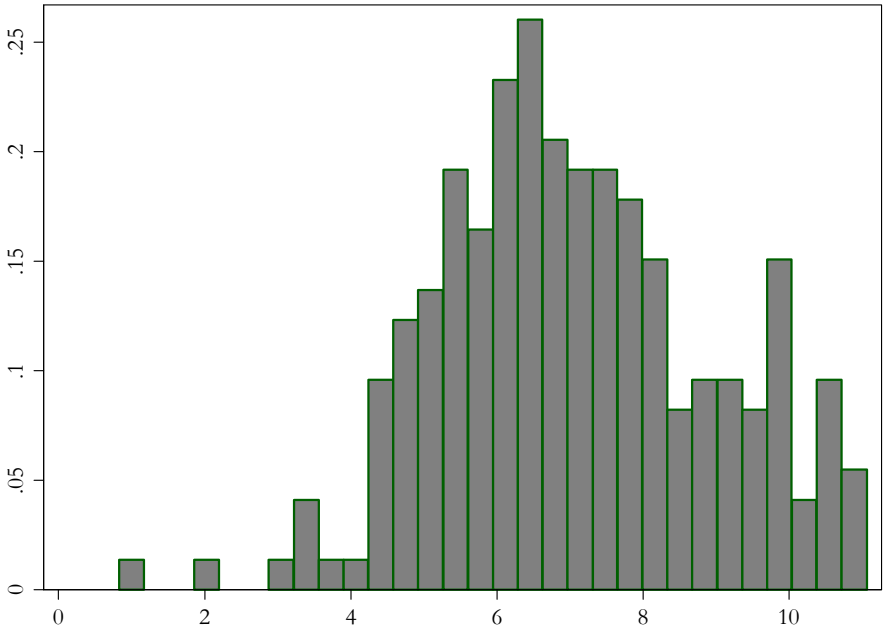
Vette, A. F., Rea, A. W., Lawless, P. A., Rodes, C. E., Evans, G., Highsmith, V. R., & Sheldon, L. (2001). "Characterization of indoor-outdoor aerosol concentration relationships during the Fresno PM exposure studies." Aerosol Science & Technology, 34(1), 118-126.

