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More than particulates matter: Multiple pollutants and productivity in Indian call centers*

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Abstract

We measure the impact of three components of air pollution on daily labor productivity in call centers in five Indian cities. We find that a one standard deviation increase in fine particulate matter $PM_{2.5}$), a pollutant that has been the primary focus of the literature on the harms of air pollution, has a large negative effect of 0.15σ on productivity. Notably, we find a comparable negative effect for a one standard deviation increase in carbon monoxide of 0.14σ as well as a negative effect of 0.09σ from ozone. In summing air pollution harms across our sample, carbon monoxide is responsible for more than half of the total productivity lost, which is more than double the losses attributable to $PM_{2.5}$. Our results underscore the importance of considering components of air pollution beyond particulate matter. To that end, we illustrate the potential productivity impacts of a national policy in India that targets $PM_{2.5}$ compared to a counterfactual policy that also targets carbon monoxide and ozone.

Keywords: environment, pollution, productivity, labor, personnel economics, India, development, health
JEL Codes: Q53, M54, I15, O15

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1 Introduction

Ambient air pollution has serious and well-documented impacts on human health, and thus, understanding the impact of pollution on economic outcomes has become an important question for research and policy. This research has largely focused on particulate matter (PM), however, which is a single component of air pollution.[1] Understanding the full effect of pollution on productivity, including that of gaseous compounds such as carbon monoxide, is particularly relevant in developing countries such as India, where both high pollution levels and low firm productivity are major policy concerns (Hsieh and Klenow, 2009; Damania et al., 2023). Recent policies in India that focus on controlling PM may only be able to address a minority of the harm caused by air pollution.

Using daily pollution and worker-level data from call centers in five cities across India, we examine the effects on productivity of three components of air pollution: two key gaseous compounds, carbon monoxide (CO) and ozone (O_3), as well as PM of less than 2.5 micrometers ($PM_{2.5}$). We first document distinct variation in the levels of the three pollutants, which confirms the importance of considering multiple pollutants rather than relying on only particulate matter as a proxy for all air pollution. We then identify significant causal effects of all three pollutants on productivity, with CO driving the majority of the harms. Finally, we use an illustrative exercise to demonstrate the potential productivity gains from adding CO and O_3 targets to a current policy in India that only addresses $PM_{2.5}$.

Our setting and data are well-suited to measuring the causal impacts of multiple ambient air pollutants on productivity for a few reasons. First, call centers are not a major contributor to pollution, thus, we do not expect changing productivity in call centers to drive changes in pollution. Second, we are exploiting the variation in daily data. This data, combined with date and worker fixed effects, allows us to abstract away from the selection effects of any sectoral shifts driven by pollution. Third, it is unlikely that productivity and pollution are moving jointly due to some third factor. In particular, the call centers in our study handle calls to and from wide geographic areas, so changes in productivity are unlikely to be systematically driven by changes in the behavior of people on the other end of the phone lines from the call center employees. Finally, the significant isolated variation in the levels of the three pollutants in our sample allows us to separately identify their effects.

Our first results examine the impact of the three pollutants on the extensive margin of productivity, which we define as being available for work. Thus, we include two extensive margin measures: being at work on a given day and net login time per day. The impact of pollution on the extensive

[1] See Aguilar-Gomez et al. (2022) for a review of the literature on non-health effects of air pollution.

margin is theoretically ambiguous. On the one hand, there could be a reduction in days worked or hours worked due to pollution-related health effects. On the other hand, there could be an increase in the time spent at work on more polluted days if workers value leisure more on days with better air quality. Given this ambiguity, it is not surprising that we do not find meaningful or significant effects on the extensive productivity margin.

We also examine the impact of the pollutants on the intensive margin of productivity and find substantial and significant results. Our analysis focuses on an intensive margin productivity index which includes two measures of efficiency of calls handled. In our main specification, we find that a one standard deviation increase in $PM_{2.5}$ induces a 0.145σ reduction in intensive margin productivity.[2] Notably, the impact of CO on pollution is similar at -0.139σ. In addition, the impact of O_3 is -0.087σ. These three results are each statistically significant at the 1% level, but the coefficients on the three pollutants are not statistically different from one another. For a one standard deviation increase in $PM_{2.5}$, CO and O_3, these effects translate to declines in the number of calls handled per shift of 11.8%, 10.6% and 6.0% respectively.

We next evaluate the share of harms from the three pollutants at the levels observed in our data. The average combined effect of these three components of air pollution on productivity is -0.39σ. Since the share of days with relatively high CO levels is larger than for the other pollutants in our sample, CO is responsible for approximately 59% of the pollution-driven reductions in productivity. In contrast, $PM_{2.5}$ and O_3 each account for approximately 21% of the harms.

We extend our analysis to a stylized illustration of the potential impact on productivity of policies that only target $PM_{2.5}$ compared to those that target multiple pollutants. Specifically, we compare the potential impact on worker-level call center productivity of a recent policy, India's National Clean Air Programme (NCAP), that set 20% $PM_{2.5}$ reduction targets against a hypothetical policy which also reduced CO and O_3 by similar amounts. Accounting for observed within-sample correlations in pollutants, we find the PM-only reduction targets of NCAP reduce the overall productivity loss from pollution by 13.5% relative to a setting without NCAP. In contrast, a hypothetical policy that targets all three pollutants would reduce productivity losses from air pollution by 24%.[3]

This study is unique in examining the effect of multiple air pollutants on labor productivity for a major sector of the economy, and we find that CO drives the majority of productivity reductions attributable to air pollution in our setting. Other studies in this literature have generally not exam-

[2] We also consider flexible functional forms and interactions of these pollutants but find no evidence of non-linear or interactive effects.

[3] The cost-effectiveness of such policies is a topic for future research.

ined CO, with the exception of Archsmith, Heyes and Saberian (2018), who study the effects of the same three pollutants we examine on umpires' decisions in American baseball. In this mostly outdoor profession, they find impacts for $PM_{2.5}$ and CO, but not O_3. Our study, however, examines the call center industry, which is a major source of private sector employment in India, employing 4.47 million people (Ministry of Electronics and IT, 2021). Other examinations of the effects of air pollution on labor productivity have largely focused on $PM_{2.5}$, specifically.[4] Some of these papers study factory work (Adhvaryu, Kala and Nyshadham, 2022; He, Liu and Salvo, 2019; Fu, Viard and Zhang, 2021), while others examine cognitive work (Holub and Thies, n.d.; Kahn and Li, 2020).[5] One study that, like this one, examines the productivity of office workers is Chang et al. (2019), which examines call centers in China. Our study advances beyond that work by uniquely examining CO and O_3, as well as by using a more precise measure of particulate matter (PM). We identify a meaningfully larger effect of PM, and furthermore find CO to be the primary driver of productivity losses from air pollution. We then also consider the implications of addressing CO and O_3 in a counterfactual policy experiment.

Our setting, in a large sector of the economy in the world's most populous country, allows us to consider the implications of policies that address air pollutants beyond $PM_{2.5}$, particularly CO. In addition to the NCAP, other air pollution policy that has been the focus of research in India has often only targeted $PM_{2.5}$ (Duflo et al., 2013; Greenstone et al., 2022). This focus is also reflected on a global level; for example, the World Health Organization (WHO) tracks only $PM_{2.5}$ across countries (WHO, 2022). It may also play a role in the setting of pollution standards. This paper finds harmful effects of CO at levels well below WHO guidelines in India, and thus contributes global evidence to recent findings from the U.S. on the effects of CO at levels below local regulatory guidelines (Archsmith, Heyes and Saberian, 2018; Schlenker and Walker, 2016). This is in contrast to $PM_{2.5}$ for which we find effects concentrated above WHO guidelines.

[4] A few other studies have examined O_3, largely in outdoor occupations, but CO remains particularly under-examined. Two studies focus on the productivity impacts of O_3 in outdoor occupations (Graff Zivin and Neidell, 2012; Wang, Lin and Qiu, 2022). Chang et al. (2016) examines the impact of $PM_{2.5}$ and O_3 on pear-packers in the U.S. and only find effects for $PM_{2.5}$.

[5] A complementary set of studies examine pollution and performance in non-work settings. These studies also largely focus on $PM_{2.5}$, or examine O_3 in outdoor settings. Three recent papers examine the impact of $PM_{2.5}$ on cognitive games (Künn, Palacios and Pestel, 2019; La Nauze and Severnini, 2021; Mo, Wu and Yuan, 2023). Other studies examine impacts of pollution on academic (Ebenstein, Lavy and Roth, 2016; Zhang, Chen and Zhang, 2018; Bedi et al., 2021) or athletic performance (Lichter, Pestel and Sommer, 2017; Mullins, 2018). None of the above studies examine CO.

2 Context

2.1 Pollution and health

This study measures the impact of air pollution on labor productivity with the health impacts of those pollutants being the likely mediator. Fine particulate matter, $PM_{2.5}$, is known to penetrate indoors (Thatcher and Layton, 1995) and its harmful health effects are well-established (Brunekreef and Holgate, 2002). In particular, $PM_{2.5}$ can cause serious health issues by impairing cardiovascular and lung functioning (Liu et al., 2017; Pope III and Dockery, 2006), or cause daily allergies resulting in nose and throat irritation and mild headaches (Bernstein et al., 2008; Ghio, Kim and Devlin, 2000). Thus, $PM_{2.5}$ can potentially hamper an individual's productivity indirectly through changes in health, and may also be able to do so directly through reductions in cognitive performance (Sakhvidi et al., 2022; Ebenstein, Lavy and Roth, 2016; Ye et al., 2023).

Carbon monoxide is an odorless gas, which also has established negative health effects (Wang et al., 2019; Bell et al., 2009; Liu et al., 2018). The main sources of CO pollution include automotive fumes and industrial combustion emissions. Because CO is not absorbed by building materials or captured by most filtration systems, indoor CO levels generally mirror outdoor levels even when no indoor emissions sources are present (WHO, 2010). When inhaled, CO reduces oxygen flow within the body (Raphael et al., 1989). The immediate symptoms of inhaling CO include headache, dizziness, confusion, and disorientation, while in the longer term (2 to 28 days), it can lead to a rise in hypertension, lethal arrythmia, electrocardiographic changes and neuropsychiatric impairment (Raub et al., 2000). A U.S. based study documenting the pollution impacts of living in proximity to airports found that the CO from airplane fumes was associated with a rise in hospitalization rates and costs (Schlenker and Walker, 2016).

Exposure to O_3 in both the short- and long-term can also impact human health. In the short-term, it can cause breathing difficulties, including shortness of breath and pain when taking a deep breath, irritation to the eye and nose, coughing and sore or scratchy throat and inflammation of airways (Zhang, Wei and Fang, 2019). Long-term exposure to O_3 increases the risk of lung infections and aggravates lung diseases such as asthma, emphysema, and chronic bronchitis (McDonnell et al., 1999; Zhang, Wei and Fang, 2019).

Ambient, outdoor O_3 readily penetrates buildings (Salonen, Salthammer and Morawska, 2018; Ma et al., 2022), but indoor exposure to O_3 was previously considered less impactful because O_3 breaks down relatively quickly in indoor environments (Chang et al., 2016). We include O_3 levels in our analyses, however, since recent studies suggest that substantial shares, 25% to 60%, of daily ozone intake still occurs indoors (Nazaroff and Weschler, 2022; Weschler, 2006) and workers are exposed to outdoor conditions during commuting.

2.2 Work in call centers

Call centers are part of the business process outsourcing (BPO) industry, which is a major source of employment in India (Ministry of Electronics and IT, 2021). The two call center companies in this study organize their work around individual contracts to provide voice support for companies that need such services. Each of these contracts leads to the establishment of a *process* or group of employees engaged in handling the same type of calls. Inbound processes receive calls for customer service, from industries such as food delivery, retail and telecommunication. In contrast, outbound processes require agents to make calls, to sell products or to conduct surveys. Our study includes ten processes (five inbound and five outbound), spread across five Indian cities (states): Noida (Uttar Pradesh), Mumbai (Maharashtra), Patna (Bihar), Hubli (Karnataka), and Udaipur (Rajasthan).

