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Particulate Pollution and the Productivity of Pear Packers[†]

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We study the effect of outdoor air pollution on the productivity of indoor workers at a pear-packing factory. Increases in fine particulate matter ($PM_{2.5}$), a pollutant that readily penetrates indoors, leads to significant decreases in productivity, with effects arising at levels below air quality standards. In contrast, pollutants that do not travel indoors, such as ozone, have little, if any, effect on productivity. This effect of outdoor pollution on indoor worker productivity suggests an overlooked consequence of pollution. Back-of-the-envelope calculations suggest the labor savings from nationwide reductions in $PM_{2.5}$ generated a sizable fraction of total welfare benefits. (*JEL* D24, J24, L66, Q13, Q51, Q53)

Firms commit sizable resources to a wide range of activities aimed at increasing worker productivity, with US 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. 2015; Bandiera, Barankay, and Rasul 2005; Pilcher, Nadler, and Busch 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

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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 gross domestic product (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 policymaking in the developed world where the institutional capacity for regulating the environment is strongest.[2]

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, Barankay, and Rasul 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.

[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, Ostro, and Wise (1984); Graff Zivin and Neidell (2014); Carson et al. (2011); Hanna and Oliva (2015).

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 United States, the bulk of whom perform tasks with similar physical demands as those faced by workers in our study. While this calculation is admittedly speculative given the assumptions required for nationwide extrapolation, 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, Freedman, and Lang 2015, Currie et al. 2015), 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 II describes the data that we use, and Section III describes our empirical strategy. Section IV presents our core results along with a series of robustness checks. Section V explores the implications of our empirical results for the US economy. Section VI concludes.

I. 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

[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 $PM_{2.5}$ was strengthened in 2006.

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 particularly 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, Kim, and Devlin 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 US 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 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 $PM_{2.5}$ on the marginal product of labor, independent from any possible effects of $PM_{2.5}$ 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.

II. 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.[6] 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.[7] 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 had been packed. If the workday lasted longer than eight hours, then the packers would be paid an overtime rate that was 50 percent higher than during regular time.[8]

The factory provided us with payroll records for the 2001, 2002, and part of the 2003 packing seasons.[9] The packing season lasts from July through November of each year. For 2003, our data ends in mid-August when the plant transitioned to a new payroll system. This data provides an unbalanced panel of 158 unique workers across the three seasons for a total of 7,242 worker-by-day observations. Appendix Figure A1 shows the distribution of workdays observed per worker.

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.[10] The dataset includes measures of regular time boxes packed, overtime boxes

[6] Similar to most factories around the globe, the factory is housed in a large structure without HEPA air filtration (the only device capable of removing fine PM), so indoor levels of fine PM are likely to closely match outdoor levels.

[7] 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.

[8] 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.

[9] We have 214 days of output across the 3 growing seasons: 84 in 2001, 104 in 2002, and 26 in 2003. For 2003, our data cuts off in mid-August when the plant tried unsuccessfully to transition to a new payroll system.

[10] 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.

packed, regular time hours, and overtime hours worked for each packer each day. Those variables compose the bulk of our data. Although we do not have explicit measures of whether the worker was absent on a given day, we approximate such a measure by labeling a worker as not present if other workers worked that day, but the particular worker did not.

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.[11] For those workers paid minimum wage, we use their implied piece rate wage based on their actual productivity.[12]

Figure 1 plots the variation in productivity as measured by earnings.[13] 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 five 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 six days, thus producing a six-day daily average measure.[14] This measure has three

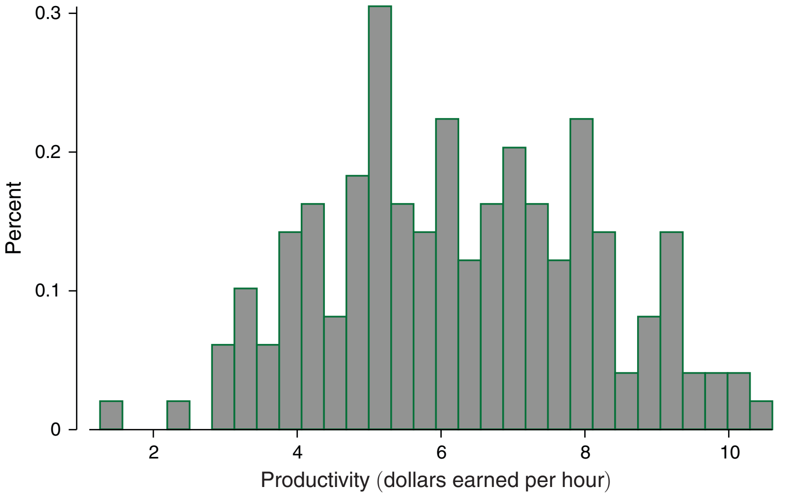
[11] We regressed the share of four-fifths boxes packed on a given day on all covariates (described below), and find that a 1 unit increase in $PM_{2.5}$ is associated with a 0.002 decrease in the share of four-fifths boxes, with a *t*-statistic of 0.52. Using a fractional logit model yielded identical results.