Figure 1. Variation in productivity across workers and across days

A. Across workers

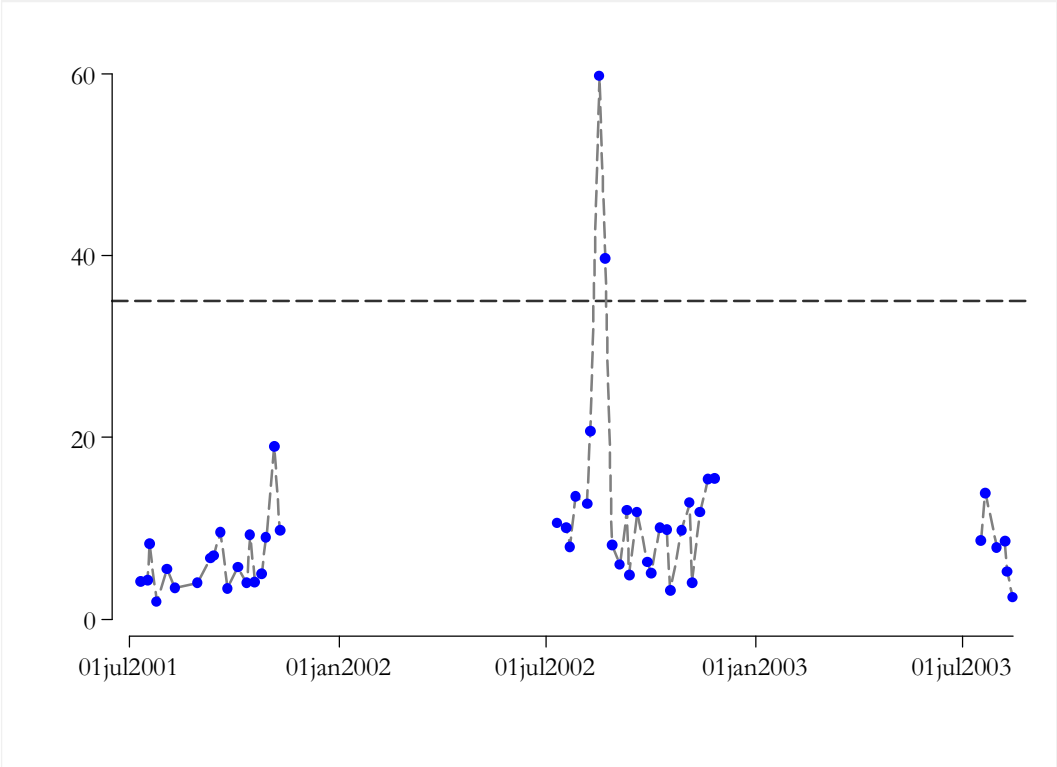


B. Across days



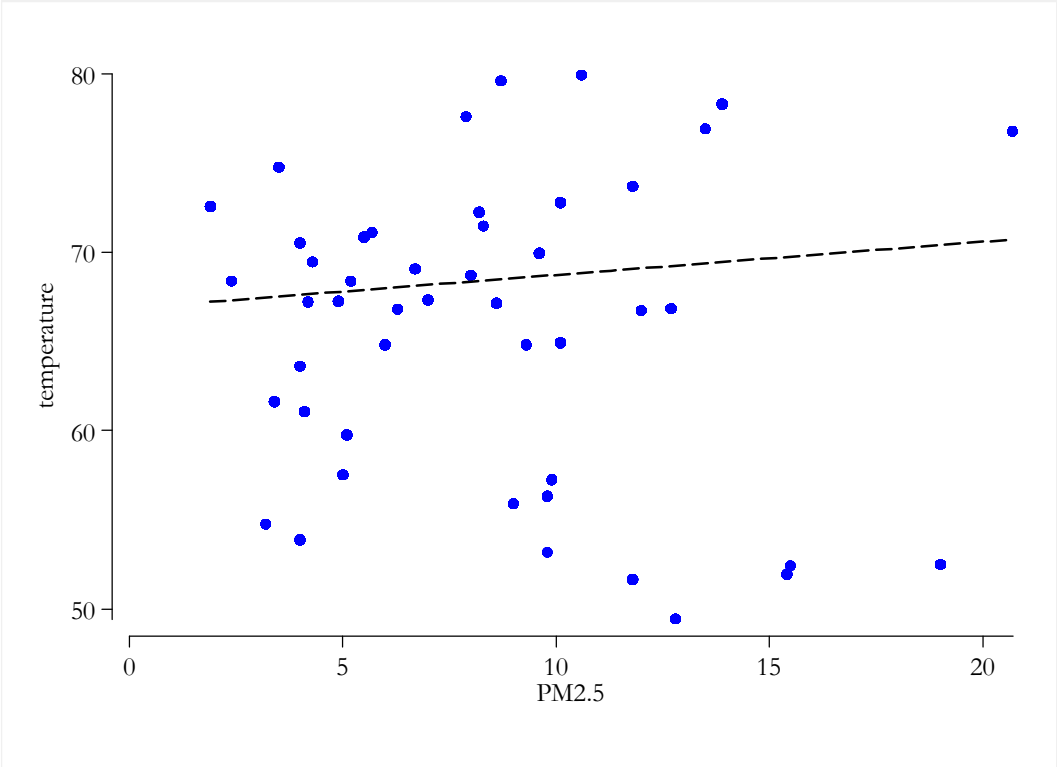
Notes: This figure presents the variation in earnings across workers (panel A) by taking each worker's mean earnings across all time periods, and across days (panel B) by taking each day's mean earnings across all workers.