The processes rely on entry-level employees, known as agents, who handle the voice support. Agents are organized into teams of 20 to 25, each of which is managed by a team leader. Agents are expected to work six days a week with staggered schedules. Call center work is a common first job for young people, and there is significant churn in the workforce (Jensen, 2012).

3 Identification Strategy

Our identification strategy relies on the increasingly common approach in this literature of exploiting relatively high-frequency variation in pollution and productivity.[6] The high-frequency aspect of our data is most important in allowing us to isolate the impact of pollution on productivity from selection or composition effects in the workforce. In particular, daily variation in pollution allows us to abstract away from seasonal or long-term shifts in the composition of the workforce of the type that is the focus of another thread of research.[7]

Identification strategies that use high-frequency pollution measurement also rely on the assumption that there is no other causal relationship that primarily explains the co-movement of daily pollution and productivity levels. In particular, we do not expect that productivity would determine pollution levels, since the call center industry is not a significant contributor to pollution.[8] We also do

[6] Adhvaryu, Kala and Nyshadham (2022) use hourly variation in pollution, Archsmith, Heyes and Saberian (2018) use three-hour variation for CO and a 12-hour/daily variation for O_3 and $PM_{2.5}$. Many other papers rely on daily variation, including Graff Zivin and Neidell (2012), Chang et al. (2019), and La Nauze and Severnini (2021).

[7] See for example, Khanna et al. (N.D.), Chen et al. (2013) and He, Xie and Zhang (2020).

[8] Furthermore, in industries that are major contributors to pollution, we typically expect to find that increased productivity would cause increased pollution, which is the opposite of what we find here.

not expect that pollution is indirectly affecting productivity through a third factor. Perhaps the most likely potential third factor is that pollution could reduce incoming calls to the call center if customers are affected by pollution. Even in this case, however, both inbound and outbound calls are from wide geographic areas in our sample. Thus, customers and employees are not in general exposed to the same pollution levels.

Finally, we note that this study is designed to identify the total impact of daily pollutant levels on productivity, that is, the joint effect of exposure to pollution during a worker's commute and the effect of indoor air pollution during the day. This effect is important in measuring the overall harms of pollution. Furthermore, any policy efforts to reduce ambient air pollution can address both these potential channels by addressing outdoor air pollution.[9]

3.1 Data and variable construction

All outcome measures in this study rely on data that is collected automatically by technology-based monitoring systems in the call centers.[10] Our data is an unbalanced worker-date panel of 2,687 workers, for a total of 131,386 observations.

Our extensive margin of productivity includes two approaches to measuring employee availability for work: attendance and net login time. Attendance is simply an indicator of whether an employee comes to work on a given day. Net login time captures the amount of time that an employee is logged into the computer system and available to work. Thus, this measure captures the time spent actually working and excludes the time spent on breaks.[11]

For the intensive margin of productivity, we consider two measures of the intensity of time spent conditional on being at work: calls per shift and average calls per hour. These are distinct measures that account for the intensive margin in two different ways. Calls per shift is the number of calls made in a day, irrespective of the time at work, while average calls per hour is based on total calls conditional on actual time spent at work on a given day. It is important to measure both as they allow us to understand the nature of intensive margin effects more precisely in the event that we also observe extensive margin effects. We index both the intensive and extensive margin measures in order to have a single, standardized outcome measure for each.

[9] Of course, if harmful effects are driven by indoor pollution, employers can potentially mitigate directly with air purification. We will examine the role of indoor air pollution in future research.

[10] Our data begins in late 2018 and ends before the COVID-19 pandemic begins in early 2020. For details, see Section SA1.2.

[11] Hence, it is zero if the employee does not come to work. We note that Chang et al. (2019) have two measures of time spent at work, all time spent at work and net login time. They assign the first of these to the extensive margin and the second to the intensive margin. In our setting, it is more natural to categorize net login time as an extensive margin measure and restrict the intensive margin to measures of intensity of work measures conditional on time spent.

For air pollution data in the main analysis, we rely on daily measures collected from five monitors maintained by the Central Pollution Control Board of India (CPCB). Specifically, we use daily data from the closest monitor to each of the five call-center offices in the productivity data.[12]

We report our results using two types of units for the pollutants in our sample. First, we benchmark the pollutants using within-sample standard deviations of those pollutants. Since the reference point for pollution should be zero (rather than the potentially harmful mean level of pollution in a given environment), we simply divide the pollutants by their standard deviations. We also report our results using pollutant concentrations, which are internationally comparable and objective measures.

3.2 Distributions of observed pollutants

In order to better understand the implications of our results, we first examine the distribution of the three pollutants in our sample.[13] Pollution levels are exceptionally high compared to the global average. For example, the mean concentration of $PM_{2.5}$ across all of the city-worker-day observations in our sample is 66.52 $\mu g/m^3$ (s.d. 68.47 $\mu g/m^3$). These concentrations of $PM_{2.5}$ are at least 10 times the current WHO guideline for safe exposure, which is an average of 5 $\mu g/m^3$ (WHO, 2021).

$PM_{2.5}$ levels in our sample are also far above the global average for cities, which was 27 $\mu g/m^3$ in 2018 (WHO, 2022). They are fairly representative of the yearly average for all cities in India, however, which had a mean of 61.41$\mu g/m^3$ in 2018.[14] In addition, such concentrations are also highly relevant for hundreds of millions of people living in cities across Sub-Saharan Africa and South Asia, in particular. For example, in 2018, the average $PM_{2.5}$ level in cities in Nigeria was 55.13 $\mu g/m^3$, while for cities in Pakistan, it was 59.51 $\mu g/m^3$ (WHO, 2022). WHO does not track CO and O_3 at the country-level globally, however, thus it is more difficult to benchmark these measures in our sample to global averages.

Unlike $PM_{2.5}$, CO and O_3 concentration averages in our sample do not exceed the WHO recommended guidelines. Specifically, the mean CO concentration observed in our sample is 1.05 mg/m^3 (s.d. 0.60 mg/m^3), and the 99$^{\text{th}}$ percentile level is 2.93 mg/m^3. In contrast, the WHO daily average guideline for the 99$^{\text{th}}$ percentile of daily averages is 4 mg/m^3.[15] The average O_3 level in our sample is 51.55 $\mu g/m^3$ (s.d. 30.87 $\mu g/m^3$), which does not exceed the WHO guideline of an average of 60

[12] See Section SA1.1 for further details on the pollution and weather data. Our results are robust to alternative pollution measures and sources as indicated in Section SA2.

[13] See Table SA1 for summary statistics and Figure SA1 for histograms of the three pollutants.

[14] For more on the representativeness of our data to India, see Section SA1.3.

[15] Note that CO measures are in milligrams per cubic meter rather than $\mu g/m^3$.

$\mu g/m^3$ during peak season.[16] The 90th percentile date-worker observation in our sample, however, is 108.4 $\mu g/m^3$, which does exceed the WHO day-level maximum guideline of 100 $\mu g/m^3$. Thus, for at least 10% of the worker-date observations in our sample, O_3 is above the recommended levels. In general, however, we will be assessing the impacts of CO and O_3 at levels below those at which the WHO has thus far recognized as important for public health (WHO, 2021).

Our identification strategy relies on short-term variation in pollution measures. Thus, we examine the extent of the granular variation in our sample both within and across individual pollutants. One concern that may arise is whether these three pollutants are highly correlated in the short term, and thus move in lock-step. This would make it challenging to separately identify the effects of these three pollutants. We find evidence, however, of rich variation across the levels of the different pollutants even within individual days. In addition, we examine variation within each pollutant from one day to the next, and find it to be meaningful as well.[17]

3.3 Estimation

Our estimation strategy relies on measuring the impact of daily variation in city-specific pollution on worker-level outcomes. Specifically, our main estimating equation,

$$Outcome_{it} = \beta_0 + \sum_k \beta_k \, Pollutant_{k,ct} + X_{ct} + \alpha_i + \delta_t + \epsilon_{it} \tag{1}$$

includes controls as well as both worker-level and date fixed effects.[18] The controls include city-specific meteorologic variables that can influence pollution and productivity, including quadratic functions of daily mean temperature, total precipitation, mean dew point and mean cloud cover. The worker fixed effects in our model account for any differences in workers that could be correlated with different pollution levels. Furthermore, the date fixed effects account for differences in productivity across dates that could also be correlated with pollution. For example, if weekends have lower pollution, but workers tend to be less productive on weekends, the date fixed effects would account for such patterns. As an alternative that has previously been used in the literature, we also show estimates based on day-of-the-week and month-year fixed effects in some specifica-

[16] The WHO defines the peak season as the six months of the year during which O_3 is at its highest levels.

[17] See histograms of within-day pairwise variation across the individual pollutants (Figure SA4) and within-pollutant variation across days (Figure SA5).

[18] Two-way fixed effect models have come under significant criticism in recent years in the context of difference-in-difference framework (Roth et al., 2022). We do not think our setting, however, directly maps into those frameworks, since we rely on different identifying assumptions than those models. Furthermore, this literature does not in general allow for a continuous treatment measure. An exception is Callaway, Goodman-Bacon and Sant'Anna (2021), but that model does assume a pre-period to test identifying assumptions, and that set-up is not relevant to our context.

tions. Finally, we account for autocorrelation in the error term over time (within worker) and on a given day across workers using two-way clustering by worker and date.

Our outcome measures include standardized indices for the intensive and extensive margin as well as their unadjusted components. Although three of the four component measures of productivity take on only positive values (net login time, average calls per hour, and calls per shift), taking logs of these measures is not our preferred specification in this setting. First, the residuals of the regressions of the unadjusted measures are largely normally distributed.[19] It is the distribution of the residuals that is relevant to implementing a linear model, as opposed to the distribution of the dependent variable. Second, we cannot reject linearity of the relationship between pollution and productivity.[20] Thus, it is preferred to analyze the unadjusted outcome in this case as opposed to a non-linear transformation of that outcome which imposes additional functional form assumptions.

4 Results

4.1 Mean impact of the pollutants

First, we examine the impact of pollution on the extensive margin index and rule out meaningful impacts (Table 1, Panel A). The measured coefficients for each of the three pollutants are close to zero, not statistically significant, and relatively precisely estimated. Specifically, focusing on the estimates in which the pollutants are measured in standard deviations, the coefficient on $PM_{2.5}$ is approximately 0.027σ with a standard error of 0.019σ. Meanwhile, the coefficients on CO and O_3 are only -0.006σ (s.e. 0.012) and 0.016σ (s.e. 0.013), respectively. The pattern of these findings also holds for both the sub-components of the extensive margin index: whether someone comes to work at all on a given day, and daily minutes of net login time. The exception being the small, but positive and significant, estimate of O_3 on net login time. Overall, we do not find compelling evidence that pollution affects the extensive margin of productivity in our context.

Next, we examine the impact of the three pollutants on the intensive margin of productivity and find meaningful and statistically significant reductions in productivity across all three pollutants (Table 1, Panel A). We first measure these impacts in terms of standard deviations of observed pollution concentrations in our sample. $PM_{2.5}$ and CO have similar average impacts on intensive

[19] See Figure SA6. Although there are a few outliers, the mass of the distribution is centered. Thus, this is more appropriately addressed by winsorizing rather than taking logs. We confirm our results are robust to winsorizing in Section SA2.