[12] While the minimum wage in California was increased during our sample period from \$6.25 an hour to \$6.75 an hour effective January 1, 2002, piece rate wages remained constant throughout. Any impacts from this change that might have occurred through channels other than the piece-rate wage will be absorbed by the year-specific fixed effects that we employ in all econometric specifications (as described below).

[13] 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.

[14] $PM_{2.5}$ was commonly measured every six 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 six-day measurement was accomplished by weighing the amount of airborne pollution of a specific size captured by specialized filters over the course of six days. The resulting measure is then divided by six to produce an average daily measure of pollution. Thus, a single average daily value is assigned to each of the six days during which a filter was active. The same process was used for PM_{10}.

Panel A. Histogram across workers



Panel B. Histogram across days

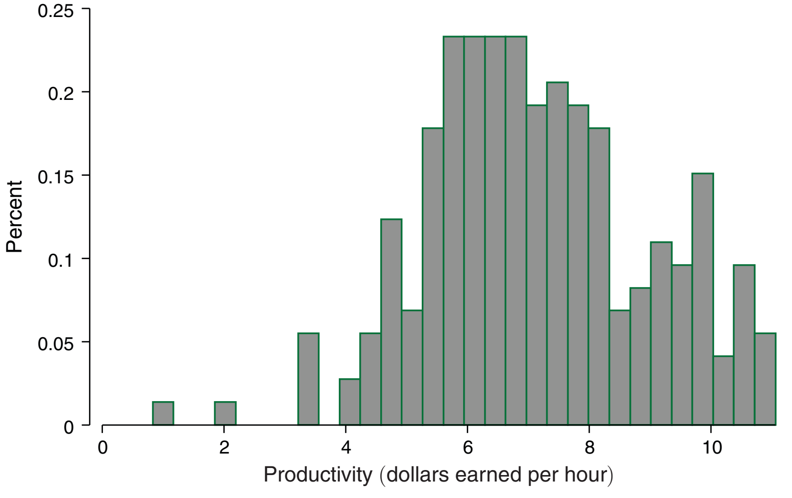


FIGURE 1. VARIATION IN PRODUCTIVITY ACROSS WORKERS AND ACROSS DAYS

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.

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 six-day measure of $PM_{2.5}$. Second, this six-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

Table 1—Sample Statistics

	Observations	Mean	Standard deviation	Minimum	Maximum
Panel A. Productivity variables					
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
Panel B. Environmental variables					
$PM_{2.5}$ ($\mu g/m^3$)	214	10.42	10.14	1.90	59.70
$PM_{2.5}$ <10	142				
$PM_{2.5}$ 10–15	46				
$PM_{2.5}$ 15–20	10				
$PM_{2.5}$ 20–25	5				
$PM_{2.5}$ >25	11				
Ozone (ppb)	214	31.66	9.73	9.88	56.88
Nitrogen dioxide (ppb)	214	9.03	3.75	1.88	23.38
Carbon monoxide (ppm)	214	0.56	0.22	0.18	1.38
PM_{10}–$PM_{2.5}$	214	10.03	5.51	1.50	36.40
Dewpoint (degrees Fahrenheit)	214	9.36	3.97	−4.00	17.00
Rain (in)	214	0.05	0.22	0	1
Wind speed (mph)	214	4.06	1.26	0.89	8.69
Wind direction (from south)	214	0.51	0.50	0	1
Solar radiation/1,000 (Wh/m^2)	214	0.63	0.17	0.07	0.86
Temperature (degrees Fahrenheit)	214	74.81	9.67	54.95	95.00

Notes: Productivity variables consist of worker-day pear packer payroll records. Environmental variables consist of daily observations.

timing of exposure over the six-day period can explain the productivity effects we find.[15] Third, while the factory is reasonably close to the monitor, there may be measurement error in our assignment of exposure to workers during nonwork 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.

III. Empirical Strategy

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

$$\mathbf{y}_{it} = \beta \times f(\mathbf{PM}_{2.5})_t + \mathbf{X}_t'\gamma + \delta_t + \alpha_i + \varepsilon_{it}. \tag{1}$$

[15] The toxicological literature suggests that the health effects from $PM_{2.5}$ generally occur on the same day of exposure but can also appear several days later. Unfortunately, we are unable to explore lagged effects of this diminutive length given the six-day measurement of $PM_{2.5}$.