Figure 2. PM2.5 levels by date



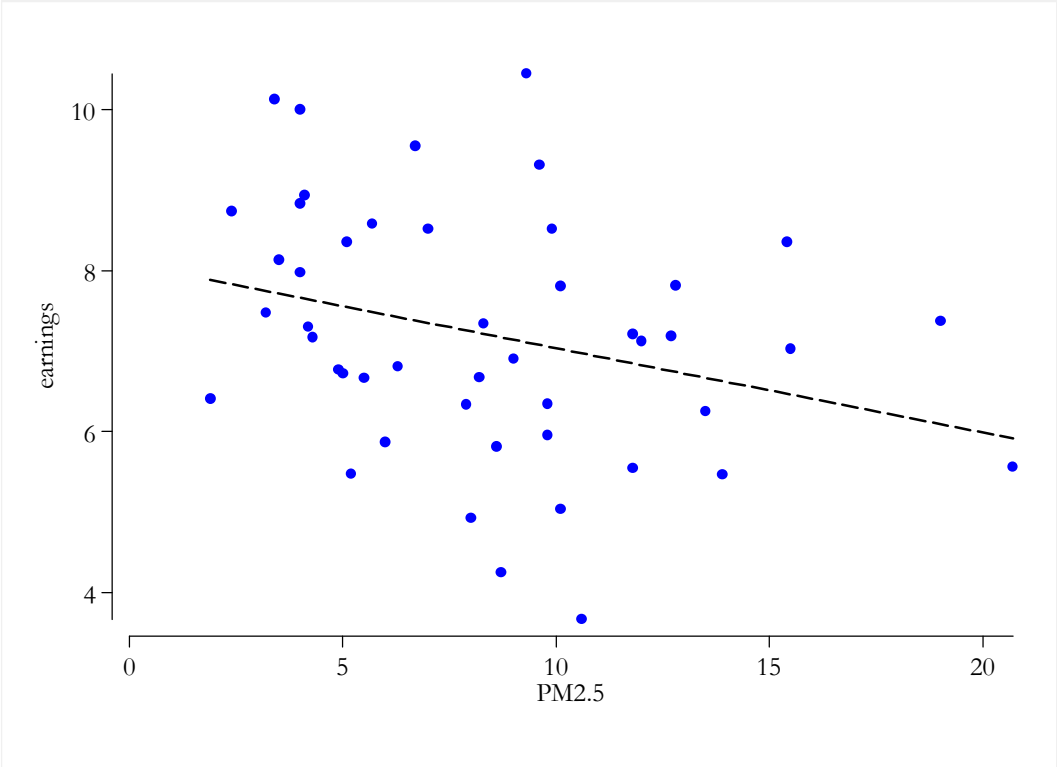
Notes: This figure presents PM2.5 levels for six-day PM-measurement intervals for the 2001, 2002, and 2003 packing seasons. The dotted line corresponds with the 1-hour National Ambient Air Quality Standards for PM2.5 of 35 ug/m3.

Figure 3. PM2.5 and temperature



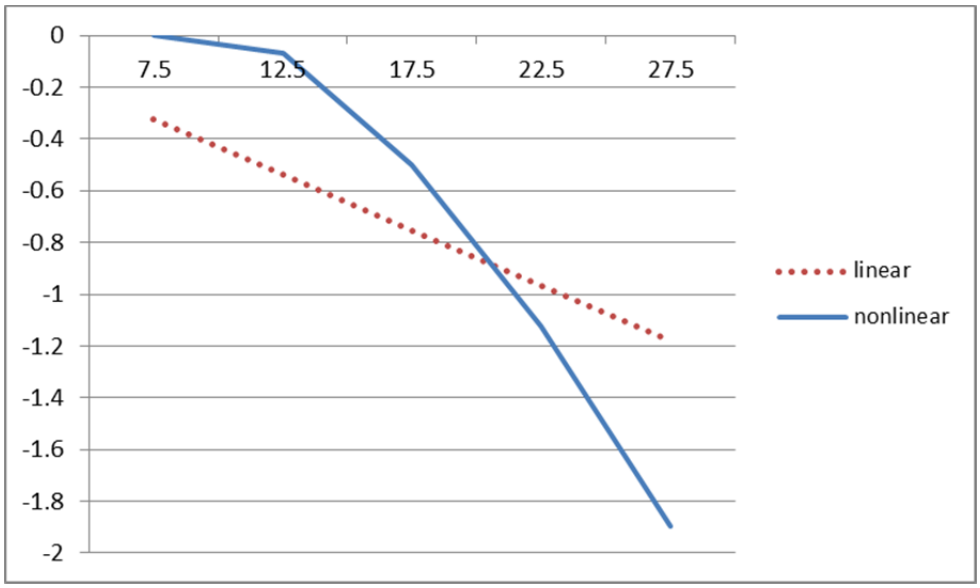
Notes: This figure presents PM2.5 levels for six-day PM-measurement intervals versus the average temperature in those six-day periods. The sample consists of the 2001, 2002, and 2003 packing seasons. We exclude two observations during which the Biscuit Fire occurred.