[20] We present evidence for linearity in two ways. We plot a linear predictor along with semi-parametric distributional impacts in Section 4.3. We also plot the predictors against the residuals. That the residuals are centered around a flat line is consistent with the assumption of linearity (see Figure SA7).

margin productivity. A one standard deviation increase in $PM_{2.5}$ or CO reduces the intensive margin productivity index by 0.145σ or 0.139σ, respectively. O_3 has a smaller average impact of -0.087σ, but that estimate is not statistically significantly different from those for $PM_{2.5}$ and O_3. All three coefficients are significant at the 1% level, and the estimates are similar across the two sub-components of the index. When using day and month fixed effects, we find qualitatively similar results on $PM_{2.5}$ and CO, of -0.103σ and -0.077σ respectively, with both significant at the 1% level (Table SA2, Panel A). In that case, however, the results on O_3 are no longer significant.

We also report these results using concentrations to understand the objective impact of the pollutants along an internationally comparable measure (Table 1, Panel B). The impact of an increase of a single $\mu g/m^3$ of $PM_{2.5}$ on the intensive margin of productivity is -0.00212σ, while the effects of a 1 mg/m^3 increase in CO and a 1 $\mu g/m^3$ increase in O_3 are -0.23105σ and -0.00281σ respectively. Although the effects of the three pollutants have similar magnitudes when they are measured in standard deviations, when measured in concentrations, the results for CO are two orders of magnitude larger. This is because ambient concentrations of CO are measured in different units to account for the typically higher observed concentrations of CO.

We implement robustness checks, including winsorizing, alternative pollution measures, and lagged pollution effects in Section SA2 and find that our results are qualitatively unchanged.

4.2 Main results in context

In comparing our results with the literature, we focus on the calls per shift outcome for ease of comparison. Using worker and date fixed effects, a one standard deviation increase in $PM_{2.5}$ decreases calls per shift by 11.8%, CO by 10.6%, and O_3 by 6.0%.[21] Using day and month fixed effects, pollution decreases productivity by 8.6% for $PM_{2.5}$ and 5.7% for CO.

Thus, our main results are substantially larger than prior related work such as Chang et al. (2019). They use day and month fixed effects and finds that a one standard deviation increase in their measure of pollution, an API-based measure of PM_{10}, reduces calls per shift by 1.45%.[22] The difference in observed impacts on PM across the two studies are most likely attributed to our more precise measure.[23] It is also possible that either workers or managers are less able to adapt to pollution in our setting relative to Chang et al. (2019)'s call center setting (Adhvaryu, Kala and

[21]It is not possible to calculate these percentages for the index since the mean is zero. Since the relative magnitude of the results for calls per shift and average calls per hour are similar, this analysis could be done for either.

[22]They find that a 10-point increase in that API, which is 24.1% of a standard deviation in their setting, decreases calls per shift by 0.35%.

[23]See Section SA1.1 for more on the limitations of API-based measures. Also, smaller particulates are generally more harmful, so $PM_{2.5}$ is a more relevant measure than PM_{10}.

Nyshadham, 2022). Of course, we are also able to measure effects of CO and O_3 as well as $PM_{2.5}$.

Given the novelty of our CO results, there is no direct comparator in the literature. It is important to note, however, that we find that CO has a meaningful impact on productivity despite the fact that CO levels in our sample are effectively always below the WHO guidelines. This result is in line with other recent work which finds harmful effects of CO in the US at levels below Environmental Protection Agency (EPA) standards (Schlenker and Walker, 2016; Archsmith, Heyes and Saberian, 2018).

4.2.1 Mechanisms and harm to call centers

In order to understand how pollution may affect call handling, it is helpful to separately consider inbound and outbound processes (Table SA3). We find that the harmful effects of pollution are particularly large for outbound processes relative to inbound. This is unsurprising given that outbound processes may require additional motivation and cognitive effort, and pollution may particularly increase the cost of effort on the margin. Workers in those processes must make active decisions to start calls, which are then subject to sharp criteria for success since there is an expectation that they will result in a sale or completed survey. In the case of inbound processes, the implication of fewer calls per shift is likely to be longer wait times for customers, and more dropped calls.[24]

Losses in employee productivity are likely to be costly for the BPO companies. According to our discussions with managers, the BPO contracts with the companies that hire them are performance-based, and typically have hard targets. Employee compensation, however, is largely salaried and does not have sharp performance incentives. Thus, if employees are handling fewer calls, it is likely to be costly to the BPO company both in terms of compensation as well as in terms of readjustments such as hiring and training additional employees.

4.2.2 Validity of the intensive margin results

A potentially important consideration in examining the intensive margin effects in this setting is whether there may be selection into the intensive margin sample. Specifically, if employees who show up on high pollution days are either more or less productive than the employees who show up on low pollution days, that could have important implications in interpreting the results. This type of selection does not appear to be a significant issue in this setting. In particular, there are no impacts on the extensive margin index here, and just one of six sub-component coefficients is significant. That means that generally the same percentage of employees show up and spend the

[24]These measures are not available in our data and are not observable at the worker-level.

same amount of time working regardless of pollution levels. Thus, under the common assumption of monotonicity of selection, this would be sufficient to determine that we do not observe selection on this margin.[25]

4.3 Distributional impact of pollutants

To better understand the role of pollution in reducing productivity, we examine the distributional impact of the three pollutants on productivity. First, we examine impacts from binned measures of the pollutants denominated in within-sample standard deviations. We initially confirm that even when examining the entire distribution, we do not find any meaningful or consistent effects of pollution on the extensive margin (Figure 1, Panel A). Next, turning to the intensive margin, we find what appear to be increasing effects across the distribution for all three pollutants (Figure 1, Panel B). We are not able to reject that the impacts of the three pollutants are similar across the distribution.

We also examine the distributional effects of the concentration-based measures of pollution on the intensive margin productivity index in order to further comparisons across settings and examine the linearity of response curves (Figure 2). We do not reject that the effects are linear for any of the three pollutants, even though the highest bin for each pollutant was chosen to isolate relatively extreme days and thus is likely to identify non-linearities.[26]

4.4 Overall impacts and policy application

Next, we estimate the combined effects of the three pollutants in our sample, as well as their respective shares of the total harm. The overall average reduction in productivity attributable to pollution exposure is -0.39σ (Figure 3). This is based on our pollutant-specific damage estimates and the observed frequency of pollutant levels in our data (see Section SA3 for details). The total productivity loss due to pollution is largely driven by carbon monoxide at approximately 59% of the total, with the remaining damages allocated equally to $PM_{2.5}$ and O_3 (approximately 21% each). Although the magnitude of the effects on productivity from $PM_{2.5}$ and CO are similar across their respective distributions, days with relatively high levels of CO are more common than days with relatively high levels of $PM_{2.5}$ in our data.[27] This suggests that policies that aim to reduce CO directly could have particularly meaningful impacts.

Thus, we examine the implications of our results for policies and regulations designed to reduce the

[25] Lee (2009), a widely-used selection correction, relies on this assumption. Since there are no meaningful differences in the extensive margin here, the upper and lower Lee bounds would converge to the treatment estimates.

[26] There is less than 8% of the sample in the highest bin for each of the pollutants.

[27] See Section SA1.3 for a discussion of the representativeness of our data.

harm from air pollution. In particular, some major policy initiatives focus solely on $PM_{2.5}$, while our findings also indicate the importance of CO and O_3 in reducing productivity. An example of such an initiative that is highly relevant to our context is India's National Clean Air Programme (NCAP). Launched in 2019, it identified more than 100 cities in India as being in "non-attainment," and forced each to undertake a series of actions to quantify and ameliorate local air quality, and specifically reduce $PM_{2.5}$ levels by 20-30% by 2024 relative to 2017 levels (Ganguly, Selvaraj and Guttikunda, 2020).

In this policy exercise, we consider the potential implications for productivity lost due to pollution of an NCAP-type policy that reduces $PM_{2.5}$ by 20% as well as a similar policy that reduces all three pollutants by 20% (Figure 3).[28] The first case in this exercise estimates productivity losses from air pollution after reducing $PM_{2.5}$ levels by 20% relative to those actually observed. In this first counterfactual case, the negative impact of pollution on productivity is modestly reduced to -0.36σ in this scenario relative to the baseline level -0.39σ. Reducing $PM_{2.5}$, however, is likely to lead to some spillover reductions in CO and O_3. Thus, our next estimate considers the 20% $PM_{2.5}$ reduction again, and accounts for such potential spillovers using the correlation in the three pollutants observed within our data.[29] This approach finds that damages to production of -0.34σ, a 12% reduction relative to the baseline without PM reductions.

Finally, we consider a policy case that imposes 20% reductions in all three pollutants: $PM_{2.5}$, CO, and O_3. In that case, the estimated impact of pollution on productivity falls to -0.30σ, a 24% reduction relative to the baseline. Whether this additional reduction would be cost-effective is beyond the scope of this paper. That calculation would depend on any additional abatement or enforcement costs from adding these two pollutants to the policy compared to the returns to increasing productivity estimated here as well as any additional health benefits that are specific to reductions in CO and O_3.

5 Conclusion

This paper contributes to the emerging and important literature on the impact of pollution on productivity, by being the first to examine the impacts of CO on productivity in a major sector of the economy. We find substantial and significant effects of all three of the pollutants we examine,

[28] All pollutant reductions are simulated as equal percentage reductions for every day in the sample. Given that our estimates suggest linearity, alternative approaches are unlikely to substantially change the main spirit of our results, and reduction approaches that focused on high-pollution days would lead to even larger advantages for programs that targeted CO and O_3 in addition to $PM_{2.5}$, as these pollutants have more relatively high-pollution days for which percentage reductions would lead to larger reductions in absolute levels. See Section SA3 for calculation details.

[29] Of course these correlations across pollutants are not known to be determined by changes in pollution policy, so it is not entirely clear if they would be replicated under NCAP.

which include $PM_{2.5}$ and O_3 as well as CO. Furthermore, our analysis of the combined effects of the pollutants finds that CO is responsible for the majority (59%) of the pollution-driven reductions in productivity in our sample. Since the call center industry is one of the largest private employers in India, these productivity effects are likely to be highly relevant to the overall economy and the well-being of workers.

Our findings suggest that the previous literature focusing on $PM_{2.5}$ may be only identifying a minority of the harms caused by air pollution. Furthermore, existing environmental policies which focus solely on $PM_{2.5}$, may be underweighting or ignoring the damaging effects of other pollutants. This study indicates that strengthening regulations of other pollutants, and particularly CO, should be carefully considered.