The outcome $\mathbf{y}_{it}$ is the measure of hourly productivity denominated in hourly earnings for worker i on date t.[16] The covariate $\mathbf{PM}_{2.5}$ is a daily average of particulate matter (based on the six-day measure), and β captures the effect of $PM_{2.5}$ on earnings. We specify $PM_{2.5}$ linearly but also allow for a nonlinear effect by including a series of indicator variables.[17] The vector $\mathbf{X}_t$ 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.[18] The fixed effects, δ, include day-of-week and year-month indicator variables to account for trends within the week and over time, respectively. The term α indicates a worker-specific effect. Given the nature of the variation in $PM_{2.5}$, we treat this term as uncorrelated with $PM_{2.5}$ in the baseline specification, though we also perform robustness checks by allowing this to be a worker-specific fixed effect. We allow for this worker-specific effect by clustering on the worker, which also allows for arbitrary serial correlation within a worker.[19] We also cluster on each six-day $PM_{2.5}$ measurement to allow for the group assignment of $PM_{2.5}$ across all workers. Our composite error term, $\alpha + \varepsilon$, therefore consists of two-way clustering on the worker and $PM_{2.5}$ measurement (Cameron, Gelbach, and Miller 2011).

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 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.[20] While it is still possible that labor supply during the regular shift could respond to pollution (Hanna and Oliva 2015), 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.

[16] 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.

[17] The indicator variables include 10–15 $\mu g/m^3$, 15–20 $\mu g/m^3$, 20–25 $\mu g/m^3$, and above 25 $\mu g/m^3$, with <10 $\mu g/m^3$ as the reference category. This binned approach is a simplified version of a nonparametric estimator. It assumes a uniform effect of temperature within each bin and no overlap across bins, which is tantamount to estimating a step function in pollution. This is a standard approach within the environmental economics literature (see, for example, Deschenes and Greenstone 2007 or Graff Zivin and Neidell 2012).

[18] Below, we also include controls for other pollutants as a robustness check, as well as further checks on the functional form assumptions about meteorology controls.

[19] Clustering on the worker is comparable to specifying worker random effects, though it invokes fewer assumptions about the distribution of the error term.

[20] 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.

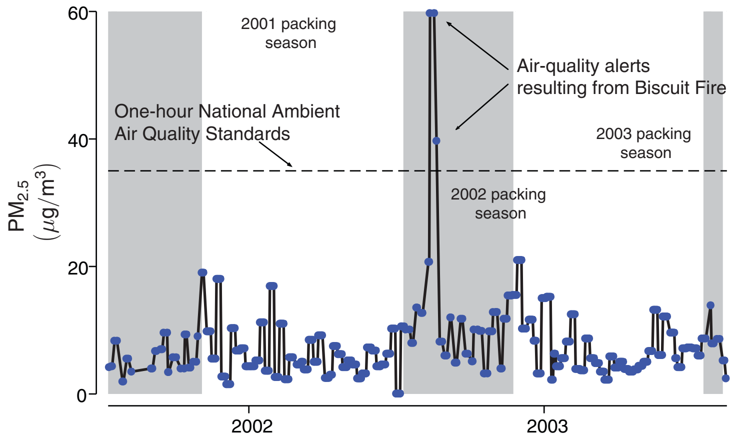


Figure 2. $PM_{2.5}$ Levels by Date

Notes: 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 $\mu g/m^3$.

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 nonrandom 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.[21] 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. Moreover, 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.[22] 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

[21] 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).

[22] 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.

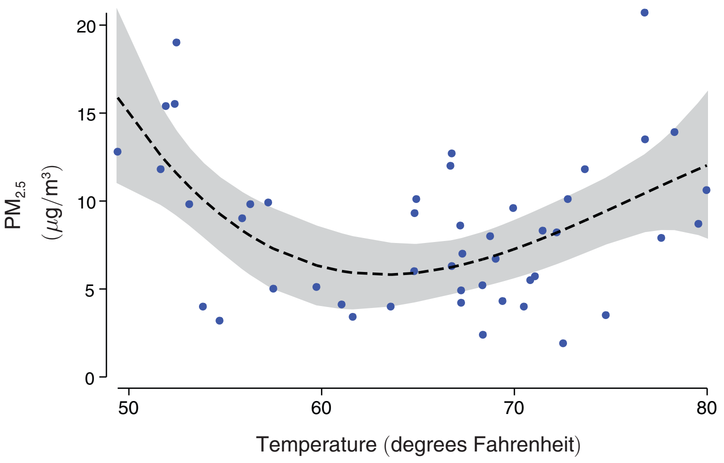


FIGURE 3. THE RELATIONSHIP BETWEEN $PM_{2.5}$ AND TEMPERATURE

Notes: This figure presents $PM_{2.5}$ levels for six-day PM measurement intervals versus the average temperature during those six-day periods. The solid line is the prediction based on a cubic series regression of $PM_{2.5}$ on temperature, with the shaded area indicating the 95 percent confidence intervals. 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.

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 intensive 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.[23] 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

[23] 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.