Figure 4. PM2.5 and productivity



Notes: This figure presents PM2.5 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 the Biscuit Fire occurred.

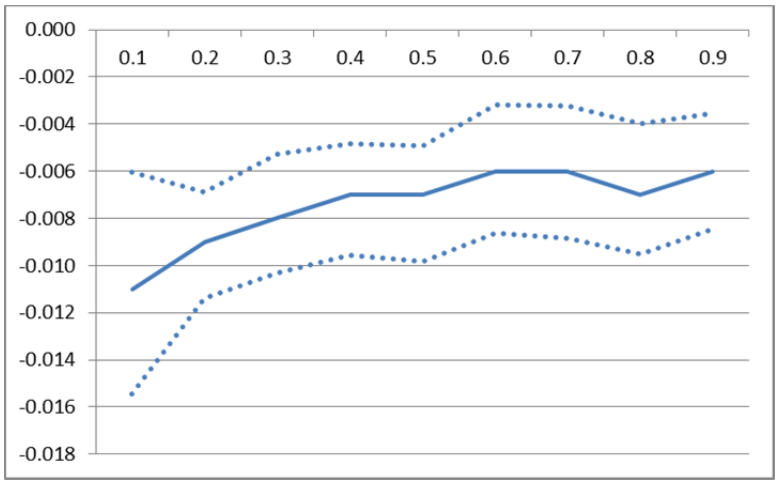
Figure 5. Implied linear and non-linear effects of PM2.5 on productivity



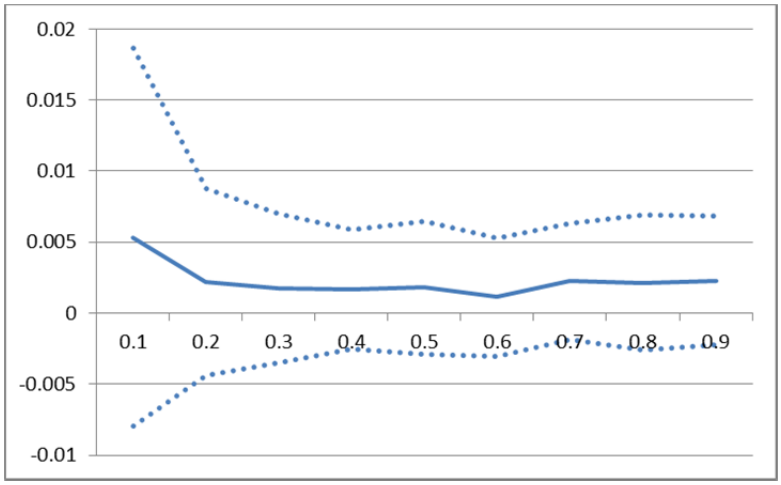
Notes: This figure presents the implied effects of PM2.5 on productivity based on estimates reported in Table 3, columns 1 (linear) and 2 (nonlinear).