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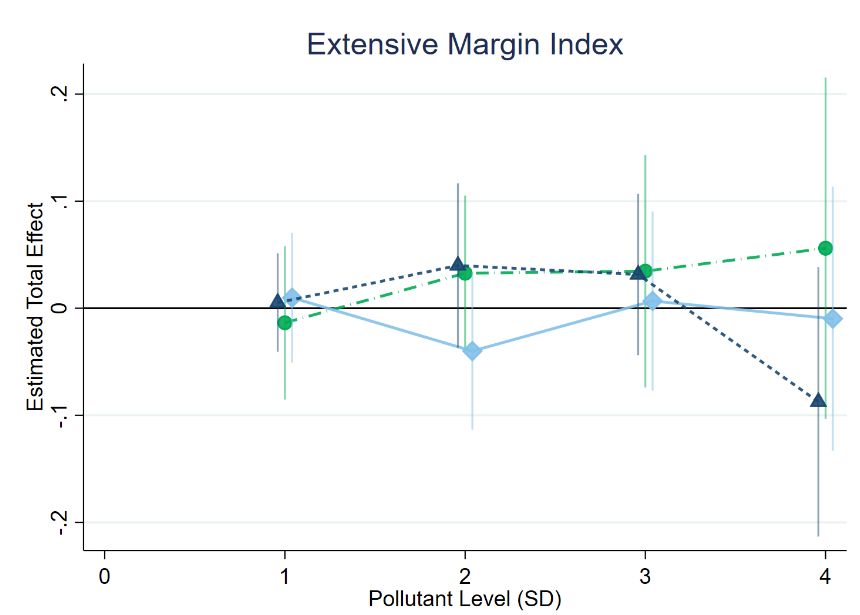
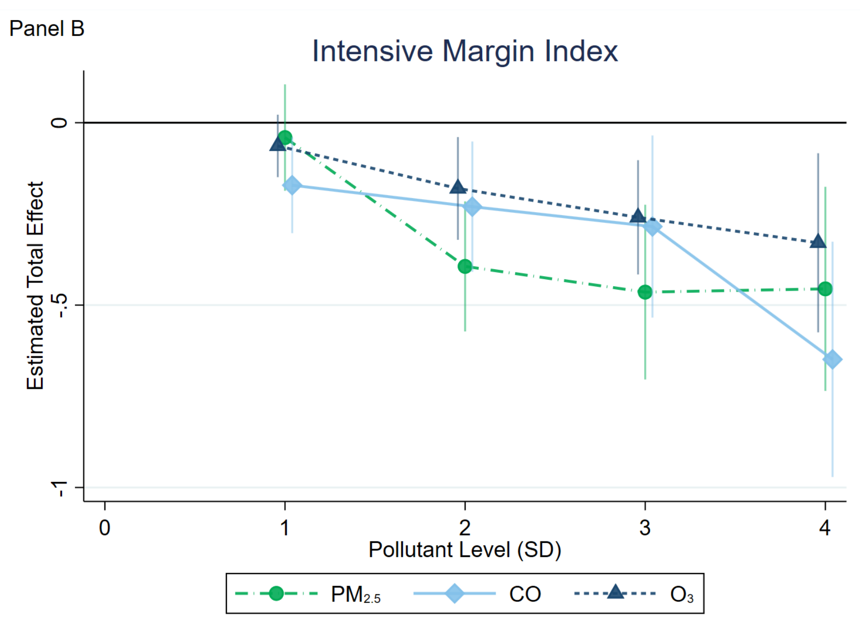
Figure 1: Semi-parametric effects in standard deviations



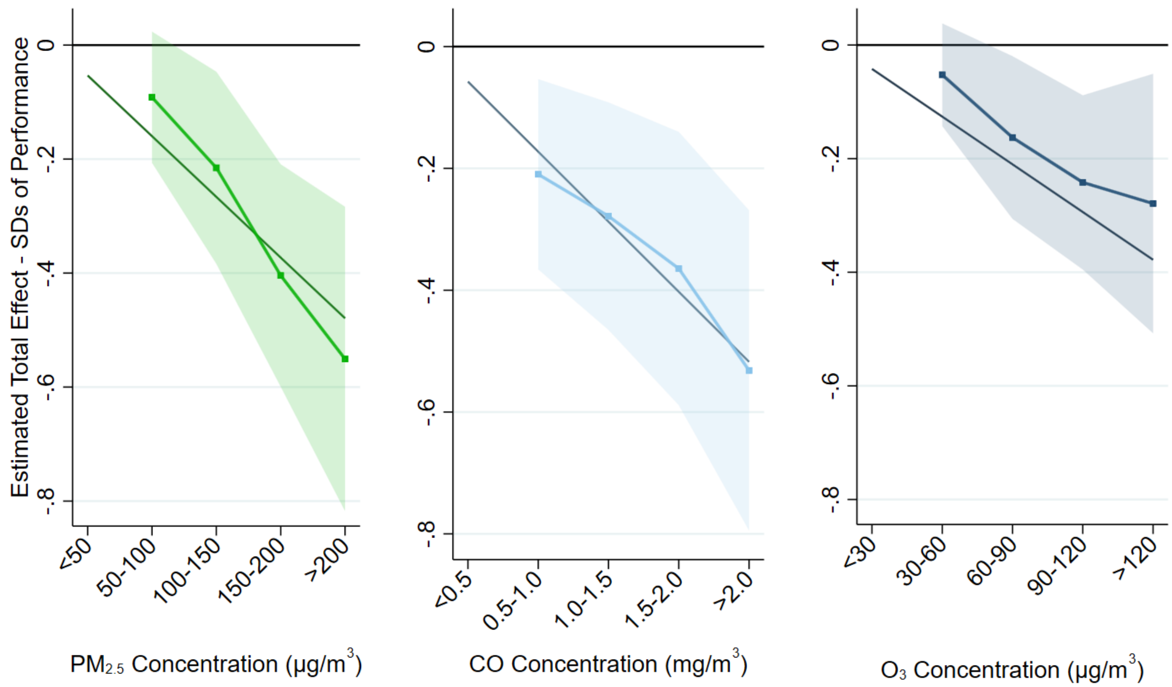
(a) Panel A: Extensive margin



(b) Panel B: Intensive margin

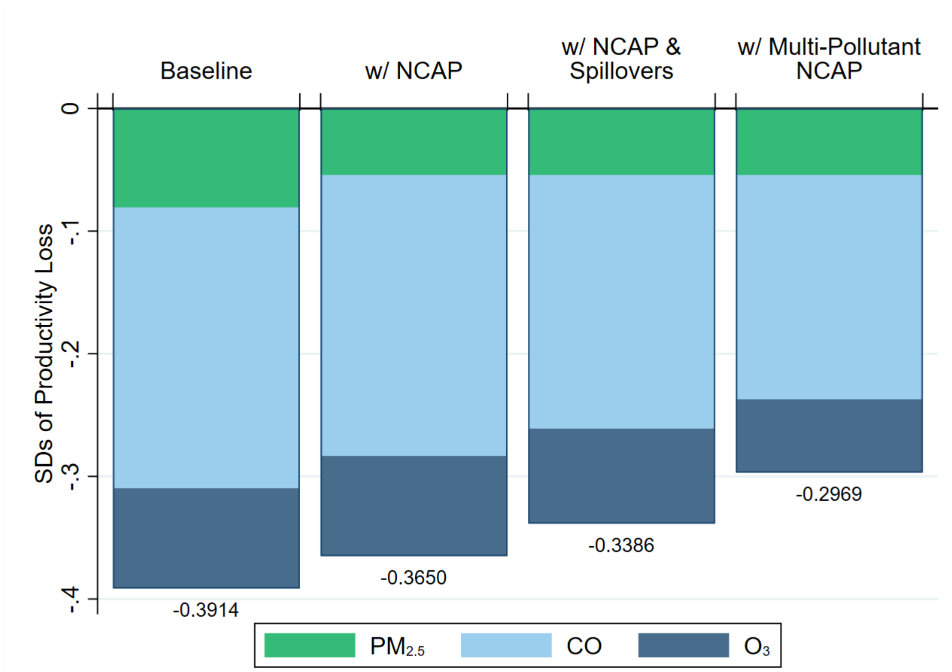
Notes: Estimates in each panel are from a single, separate regression (see Table SA8). The outcome variables are standardized relative to the mean and standard deviation of the extensive margin sample. In contrast, the pollution variables are standardized relative to *zero pollution levels*. For the extensive margin index n=131,386. For the intensive margin index n=93,971. Dots indicate point estimates of the coefficient on the indicator for the daily average pollutant level falling in the indicated bin. All estimates are based on specifications which also include quadratic controls for temperature, precipitation, humidity, and cloud cover, as well as worker and date fixed effects. Whiskers indicate 95% confidence intervals based on robust standard errors two-way clustered by worker and date.

Figure 2: Semi-parametric effects in concentrations on intensive margin index



Notes: Estimates in three plots are from a single regression, n=93,971 (see Table SA9). The outcome measure is the intensive margin productivity index. Dots indicate point estimates of indicator for the pollutant measure falling in the indicated bin. The lowest bin is omitted for each pollutant, so all estimates are relative to the lowest concentration category for the pollutant. The first non-omitted bin for each pollutant includes the median and the remaining bins are designed to particularly examine the upper half of each distribution. Estimates are based on the main model which also includes quadratic controls for temperature, precipitation, humidity, and cloud cover, as well as worker and date fixed effects. Shading indicates 95% confidence intervals based on robust standard errors two-way clustered by worker and date. The additional line on each panel has the slope of the linear estimated effect from the main specification reported in Column 4 Panel B of Table 1 and passes through the point (0,0).

Figure 3: Damages by regulatory approach



Notes: Damage estimates are averages based on pollution coefficients from our main binned specification using the intensive margin productivity index as the outcome variable as reported in Figure 2. The baseline case represents the observed exposure levels in our data. "w/ NCAP" reduces observed exposure levels of $PM_{2.5}$ by 20% for every observation in our sample. "w/ NCAP & Spillovers" represents exposures equivalent to an across-the-board 20% reduction in $PM_{2.5}$, and reductions in CO and O_3 equal to the expected reductions in these pollutants given the 20% reduction in $PM_{2.5}$ based on the correlations of pollutant levels in our sample: 0.4124 for CO and 0.2197 for O_3. The "w/ Multi-Pollutant NCAP" is a scenario in which each observed level of all three pollutants is assumed to have been reduced by 20% relative to the observed level in our data. Damages are not reduced proportionally to the reduction in exposure levels because the binned specification allows for non-linear relationships between exposure levels and damages.

Table 1: Average effects of pollutants on productivity

	Extensive margin			Intensive margin		
	(1)	(2)	(3)	(4)	(5)	(6)
	EM index	At work	Net login time	IM index	Calls per shift	Average calls per hour
Panel A: Pollutants in standard deviations						
$PM_{2.5}$ (SD)	0.027	0.012	6.047	-0.145***	-12.955***	-1.268***
	(0.019)	(0.007)	(5.207)	(0.034)	(2.950)	(0.310)
CO (SD)	-0.006	-0.005	0.185	-0.139***	-11.647***	-1.303***
	(0.012)	(0.005)	(3.405)	(0.035)	(2.945)	(0.333)
O_3 (SD)	0.016	0.001	7.062**	-0.087***	-6.628***	-0.877***
	(0.013)	(0.005)	(3.365)	(0.029)	(2.495)	(0.267)
p-value: $\beta_{PM} = \beta_{CO}$	0.190	0.090	0.390	0.910	0.764	0.942
p-value: $\beta_{O3} = \beta_{CO}$	0.202	0.420	0.134	0.236	0.181	0.306
Panel B: Pollutants in concentrations						
$PM_{2.5}$ ($\mu g/m^3$)	0.00040	0.00017	0.08832	-0.00212***	-0.18921***	-0.01852***
	(0.00027)	(0.00011)	(0.07606)	(0.00050)	(0.04309)	(0.00453)
CO (mg/m^3)	-0.00971	-0.00881	0.30619	-0.23105***	-19.2987***	-2.15831***
	(0.02037)	(0.00830)	(5.64177)	(0.05843)	(4.87982)	(0.55169)
O_3 ($\mu g/m^3$)	0.00052	0.00002	0.22879**	-0.00281***	-0.21473***	-0.02840***
	(0.00041)	(0.00018)	(0.10903)	(0.00094)	(0.08083)	(0.00865)
Mean DV	0.00000	0.74014	348.75893	-0.00000	110.23209	12.84334
SD DV	1.00000	0.43856	237.26865	1.00000	86.32482	9.27893
N	131,386	131,386	131,386	93,971	93,971	93,971

Notes: All regressions include worker and date fixed effects. Standard errors clustered by worker and date are reported in parentheses. Indexed outcomes are standardized such that the in-sample mean is zero and standard deviation is one. Pollutants in the top panel are measured in standard deviations relative to *zero pollution levels.* All estimates include quadratic controls for temperature, precipitation, humidity, and cloud cover.