TABLE 2—THE RELATIONSHIP BETWEEN $PM_{2.5}$ AND LABOR SUPPLY

Dependent variable:	Working that day				Hours			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$PM_{2.5}$ (μg/m^3)	0.000	0.001			−0.001	0.012		
	[0.000]	[0.001]			[0.005]	[0.027]		
$PM_{2.5}$ 10–15			0.022	0.022			0.101	0.123
			[0.013]	[0.013]			[0.191]	[0.185]
$PM_{2.5}$ 15–20			0.025	0.030			0.078	0.090
			[0.017]	[0.016]			[0.489]	[0.451]
$PM_{2.5}$ 20–25			0.030	0.026			−0.337	−0.194
			[0.023]	[0.021]			[0.240]	[0.214]
$PM_{2.5}$ >25			0.011				−0.249	
			[0.021]				[0.206]	
Ozone (ppb)	0.000	0.000	0.000	0.001	−0.008	−0.010	−0.006	−0.009
	[0.001]	[0.001]	[0.001]	[0.001]	[0.010]	[0.011]	[0.011]	[0.011]
Solar rad./1,000 (Wh/m2)	0.101	0.114	0.107	0.117	0.954	1.278	0.926	1.173
	[0.062]	[0.063]	[0.062]	[0.063]	[1.185]	[1.096]	[1.150]	[1.063]
Temperature (°F)	0.004	0.007	0.006	0.008	0.231	0.218	0.220	0.204
	[0.006]	[0.005]	[0.005]	[0.005]	[0.143]	[0.139]	[0.149]	[0.146]
Temperature squared	0.000	0.000	0.000	0.000	−0.001	−0.001	−0.001	−0.001
	[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	Yes	No	Yes	No	Yes	No	Yes	No
R^2	0.081	0.079	0.083	0.081	0.353	0.405	0.355	0.406
Observations	8,222	7,729	8,222	7,729	7,242	6,808	7,242	6,808

Notes: Standard error based on estimates clustered by date of $PM_{2.5}$ assignment and worker in brackets. 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, a wind direction dummy variable, dew point, a rain dummy variable, day of week dummy variables, and year-month dummy variables. All variables are measured on a daily basis except $PM_{2.5}$, which is measured on a six-day basis.

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 nonlinear 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 $PM_{2.5}$.

IV. 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 (0.000) on the likelihood of working. Based

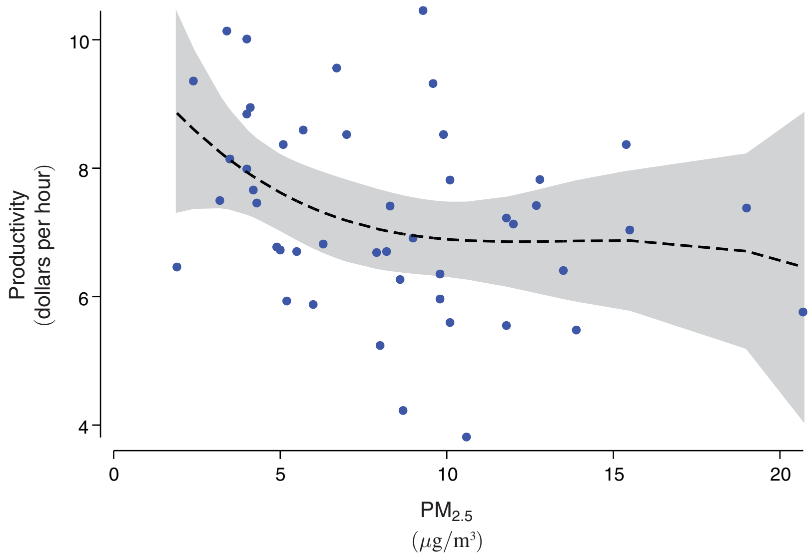


FIGURE 4. THE RELATIONSHIP BETWEEN $PM_{2.5}$ AND PRODUCTIVITY

Notes: 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 solid line presents the predictions from a local polynomial regression (Epanechnikov kernel) of productivity on $PM_{2.5}$ levels, with the shaded area indicating the 95 percent confidence interval. 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.

on this estimate we can rule out even very small effects. Using the lower 95 percent confidence interval of this estimate, a 1 standard deviation change in $PM_{2.5}$ leads to a miniscule 0.6 percent change in the probability 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 statistically 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. We can again rule out very small effects—using the lower 95 percent confidence interval of the estimate suggests a 7 minute decline in work time from a 1 standard deviation change in $PM_{2.5}$. 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

Table 3—The Relationship between $PM_{2.5}$ and Productivity

Dep. variable:	Productivity				Logarithm of productivity			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$PM_{2.5}$ ($\mu g/m^3$)	−0.041	−0.053			−0.008	−0.007		
	[0.008]	[0.034]			[0.001]	[0.006]		
PM2.5 10–15			−0.062	−0.062			−0.014	−0.012
			[0.250]	[0.251]			[0.041]	[0.041]
PM2.5 15–20			−0.533	−0.504			−0.084	−0.079
			[0.460]	[0.466]			[0.073]	[0.074]
PM2.5 20–25			−1.001	−0.999			−0.148	−0.144
			[0.338]	[0.345]			[0.065]	[0.068]
PM2.5 >25			−1.853				−0.348	
			[0.313]				[0.051]	
Ozone (ppb)	0.012	0.013	0.010	0.012	0.004	0.004	0.004	0.004
	[0.017]	[0.019]	[0.018]	[0.018]	[0.003]	[0.004]	[0.004]	[0.004]
Solar rad./1,000 (Wh/m^2)	−0.162	−0.095	−0.075	−0.014	−0.013	0.028	0.013	0.035
	[1.334]	[1.353]	[1.334]	[1.341]	[0.256]	[0.257]	[0.256]	[0.256]
Temperature (°F)	0.311	0.302	0.301	0.287	0.052	0.049	0.052	0.047
	[0.154]	[0.155]	[0.159]	[0.159]	[0.025]	[0.025]	[0.026]	[0.026]
Temperature squared	−0.002	−0.002	−0.002	−0.002	−0.000	−0.000	−0.000	−0.000
	[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	Yes	No	Yes	No	Yes	No	Yes	No
R^2	0.181	0.171	0.181	0.171	0.127	0.123	0.127	0.123
Observations	7,242	6,808	7,242	6,808	7,242	6,808	7,242	6,808