Figure 6. Quantile estimates

A. Linear PM2.5

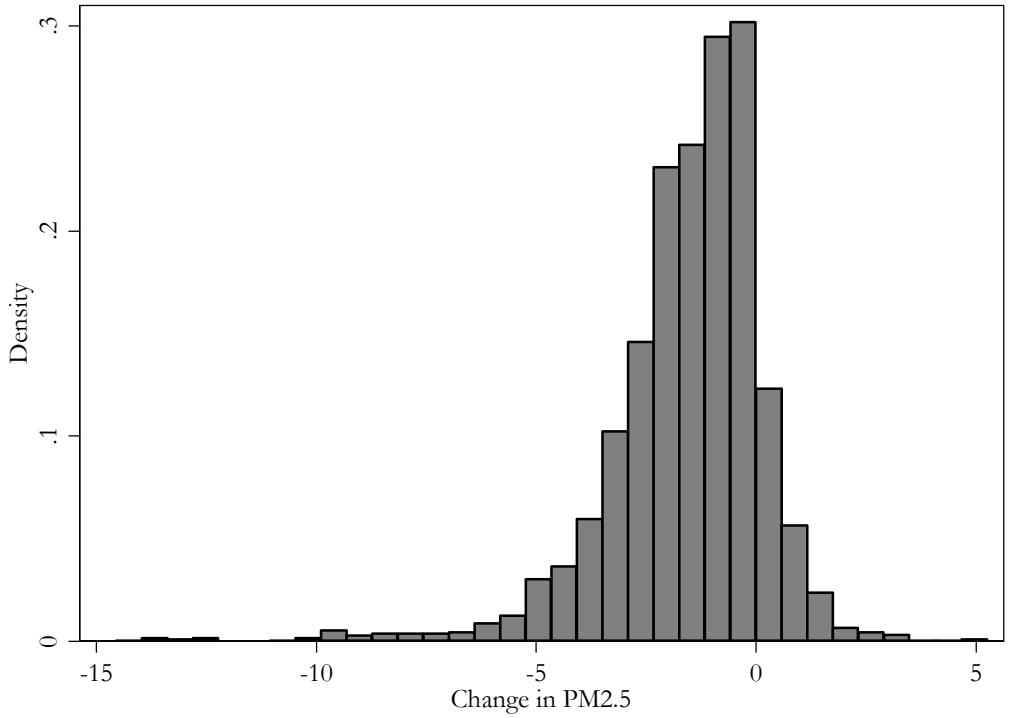


B. Ozone



Notes: This figure presents the quantile estimates for productivity based on a linear control for PM2.5 (panel A) and ozone (panel B).

Figure 7. County-Level Changes in PM2.5, 1999-2008



Notes: This figure presents the variation in county-level changes in PM2.5 across the US between 1999 and 2008. All changes are expressed in micrograms per meter cubed as inferred from emissions data as described in Muller, 2013.

Table 1. Summary Statistics

	N	Mean	Std. Dev.
A. Dependent variables			
work (0/1)	8,736	0.947	0.225
hours worked |work=1	7,610	6.919	1.663
earnings	7,610	6.823	2.868
work OT (0/1)	7,610	0.279	0.449
OT hours worked	7,610	0.500	1.121
OT hours | work OT=1	2,111	1.798	1.482
OT earnings	2,111	11.350	5.482
Penalty	5,677	0.050	0.219
B. Independent variables, assigned to individual (N=7,610)			
PM2.5 (ug/m3)		10.984	11.249
Ozone (ppb)		32.735	9.467
NO2 (ppb)		8.623	3.422
CO (ppm)		0.547	0.212
PM10 (ug/m3)		9.512	5.050
Dewpoint (F)		10.179	3.733
Rain (0/1)		0.035	0.183
Wind speed (mph)		4.206	1.192
Solar radiation/1000 (Wh/m2)		0.676	0.153
Temperature (F)		76.784	8.729
C. Independent variables, at level of PM2.5 measurement (N=49)			
PM2.5 (ug/m3)		10.057	9.499
Ozone (ppb)		31.659	9.883
NO2 (ppb)		8.874	3.742
CO (ppm)		0.538	0.208
PM10 (ug/m3)		10.086	5.306
Dewpoint (F)		9.234	3.667
Rain (0/1)		0.061	0.242
Wind speed (mph)		4.041	1.297
Solar radiation/1000 (Wh/m2)		0.625	0.179
Temperature (F)		74.348	10.265

Table 2. Relationship between PM2.5 and labor supply

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Worked that day				RT hours worked			
PM2.5 (ug/m3)	0.000		0.002		-0.003		0.004	
	[0.000]		[0.001]		[0.005]		[0.029]	
PM2.5 10–15		0.023		0.023		0.092		0.111
		[0.013]		[0.013]		[0.190]		[0.185]
PM2.5 15–20		0.025		0.028		0.104		0.119
		[0.017]		[0.016]		[0.488]		[0.449]
PM2.5 20–25		0.029		0.026		-0.468		-0.332
		[0.023]		[0.021]		[0.266]		[0.243]
PM2.5 >25		0.016				-0.286		
		[0.022]				[0.209]		
Ozone	-0.001	-0.000	-0.000	0.000	-0.004	-0.002	-0.006	-0.005
	[0.001]	[0.001]	[0.001]	[0.001]	[0.008]	[0.009]	[0.009]	[0.009]
Solar	0.098	0.105	0.114	0.115	0.708	0.676	0.966	0.905
radiation/1000	[0.059]	[0.060]	[0.060]	[0.059]	[1.208]	[1.193]	[1.170]	[1.137]
Temp. (F)	0.003	0.005	0.007	0.007	0.235	0.217	0.219	0.2
	[0.006]	[0.005]	[0.005]	[0.005]	[0.142]	[0.146]	[0.137]	[0.144]
Squared	-0.000	-0.000	-0.000	-0.000	-0.002	-0.001	-0.001	-0.001
Temp.	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.001]	[0.001]	[0.001]
Mean of Dep. Var.	0.947	0.947	0.950	0.950	6.919	6.919	6.941	6.941
Includes Biscuit Fire	Y	Y	N	N	Y	Y	N	N
R^2	0.071	0.073	0.067	0.069	0.333	0.335	0.381	0.383
N	8,736	8,736	8,210	8,210	7,610	7,610	7,151	7,151