More than particulate matters:
Pollution and productivity in Indian call centers

Deepshikha Batheja, Sarojini R. Hirshleifer, Jamie T. Mullins

Supplemental Appendix for Online Publication

SA1 Data

SA1.1 Pollution and weather data

Our pollution data comes from monitors that are maintained by the Central Pollution Control Board of India (CPCB). While the CPCB provides access to the raw measures online, for our main specifications we opt to use data maintained by the World Air Quality Index (WAQI) Project (WAQI, 2021). The WAQI Project data is cleaned version of the raw CPCB data. While the WAQI Project data includes fewer observations than the raw data, we believe this data more consistently reflects actual conditions than does the noisy, unprocessed CPCB data. That said, we show that our results are robust to alternative pollutant measures, including the raw CPCB data, in Section SA2 below. In both cases, pollution levels are assigned from the closest monitor to each of the five call-center offices in the productivity data.[30]

We use concentration measures for $PM_{2.5}$, CO and O_3 in order to maximize the accessibility and comparability of our estimates across time and contexts. Ambient concentrations are an objective, consistent, scientific measure of pollution.[31] In contrast, AQI measures (even pollutant-specific AQI measures) are scaled based on subjective assessments of the harm caused by different concentration levels of a given pollutant. AQI measures from different times or data sources may be constructed differently, making comparisons potentially invalid for both levels and changes. AQI measures can also have nonlinear relationships to concentrations given agencies' assumptions and calibration methods. As a result, estimation using AQI measures may not be straightforward to interpret in terms of pollutant levels. Even within agencies, AQI measures can change over time as they are updated based on new research. Finally, since we are continuing to learn more about the impacts of pollution, it is not possible to have a fully accurate AQI at this point.

[30] The five pollution monitors from which data are used for this project are: i) IGSC Planetarium Complex, Patna - BSPCB (Bihar), ii) Ashok Nagar, Udaipur - RSPCB (Rajasthan) iii) Deshpande Nagar, Hubli - KSPCB (Karnataka), iv) Bandra, Mumbai - MPCB (Maharashtra) v) Sector 62, Noida - IMD (Uttar Pradesh).

[31] Because the WAQI Project data is maintained in pollutant-specific AQI measures, we obtain concentrations by converting from individual, pollutant-specific air quality index (AQI) values to concentration measures for each pollutant based on the guidance in U.S. EPA technical documents (EPA, 2018).

Weather data comes from the ERA5 (cloud cover) and ERA5-Land (all other weather variables) data sets, which are maintained by the European Centre for Medium-Range Weather Forecasts (ECMWF) (Hersbach, 2023; Muñoz Sabater, 2019). These are hourly, gridded datasets (0.25°x 0.25°for ERA5 and 0.1°x 0.1°for ERA5-Land), and we assign daily average weather conditions to each call center office based on the closest grid-point to each.

SA1.2 Call center data

We worked with two business process outsourcing companies (BPO) companies, called Call-2-Connect and Five Splash. The individual processes included in this study were originally selected for a field experiment on gender peer effects in the workplace (Batheja, 2019). That said, this dataset includes almost three times as many workers as the experimental dataset. This is because we have pre- and post-experiment data from some processes for several months and there is turnover within processes. Our full sample for this study includes 2,687 workers across Hubli (15.00%), Mumbai (11.20%), Noida (21.03%), Patna (17.34%) and Udaipur (35.43%).

This is an unbalanced panel, however, for a few reasons. Once a process ends, there is no longer data available from those workers. In addition, the experiment had a staggered launch, and began in one call center firm later than the other.[32] Finally, we only have data for processes with at least 60 workers, since that was an inclusion criteria for the experiment.[33] Nonetheless, there is substantial evidence that the distribution of pollution across dates observed in this data is broadly representative of all dates during this time period (see Section SA1.3.)

We included all the data available from all experiment processes from the beginning of the time we worked with these two companies up until March 1, 2020. We never analyzed data collected after this date, since we prefer to avoid analyzing data collected during the pandemic. We expect that this data would have substantial issues as the call centers abruptly shifted to work from home. Furthermore, the relationship between pollution and productivity may change, and overall pollution is expected to be much lower during this period.

SA1.3 Representativeness of the data

To better understand the representativeness of our data, we compare our own pollution measures for the city-day observations for which we have productivity data to those measures for all day-level

[32] Call-2-Connect employees (from Mumbai, Noida and Patna) were phased into the experiment between between December 2018 to April 2019, while employees from FiveS Digital (from Udaipur and Hubli) were phased in between May 2019 and September 2019. The only exception is a process in Patna from Call-2-Connect, which was included in the experiment between May and August in 2019.

[33] This was necessary since the experiment randomized gender composition of teams within processes, and thus, the design required constructing at least three teams (two mixed and one same gender team).

observations across the entire period of our study (2018 through February 2020) for the cities in our study (Figure SA2). This exercise indicates that the pollution levels captured by the days in our sample are remarkably similar to the full distribution of days in those cities (Figure SA3). Although these distributions do indicate that there is a small handful of very high CO and O_3 that are not captured in our sample, having productivity data for these few outlier days would be unlikely to substantively change our results. Furthermore, we find in this study that $PM_{2.5}$ contributes a relatively modest share of the pollution damages in our sample due to the large number of low to moderate $PM_{2.5}$ days. These distributions suggest that, if anything, we may be undercounting such days. Thus, the comparison of these distributions further confirms our results regarding the importance of CO to the share of damages.

Furthermore, the available evidence suggests that our sample is largely representative of pollution levels in India, and thus captures its likely overall impact on the BPO sector in India. As discussed in the main text, the average level of $PM_{2.5}$ across all of the city-worker-day observations in our sample is 66.52 $\mu g/m^3$. This is similar to the yearly average for all cities in India, which had a mean of 61.41 $\mu g/m^3$ in 2018 and 55.57 $\mu g/m^3$ in 2019. The distance between these means is small compared to their distance from the global average, which was 27 $\mu g/m^3$ in 2018 (WHO, 2022).[34] Unfortunately, the WHO data does not include the same global averages for the other pollutants of interest in this study or for additional moments of the data.

SA2 Robustness Analysis

SA2.1 Additional analysis for main pollutant outcomes

Table SA4 presents two robustness checks that confirm the independence of the individual effects of the three pollutants as reported in the main results in Table 1. Panel A presents a specification that only includes $PM_{2.5}$ and does not include the other pollutants. This is to provide a comparison with other papers that only examine the impact of $PM_{2.5}$ on productivity. We find that this specification does not change the estimated effect of $PM_{2.5}$ relative to our main results (reproduced in Panel B for convenient comparison). This suggests that $PM_{2.5}$ is not a good proxy for air pollution more generally in our setting.

In Panel C, we include the pairwise interaction effects of the pollutants in the main results from Table 1. We do not find meaningful evidence of interactions among the three pollutants, as none of the interactions are significant or have coefficients of meaningful size. Furthermore, adding these

[34]Data for 2020 is not available, and it is a small portion of our sample. It is not surprising that our average is slightly higher than the average for India, since Noida (near Delhi) is 20% of our sample and has higher pollution levels than many Indian cities.

interactions does not have a substantive effect on the magnitude of the pollutant coefficients relative to the original estimates. While the coefficients on O_3 do lose some significance, the coefficients on $PM_{2.5}$ and CO maintain their statistical significance (as well as their magnitudes).

Table SA5 reports the main specification including three days of lagged pollutant levels. We do not find any consistent pattern of lagged effects for any of the three pollutants.

SA2.2 Alternative pollution measures

Table SA6 presents three robustness checks on our pollution measures. In Panel A, we present our results using the data downloaded directly from the CPCB. These data are much noisier than our main data, since the WAQI data are cleaned and processed, with many observations being dropped. Thus, the WAQI data presents a more coherent picture of pollutant levels than do the raw data directly from CPCB (CPCB, n.d.). Nevertheless, our main results are comparable, though somewhat attenuated, when estimates are based on pollutant measures obtained directly from CPCB. We also consider specifications with geographically interpolated $PM_{2.5}$ data from Berkeley Earth (Berkeley Earth, N.D.), while keeping our main measures of CO and O_3 from WAQI (Panel B). Notably, these results are remarkably similar to our original estimates.

Finally, we confirm that our results are not being driven by any outliers. The maximum values for each pollutant are substantially higher than the 99^{th} percentile values (Table SA1). Thus, in Panel C, we report the main results from Table 1, but with all three pollutants winsorized at the 99^{th} percentile. We find that the coefficients on the winsorized regressions are remarkably similar to our main specifications, suggesting our results are not primarily driven by outliers. This is not surprising, given that we find effects across the distribution in our non-parametric results.

SA2.3 City-level results

Table SA7 presents the results disaggregated by city using indicators for each city interacted with our pollutant measures.

This analysis is simply to confirm that the patterns of impacts are broadly similar across locations even though we expect significant noise given the limitations inherent in slicing our data to this degree. In that sense, this analysis is reassuring in that we do not find that a single city is entirely driving our overall results. In addition, the coefficients are generally the expected sign.

SA2.4 Joint impact of the pollutants

Finally, we consider the total impact of pollution and the contribution of each pollutant to productivity loss (Figure SA8). To calculate the combined impact of the pollutants observed in our data, we add together the binned non-parametric estimates of the impacts of the pollutants for each of the observed combinations of the three pollutants in our data at the city-date level.[35] Since a high pollution day for one pollutant is not necessarily a high pollution for another (see Section 3.2), we report these results framed separately by the distribution of each pollutant.

Examining these three distributions demonstrates the significant damage to productivity induced by the combined effect of these three pollutants. It is not surprising that on days that are in the upper tail of the distribution for a given pollutant that pollutant contributes a relatively large share of the lost productivity.[36] Overall the distributions of productivity loss for the three pollutants are broadly similar. In the bins including the median day for each of the pollutants, the total damages range from -0.26σ to -0.34σ, while for a day in the bin that includes the 80$^{\text{th}}$ percentile day for each of the pollutants, the total damages range from -0.43σ to -0.48σ. These impacts are substantive from a policy perspective.

SA3 Calculating Overall Average Productivity Reductions

In Section 4.4, we calculate the average reduction in productivity attributable to pollution in our sample, and then again under three distinct counterfactual air pollution policy cases. The method for this exercise is as follows: i) create indicators for the bin in which the level of each pollutant falls for each day and worker in the data, ii) sum the coefficients for the relevant bins from the bin-based regression (reported in Table SA9) across the three pollutants for each worker-day, and iii) calculate the average of the summed damage coefficients across the worker-day observations in our sample. Because the bin-based estimates measure effects relative to the omitted category (which is the lowest category for each of the three pollutants), the total damages from air pollution on a given day should be interpreted as the productivity losses relative to a day with low (but not necessarily zero) concentrations of all three air pollutants.

First, we illustrate the process of calculating damages as described above. Consider a (hypothetical) day in which a worker has ($PM_{2.5}$, CO, O_3) levels of (44 $\mu g/m^3$, 1.05 mg/m^3, 130 $\mu g/m^3$). These pollution levels correspond to the lowest $PM_{2.5}$ bin (<50$\mu g/m^3$), the middle of the five CO

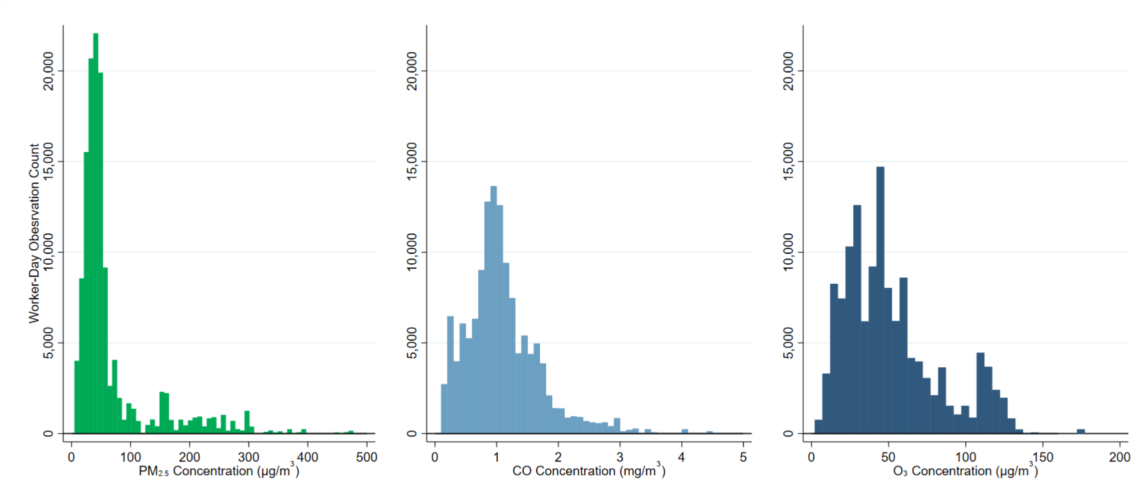
[35] The impacts of pollutants are estimated in Figure 2. We do not find interaction effects across the pollutants as indicated in Section SA2.