Notes: Standard error based on estimates clustered by date of $PM_{2.5}$ assignment and worker in brackets. 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, a wind direction dummy variable, dew point, a rain dummy variable, day of week dummy variables, and year-month dummy variables. All variables are measured on a daily basis except $PM_{2.5}$, which is measured on a six-day basis. Productivity is measured as earnings per hour.

of the firm and the six-day $PM_{2.5}$ measurement period, which is our effective level of variation in $PM_{2.5}$.[24] The figure plots unadjusted sample means for the six-day periods and a smoothed polynomial fit. 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, shown in column 1. Each additional unit of $PM_{2.5}$ decreases hourly earnings by \$0.041, which is 1.5 percent of a standard deviation. Based on the means in our data, this translates into an elasticity of 0.059. 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 $PM_{2.5}$ levels during the alerts improve the precision of our estimates, they do not

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

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 nonlinear 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 $\mu g/m^3$. Furthermore, since this bin does not include days with air quality alerts, it suggests the results are not caused merely by the Biscuit Fire. 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, shown in column 4, yields virtually identical results for the three lowest bins, further underscoring 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).[25]

The next set of columns in Table 3 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 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 three 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.[26] 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

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

[26] 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).

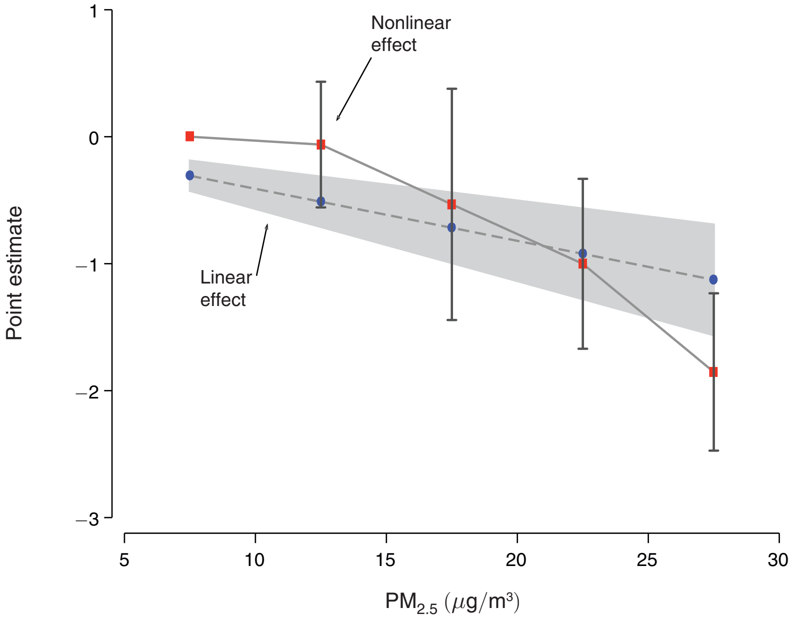


Figure 5. Linear and Nonlinear Effects of $PM_{2.5}$ on Productivity

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).

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 a relationship between outside temperature and worker productivity. Specifically, in our preferred specification (Table 3, column 3) we find that the coefficient on the first-order term for temperature is positive and the quadratic term is negative, with both statistically significant. These point estimates imply 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, Ross, and Szalma 2007).

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.[27] 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.

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. Although we begin with a parsimonious baseline specification, the next three columns explore alternative assumptions. 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).[28] 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 six days. Although we perform a daily analysis and cluster standard errors on these six-day periods, we also perform an alternative analysis aggregated

[27] 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.

[28] Coarse PM is PM between 2.5 and 10 microns. The controls for temperature here consist of indicator variables for each 5°F, ranging from less than 60 to over 90, corresponding to the fifth and ninety-fifth percentile of the temperature distribution, respectively.