Notes: Standards errors based on estimates clustered by date of PM2.5 assignment and worker in brackets. *,** indicates significant at 5% or 1%, 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)
	Productivity				Logarithm of Productivity			
PM2.5	-0.041**		- 0.052		-0.008**		-0.007	
(ug/m3)	[0.008]		[0.033]		[0.001]		[0.006]	
PM2.5 10–15		- 0.070		- 0.079		-0.023		-0.024
		[0.229]		[0.230]		[0.041]		[0.040]
PM2.5 15–20		- 0.498		- 0.462		-0.075		-0.068
		[0.465]		[0.472]		[0.075]		[0.076]
PM2.5 20–25		-1.126**		-1.154**		-0.179**		-0.182**
		[0.266]		[0.279]		[0.050]		[0.053]
PM2.5 >25		-1.897**				-0.368**		
		[0.284]				[0.043]		
Ozone	0.014	0.013	0.018	0.018	0.004	0.004	0.005	0.005
	[0.015]	[0.018]	[0.016]	[0.016]	[0.003]	[0.003]	[0.003]	[0.003]
Solar	- 0.253	- 0.185	- 0.251	- 0.202	0.015	0.038	0.041	0.043
radiation/1000	[1.293]	[1.290]	[1.300]	[1.303]	[0.252]	[0.252]	[0.250]	[0.254]
Temp. (F)	0.286	0.271	0.278	0.257	0.043	0.042	0.041	0.038
	[0.151]	[0.155]	[0.151]	[0.156]	[0.025]	[0.025]	[0.025]	[0.025]
Squared	-0.002*	- 0.002	-0.002*	- 0.002	0*	0	0	0
Temp.	[0.001]	[0.001]	[0.001]	[0.001]	[0.000]	[0.000]	[0.000]	[0.000]
Mean of Dep. Var.	6.823	6.823	6.924	6.924	1.792	1.792	1.808	1.808
Includes Biscuit Fire	Y	Y	N	N	Y	Y	N	N
R^2	0.196	0.196	0.188	0.188	0.136	0.137	0.135	0.136
N	7,610	7,610	7,151	7,151	7,610	7,610	7,151	7,151

Notes: See notes to Table 2. All columns present results from ordinary least squares regressions. Productivity is measured as earnings per hour.

Table 4. Robustness checks

	(1) baseline	(2) exclude meteor.	(3) f(temp)	(4) additional pollutants	(5) fixed effects	(6) 6-day
PM2.5	-0.041**	-0.036**	-0.039**	-0.040**	-0.039**	-0.049**
(ug/m3)	[0.008]	[0.009]	[0.008]	[0.009]	[0.014]	[0.015]
R^2	0.196	0.188	0.202	0.198	0.487	0.315
N	7,610	7,610	7,610	7,610	7,610	1,916

	(7) median	(8) censored median	(9) penalty	(10) OT hours	(11) RT prod. if work OT	(12) OT prod
PM2.5	-0.043**	-0.034**	-0.001	-0.022*	-0.041*	-0.098**
(ug/m3)	[0.008]	[0.012]	[0.002]	[0.010]	[0.019]	[0.027]
R^2			0.161	0.165	0.204	0.196
N	7,610	3,537	3,046	7,610	2,111	2,111

Notes: See notes to Table 2. All regressions include data from the Biscuit fire. Column 9 present marginal effects from a logit model, and all other columns present results from ordinary least squares regressions. RT = regular time, OT = overtime.