[36] Because our specification omits the lowest bin for each pollutant, there is no estimated damage from each pollutant at the low end of its own distribution.

bins (1.0-1.5mg/m^3), and the highest O_3 bin (>120$\mu g/m^3$). Thus, $PM_{2.5}$, CO and O_3 have coefficients of 0 (because the lowest bin is the omitted category), -0.278, and -0.279 respectively (from Table SA9). Summing these coefficient yields a total estimated productivity reduction attributable to air pollution for this (hypothetical) worker-day of: 0 + -0.278 + -0.279 = -0.557σ. Harm from each pollutant is estimated separately and the results are simply summed across pollutants for each worker-day, since we do not find significant effects of the interactions of pollutant levels (see panel C of Table SA4). The average of all such total air pollution effects is then taken across the worker-days in our sample leading to the single value reported in the text for each scenario.

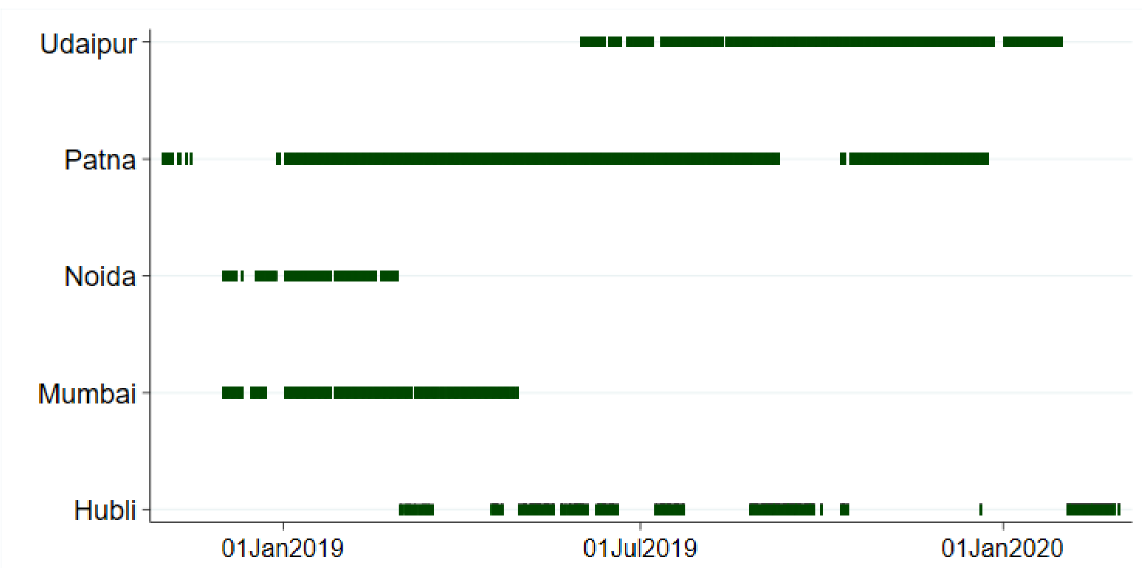
Next, we turn to the first of the three policy cases, in which the 20% $PM_{2.5}$ reduction targeted by NCAP is modelled. In this first case, we consider pollution conditions equivalent to those observed, but include a 20% reduction in $PM_{2.5}$ levels for every worker-day observation. The second case is the same as the first with regards to the policy, but accounts for spillovers from the 20% reduction of $PM_{2.5}$ to the other pollutants based on the correlation of the levels of those pollutants with $PM_{2.5}$ in the observed data, namely 0.4124 for CO and 0.2197 for O_3. Thus, in the second case, $PM_{2.5}$ levels are taken to be 20% lower than observed, CO levels are taken to be 20%*0.4124=8.3% lower than actually observed, and O_3 levels are taken to be 20%*0.2197=4.4% lower than actually observed. The final case considers air pollution conditions with levels of all three pollutants which are 20% lower than actually observed.

Figure SA1: Pollutant histograms



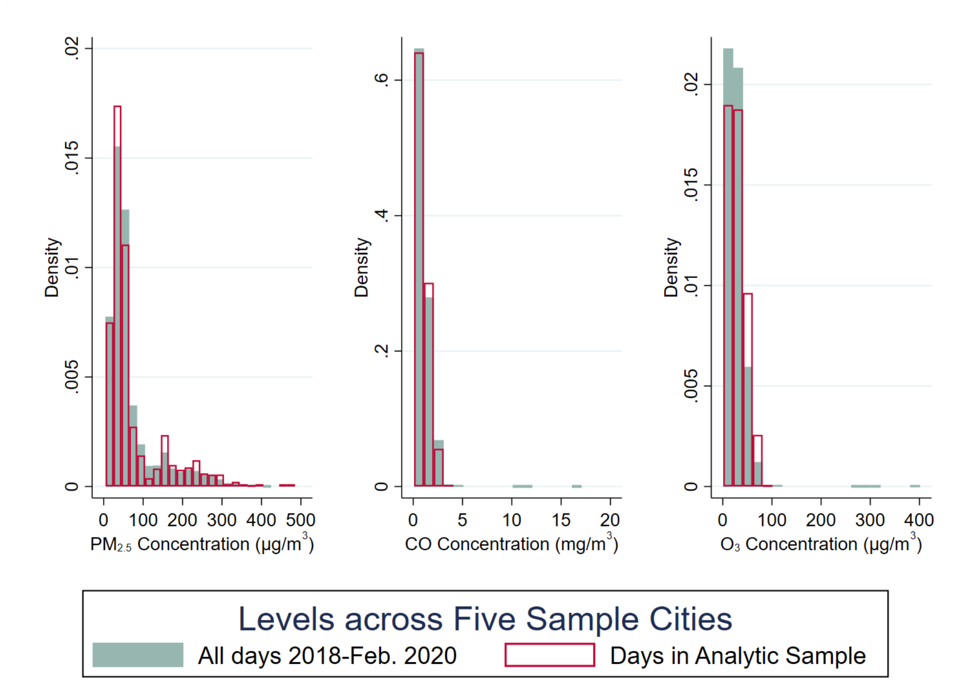
Notes: Histograms represent counts of the number of worker-days that are observed in the extensive sample at a given pollution level in the data. Histogram bin widths are 8, 0.1, and 5 $\mu g/m^3$ for PM$_{2.5}$, CO, and O_3 graphs, respectively.

Figure SA2: Sample dates by city

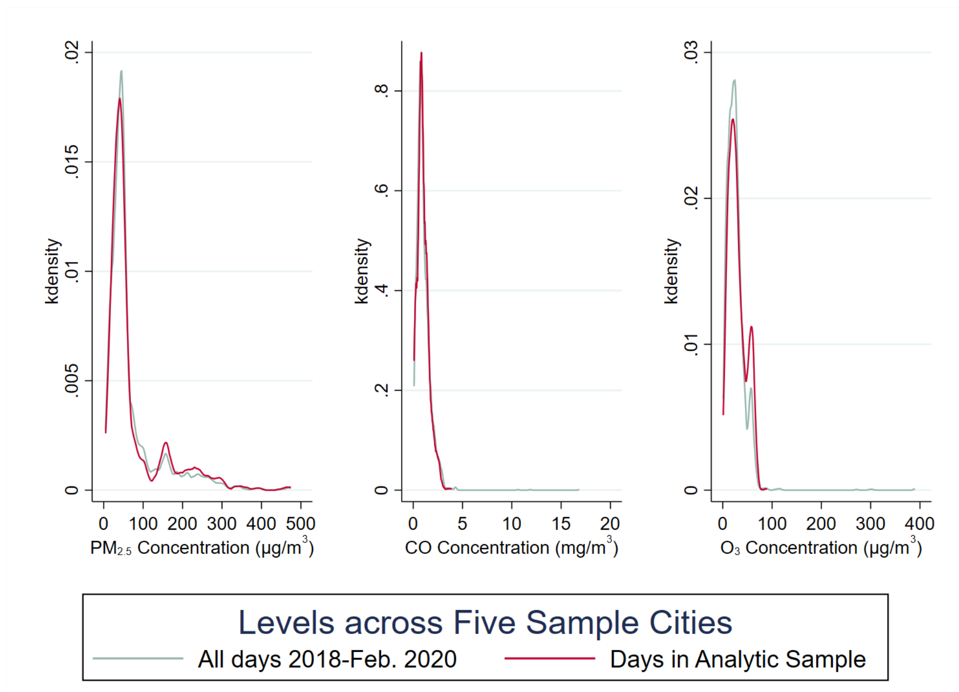


Notes: Bars indicate dates of observations used in the main sample. Intermittent gaps are generally due to missing pollutant values. For more on the span of the productivity data, see Section SA1.2. For more on the representativeness of the pollution data to the entire time span, see Section SA1.3.