Table 4—Robustness Checks

	Baseline estimates (1)	Exclude meteorological controls (2)	Control flexibly for temperature (3)	Control for additional pollutants (4)	Add worker fixed effects (5)
$PM_{2.5}$ (μg/m^3)	−0.041	−0.036	−0.040	−0.039	−0.039
	[0.008]	[0.009]	[0.008]	[0.009]	[0.016]
R^2	0.181	0.172	0.188	0.184	0.445
Observations	7,242	7,242	7,242	7,242	7,242
	Aggregate to six-day PM-measurement periods (6)	Median regression (7)	Minimum wage binds (8)	Censored median regression (9)	Low-quality packing (10)
$PM_{2.5}$ (μg/m^3)	−0.047	−0.044	0.007	−0.040	−0.001
	[0.013]	[0.009]	[0.001]	[0.035]	[0.002]
R^2	0.309	—	—	—	0.161
Observations	1,810	7,242	7,242	5,084	3,046

Notes: Standard error based on estimates clustered by date of $PM_{2.5}$ assignment and worker in brackets. 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 day of week dummy variables and year-month dummy variables. All regressions except column 2 include wind speed, a wind direction dummy variable, dew point, and a rain dummy variable. Column 3 controls for temperature flexibly by including a series of indicator variables for each 5°F. Column 4 includes nitrogen dioxide, carbon monoxide, and coarse PM. All variables are measured on a daily basis except $PM_{2.5}$, which is measured on a six-day basis. In all regressions except for columns 8 and 10, the dependent variable is productivity during the regular-time shift, which is measured in earnings per hour. Column 8 uses whether the minimum wage binds as the dependent variable and column 10 uses "low-quality packing" as the dependent variable; both present marginal effects from a logit model.

to the six-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 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. In column 8, we show that the probability that the minimum wage binds is increasing in $PM_{2.5}$ and statistically significant. The censored median result of -0.040, shown in column 9, is slightly smaller than the uncensored median estimated, 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.

Appendix Figure A2 shows the distribution in OT hours, conditional of OT hours greater than zero, both across workers and across days, similar to Figure A1. It suggests some variation in average overtime by worker, with the typical worker facing slightly less than two hours of overtime. There is much less variation across days, however, with most days less than two hours. Shown in column 1 of Table 5, 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 -0.022 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 Table 5, column 2, 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.[29] Table 5, column 3 suggests that $PM_{2.5}$ has a significant,

[29] 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.

Table 5—The Relationship between $PM_{2.5}$ and Overtime Productivity

	Overtime hours (1)	Regular-time productivity (2)	Overtime productivity (3)	Overtime productivity (4)
$PM_{2.5}$ (μg/m^3)	−0.022	−0.042	−0.106	−0.081
	[0.010]	[0.020]	[0.027]	[0.027]
Include RT productivity	—	—	No	Yes
R^2	0.175	0.198	0.192	0.337
Observations	7,242	2,058	2,058	2,058

Notes: Standard error based on estimates clustered by date of $PM_{2.5}$ assignment and worker in brackets. 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 wind speed, a wind direction dummy variable, dew point, a rain dummy variable, day-of-week dummy variables and year-month dummy variables. All variables are measured on a daily basis except $PM_{2.5}$, which is measured on a six-day basis. In columns 1 and 2, the dependent variable is the number of overtime hours worked. The dependent variable in column 3 is regular-time productivity and in columns 4 and 5 is overtime earnings, both limited to the sample of worker-days for which overtime hours exists. Productivity is measured in earnings per hour, though overtime productivity is deflated by 1.5 to account for time-and-a-half overtime pay.

negative effect on productivity. OT productivity decreases by −0.106 for each additional unit of $PM_{2.5}$, which is larger than the effect of $PM_{2.5}$ on productivity during regular time. In the last column of Table 5, we also control for regular-time productivity to account for the fact that overtime productivity may be sensitive to earlier productivity. This decreases the estimate to −0.081, though it is still considerably larger than the effects on regular-time productivity. 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 account 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 $PM_{2.5}$.

V. 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. Given the many uncertainties involved in this

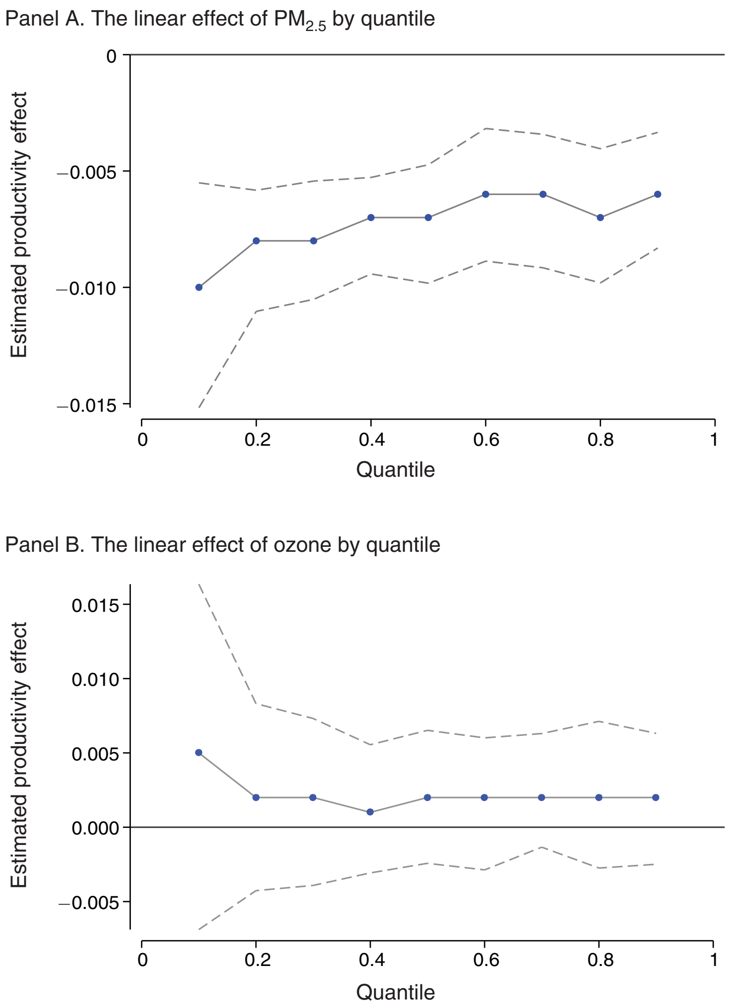


FIGURE 6. QUANTILE REGRESSION RESULTS

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

exercise, we caution upfront that these calculations are meant to be illustrative rather than providing a definitive estimate of welfare impacts on a national scale. Recall that 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 United States from 1999 to 2008.[30]

[30] We focus on the years 1999 and 2008 because, for these two years, we have measures of $PM_{2.5}$ for all counties in the United States. Pollution monitors provide incomplete coverage for the United States, so we use estimates inferred from emissions data (Muller 2014). 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.

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 United States. 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 $PM_{2.5}$. 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.[31]

As shown in Appendix Figure A3, 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, Greenstone, and Shapiro 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, Freedman, and Lang (2013) have estimated this relationship for PM_{10}, which is closely related to $PM_{2.5}$. Exploiting plausibly exogenous 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,[32] with evidence suggesting that roughly 60 percent of PM_{10} concentrations in the United States are comprised of $PM_{2.5}$ (Eldred, Cahill, and Flocchini 1997).[33] Applying this number to the estimates from Bento, Freedman, and Lang (2015) suggests that

[31] There is also growing evidence that $PM_{2.5}$ affects cognitive performance (Lavy, Ebenstein, and Roth 2014), which implies potential productivity impacts across high-skilled workers as well.

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

[33] 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, Cahill, and Flocchini (1997).

the changes in $PM_{2.5}$ from 1999–2008 increased housing values by approximately \$57.3 billion (in year 2000 dollars).[34]

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, Freedman, and Lang (2013) finds that housing values more than five miles from a pollution monitor are unaffected by air quality levels. Currie et al. (2015) find a similar result for air toxins, 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.

It is important to recognize that our economy-wide calculations extrapolate from our setting to all US manufacturing. In practice, the effect of pollution on a pear-packing facility in Northern California may be very different from the effect of pollution on a car manufacturer in Michigan or a steel mill in the Ohio River Valley. Moreover, the composition of $PM_{2.5}$ differs across regions, and the differential health effects by particle type are not well understood (Bell et al. 2007). That said, research in this area has found that the vast majority of buildings are quite porous to fine PM (Thatcher and Layton 1995), and air conditioning, in particular, does not filter $PM_{2.5}$ (Batterman et al. 2012). In fact, the only device that can remove $PM_{2.5}$ is a high-efficiency particulate arrestance (HEPA) filter, and HEPA filters are uncommon in manufacturing, used mainly for specialized manufacturing, such as microchip production, that requires a clean room to limit damage to the production process itself (Whyte 1999). Thus, our back-of-the-envelope figures should be interpreted with caution, providing a rough estimate for aggregate impacts in the absence of additional knowledge about how productivity impacts may vary across settings.

VI. 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

[34] We arrive at the estimate of \$57.3 billion as follows. We divide the \$43.9 billion estimate from Bento, Freedman, and Lang (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 consumer price index growth from 1990 to 2000 of 1.32.

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, Ekberg, and Langer 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 policymakers 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. Our findings also suggest that pollution may have a complex effect on the overall economy. Typically, pollution is a necessary condition for production, and thus for economic growth. But our findings suggest that pollution lowers labor productivity, and labor productivity is itself an important determinant of economic growth. 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, Ebenstein, and Roth 2014), 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.