Figure SA3: Pollutant distributions for analytic and full samples



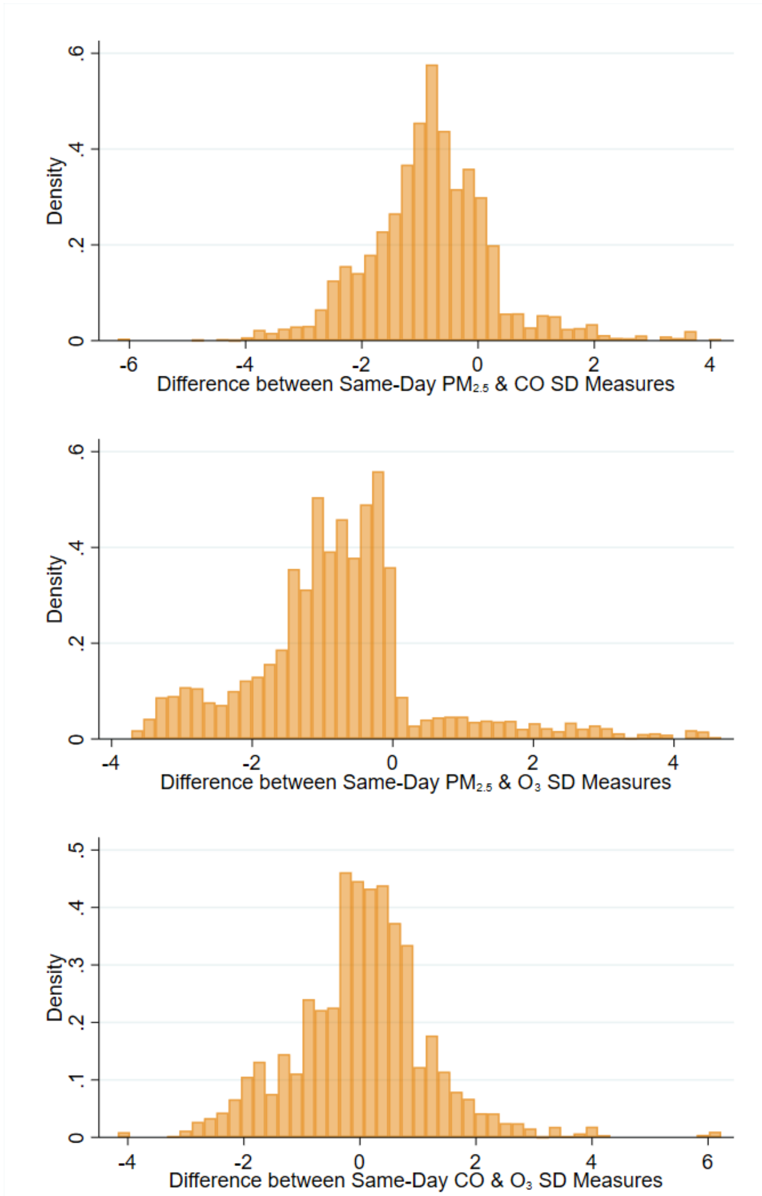
(a) Histograms



(b) K-densities

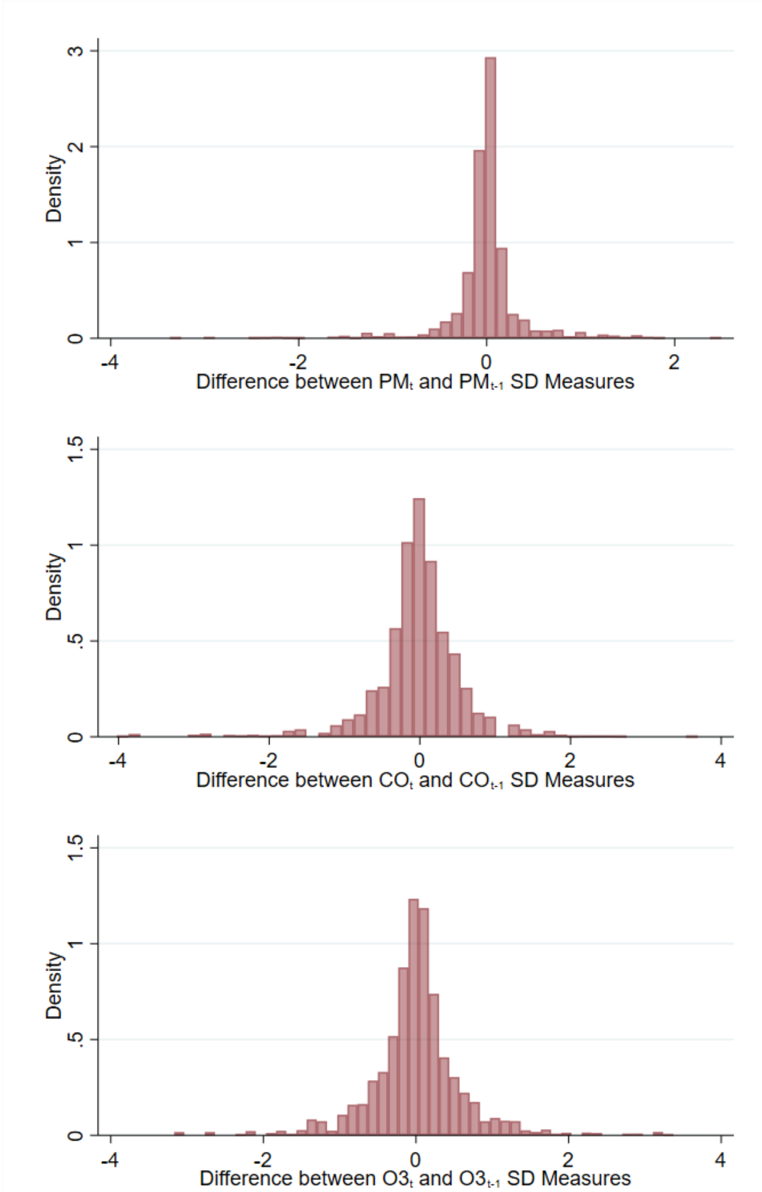
Notes: Depicts densities of pollution levels for city-days in our analytic sample and days in the five cities we study over the full period of our sample from late 2018 to February 2020. Panel A depicts histograms of bin widths are 20 $\mu g/m^3$, 1 mg/m^3, and 20 $\mu g/m^3$ for $PM_{2.5}$, CO, and O_3 graphs, respectively. Panel B represents k-densities.

Figure SA4: Differences in same-day pollutant levels



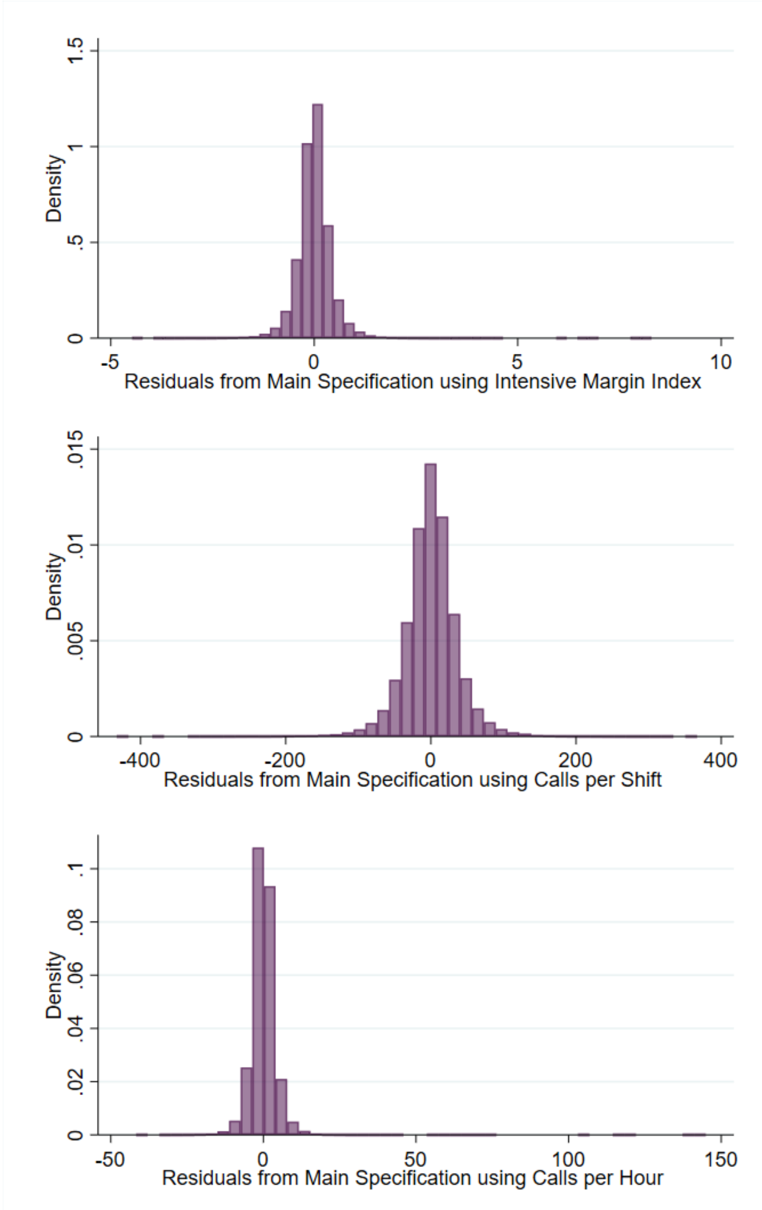
Notes: Each graph represents the differences between the measures of the two indicated pollutants experienced by a worker on a date in the full sample. Pollutants are measured in standard deviations and winsorized at the 99^{th} percentile before differencing.

Figure SA5: Differences across contemporaneous and one-day lag pollution levels



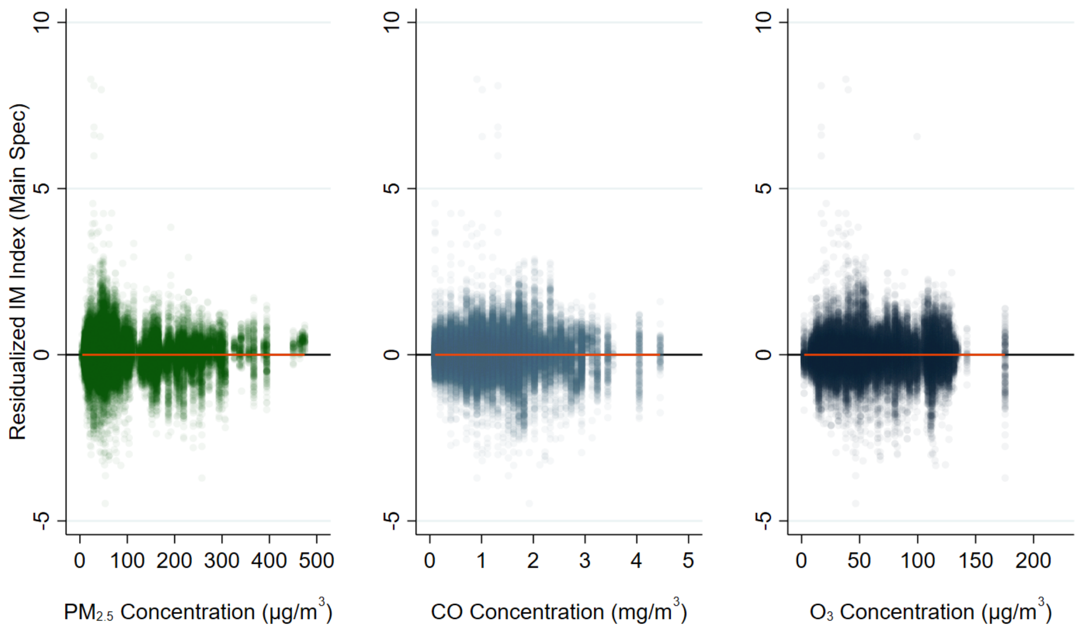
Notes: Each graph represents the differences between the measures of the contemporaneous and one-day-lag levels of the indicated pollutant experienced by a worker on a day in our extensive margin sample. Pollutants are measured in standard deviations and winsorized at the 99^{th} percentile before differencing.

Figure SA6: Residuals from the main specification by intensive margin outcome



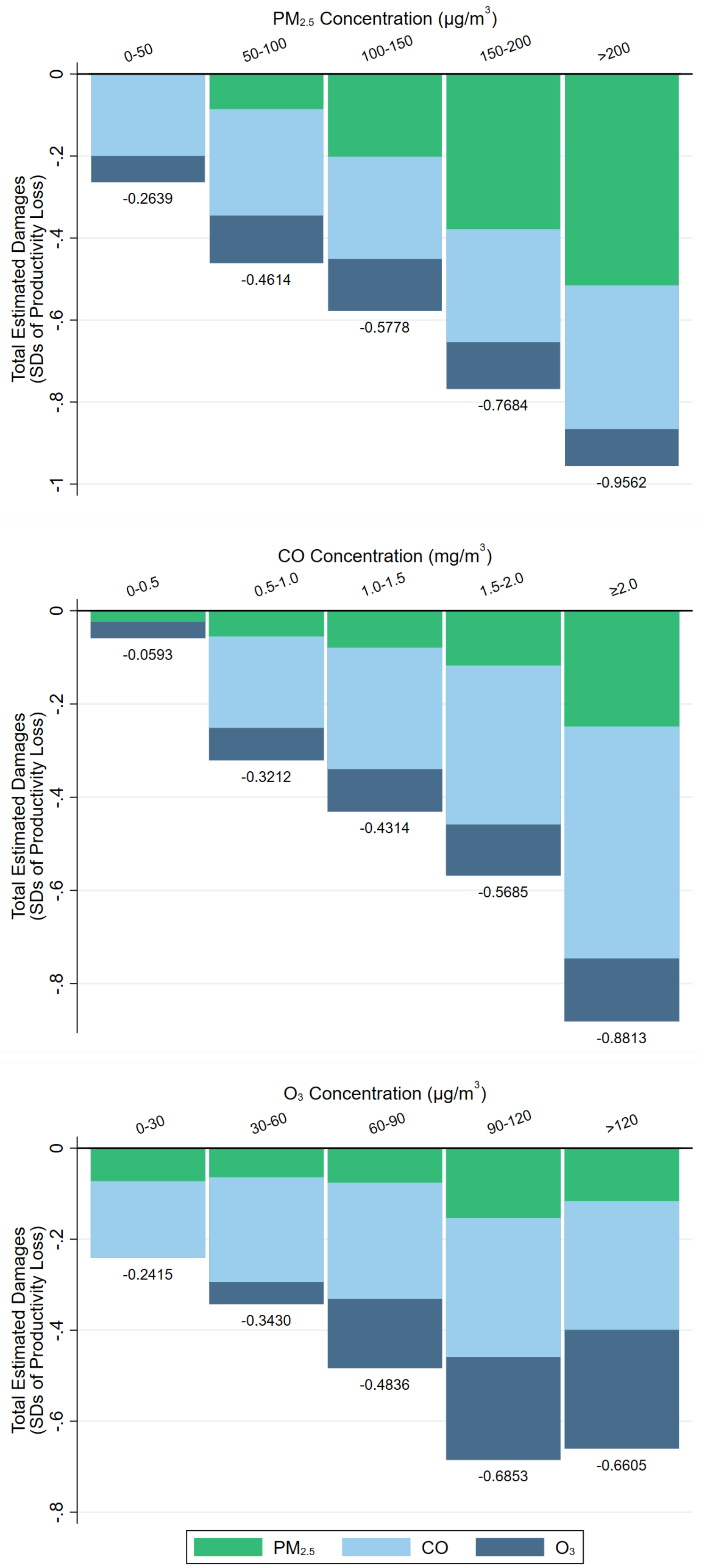
Notes: Each graph represents the distribution of the residuals that result from estimates in Columns 4-6 of Panel B of Table 1 for the indicated outcome variable.