Appendix

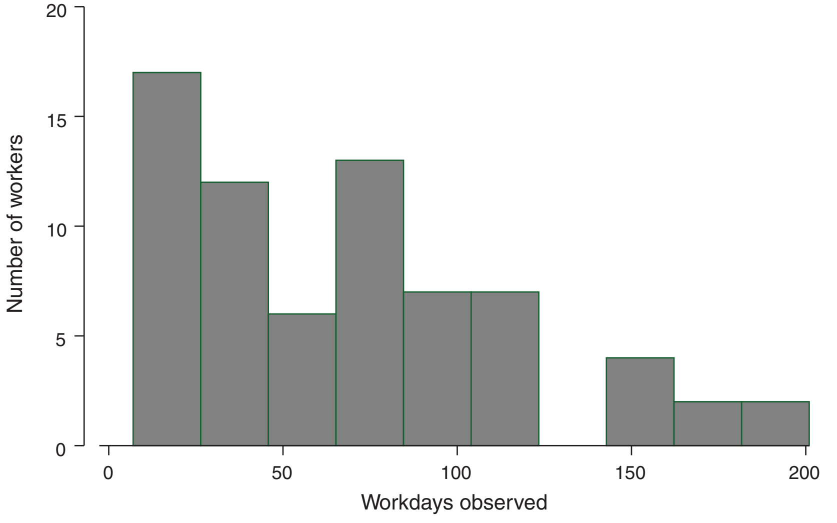
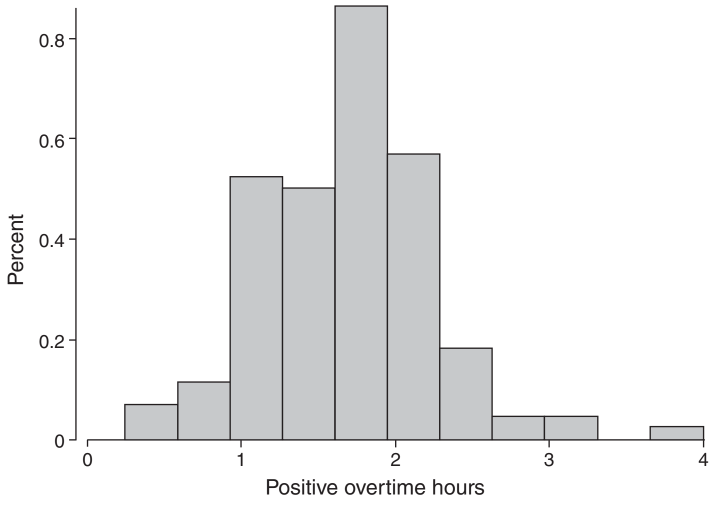


Figure A1. Variation in Observations per Worker

Notes: This figure presents the distribution of workdays observed per worker. There are 158 unique workers in the sample across the 2001, 2002, and 2003 packing seasons.

Panel A. Histogram across workers



Panel B. Histogram across days

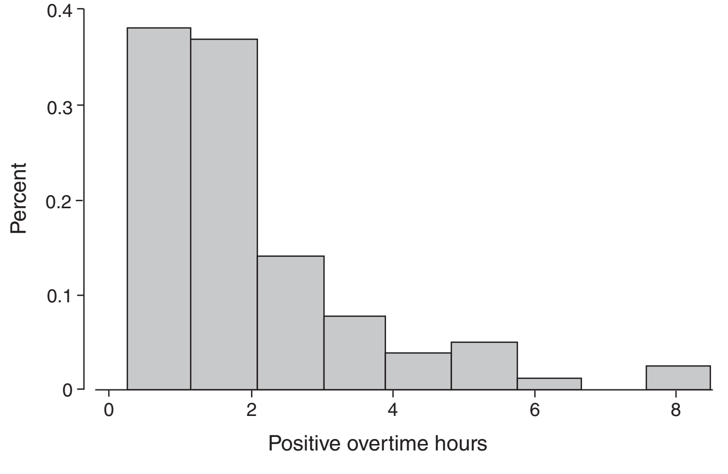


Figure A2. Variation in Overtime Hours across Workers and across Days

Note: This figure presents the variation in overtime hours across workers (panel A) by taking each worker's mean overtime hours across all time periods, and across days (panel B) by taking each day's mean overtime hours across all workers, conditional on positive overtime hours.

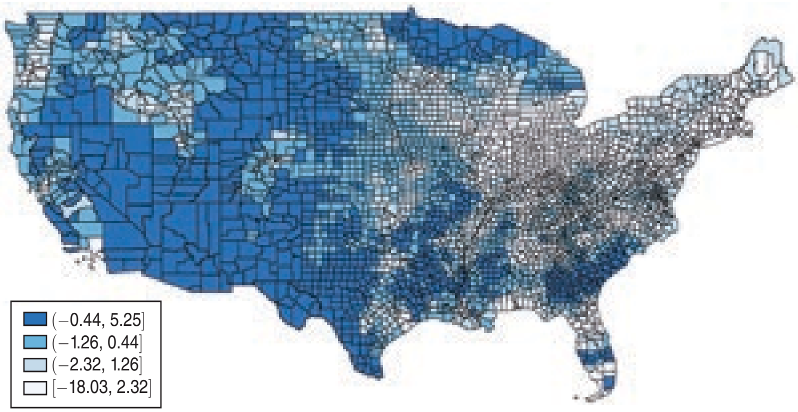


FIGURE A3. VARIATION IN CHANGE IN $PM_{2.5}$, 1999–2008, BY COUNTY

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

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