Figure SA7: Residuals graphed against pollutant predictors



Notes: Each panel represents the distribution of the residuals that result from estimates in Columns 4 of Panel B of Table 1 plotted against the level of each pollutant for the same observation. Each point is plotted with 5% opacity. Orange lines denote the best linear fit of the data in each panel.

Figure SA8: Combined productivity losses from $PM_{2.5}$, CO, and O_3



Notes: Productivity losses are estimated using the intensive margin productivity index and the binned specification from Figure 2. Estimates include quadratic controls for temperature, precipitation, humidity, and cloud cover, as well as worker and date fixed effects. The total productivity losses are estimated as the average of the dot product between the vector of pollutant coefficient estimates and the corresponding vector of variable values for each worker-day observed in our data.

Table SA1: Summary statistics

	Mean	SD	Min	p10	Median	p90	p99	Max
Pollutants								
$PM_{2.5}$ ($\mu g/m^3$)	66.52	68.47	5.04	21.61	42.81	163.62	307.01	474.66
CO (mg/m^3)	1.05	0.60	0.10	0.30	0.91	1.72	2.93	4.45
O_3 ($\mu g/m^3$)	51.55	30.87	2.12	19.05	44.45	108.40	127.60	175.40
Weather controls								
Avg. Daily Temp. ($°C$)	23.98	5.59	11.85	15.10	25.03	30.21	35.77	38.98
Total Daily Precip. (m)	0.03	0.08	0	0	0	0.11	0.33	0.95
Dew Point ($°C$)	16.92	6.04	0.52	8.42	17.21	24.07	27.01	28.14
Cloud Cover (%)	0.43	0.36	0	0	0.33	0.98	1	1

City-Days: 914 Workers: 2,687 Worker-Days: 131,386

Notes: Extensive margin sample includes worker-level absentee days as long as they are both preceded and followed by work days and are not part of a stretch of absentee days that is 6 days or longer. Days in which a whole process is inactive are not considered. Only observations for which local measures of temperature, $PM_{2.5}$, CO, and O_3 are available are included in the analysis.

Table SA2: Main estimates using day and month fixed effects

	Extensive margin			Intensive margin		
	(1)	(2)	(3)	(4)	(5)	(6)
	EM index	At work	Net login time	IM index	Calls per shift	Average calls per hour
Panel A: Pollutants in standard deviations						
$PM_{2.5}$ (SD)	-0.001	0.000	-0.457	-0.103***	-9.454***	-0.867***
	(0.011)	(0.005)	(3.023)	(0.027)	(2.570)	(0.223)
CO (SD)	0.000	-0.000	0.189	-0.077***	-6.307***	-0.732***
	(0.009)	(0.004)	(2.229)	(0.022)	(1.962)	(0.190)
O_3 (SD)	0.004	-0.001	2.564	-0.019	-1.032	-0.241
	(0.009)	(0.004)	(2.405)	(0.018)	(1.569)	(0.165)
p-value: $\beta_{PM} = \beta_{CO}$	0.951	0.962	0.878	0.531	0.425	0.690
p-value: $\beta_{O_3} = \beta_{CO}$	0.765	0.812	0.456	0.008	0.006	0.013
Panel B: Pollutants in concentrations						
$PM_{2.5}$ ($\mu g/m^3$)	-0.00001	0.00000	-0.00667	-0.00150***	-0.13808***	-0.01267***
	(0.00017)	(0.00007)	(0.04416)	(0.00040)	(0.03753)	(0.00326)
CO (mg/m^3)	0.00041	-0.00023	0.31255	-0.12754***	-10.4498***	-1.21320***
	(0.01458)	(0.00629)	(3.69368)	(0.03589)	(3.25091)	(0.31499)
O_3 ($\mu g/m^3$)	0.00013	-0.00005	0.08308	-0.00062	-0.03345	-0.00780
	(0.00030)	(0.00013)	(0.07791)	(0.00058)	(0.05082)	(0.00534)
Mean DV	0.00000	0.74014	348.75893	-0.00000	110.23209	12.84334
SD DV	1.00000	0.43856	237.26865	1.00000	86.32482	9.27893
N	131,386	131,386	131,386	93,971	93,971	93,971

Notes: All regressions include worker, year-month of sample, and day-of-week fixed effects, replicating the fixed effects used by Chang et al. (2019). Standard errors clustered by worker and date are reported in parentheses. Indexed outcomes are standardized such that the in-sample mean is zero and standard deviation is one. Pollutants in the top panel are measured in standard deviations relative to *zero pollution levels.* All estimates include quadratic controls for temperature, precipitation, humidity, and cloud cover.

Table SA3: Main estimates by process type

	Extensive margin			Intensive margin		
	(1)	(2)	(3)	(4)	(5)	(6)
	EM index	At work	Net login time	IM index	Calls per shift	Average calls per hour
Outbound						
$PM_{2.5}$ ($\mu g/m3$)	0.00014	-0.00004	0.08879	-0.00472***	-0.41075***	-0.04228***
	(0.00039)	(0.00017)	(0.09550)	(0.00104)	(0.09195)	(0.00932)
CO (mg/m3)	-0.01250	-0.01146	0.45978	-0.58350***	-48.3345***	-5.49395***
	(0.03723)	(0.01662)	(8.63242)	(0.09490)	(8.09214)	(0.87760)
O_3 ($\mu g/m3$)	0.00037	0.00012	0.10457	-0.00385**	-0.31429**	-0.03672**
	(0.00055)	(0.00022)	(0.14461)	(0.00158)	(0.13537)	(0.01458)
Inbound						
$PM_{2.5}$ ($\mu g/m3$)	0.00048	0.00022**	0.10035	-0.00186***	-0.16424***	-0.01633***
	(0.00029)	(0.00011)	(0.08302)	(0.00042)	(0.03554)	(0.00396)
CO (mg/m3)	-0.01131	-0.01197	1.28514	-0.05789	-5.04336	-0.51849
	(0.02588)	(0.01038)	(7.40099)	(0.04701)	(4.03039)	(0.43658)
O_3 ($\mu g/m3$)	0.00073	-0.00002	0.34402**	-0.00091	-0.04344	-0.01191*
	(0.00054)	(0.00023)	(0.14803)	(0.00070)	(0.05828)	(0.00671)
	(0.00045)	(0.00019)	(0.11897)	(0.00056)	(0.04822)	(0.00525)
p-values for test of $\beta_{OB} = \beta_{IB}$						
$PM_{2.5}$	0.421	0.139	0.914	0.002	0.003	0.002
CO	0.980	0.980	0.942	0.000	0.000	0.000
O_3	0.624	0.631	0.231	0.072	0.052	0.104
N	131,386	131,386	131,386	93,971	93,971	93,971

Notes: All regressions include worker and date fixed effects. Standard errors clustered by worker and date are reported in parentheses. Estimates in each column are from a single regression. Inbound and outbound estimates are obtained by interacting process-type indicators with pollutant variables. Indexed outcomes are standardized such that the in-sample mean is zero and standard deviation is one. All estimates include quadratic controls for temperature, precipitation, humidity, and cloud cover.

Table SA4: Individual and interacted pollutant measures

	Extensive margin			Intensive margin		
	(1)	(2)	(3)	(4)	(5)	(6)
	EM index	At work	Net login time	IM index	Calls per shift	Average calls per hour
Panel A: Model with only $PM_{2.5}$						
$PM_{2.5}$ ($\mu g/m^3$)	0.00033	0.00017*	0.05197	-0.00238***	-0.20326***	-0.01907***
	(0.00027)	(0.00009)	(0.06437)	(0.00049)	(0.03635)	(0.00390)
N	131,386	131,386	131,386	93,971	93,971	93,971
Panel B: Main Estimates Repeated for Ease of Comparison						
$PM_{2.5}$ ($\mu g/m^3$)	0.00040	0.00017	0.08832	-0.00212***	-0.18921***	-0.01852***
	(0.00027)	(0.00011)	(0.07606)	(0.00050)	(0.04309)	(0.00453)
CO (mg/m^3)	-0.00971	-0.00881	0.30619	-0.23105***	-19.2987***	-2.15831***
	(0.02037)	(0.00830)	(5.64177)	(0.05843)	(4.87982)	(0.55169)
O_3 ($\mu g/m^3$)	0.00052	0.00002	0.22879**	-0.00281***	-0.21473***	-0.02840***
	(0.00041)	(0.00018)	(0.10903)	(0.00094)	(0.08083)	(0.00865)
N	131,386	131,386	131,386	93,971	93,971	93,971
Panel C: Pollutants interacted						
$PM_{2.5}$ ($\mu g/m^3$)	0.00028	0.00009	0.07733	-0.00300***	-0.26501***	-0.02647***
	(0.00049)	(0.00020)	(0.13427)	(0.00093)	(0.08164)	(0.00839)
CO (mg/m^3)	-0.02649	-0.00747	-8.11738	-0.28213**	-24.7382***	-2.50937**
	(0.04584)	(0.01846)	(12.42749)	(0.11098)	(9.35131)	(1.03940)
O_3 ($\mu g/m^3$)	0.00113	0.00036	0.32529	-0.00325	-0.23762	-0.03390*
	(0.00085)	(0.00040)	(0.20416)	(0.00201)	(0.16771)	(0.01902)
$PM_{2.5}$ ($\mu g/m^3$)$\times$ CO (mg/m^3)	0.00021	0.00008	0.05382	0.00038	0.03925	0.00267
	(0.00017)	(0.00006)	(0.05082)	(0.00041)	(0.03497)	(0.00383)
$PM_{2.5}$ ($\mu g/m^3$)$\times$ O_3 ($\mu g/m^3$)	-0.00000	-0.00000	-0.00108	0.00000	0.00021	0.00006
	(0.00000)	(0.00000)	(0.00118)	(0.00001)	(0.00091)	(0.00010)
CO (mg/m^3)$\times$ O_3 ($\mu g/m^3$)	-0.00022	-0.00020	0.01060	-0.00002	-0.00054	-0.00027
	(0.00048)	(0.00020)	(0.12901)	(0.00127)	(0.10657)	(0.01191)
N	131,386	131,386	131,386	93,971	93,971	93,971

Notes: All regressions include worker and date fixed effects. Standard errors clustered by worker and date are reported in parentheses. Indexed outcomes are standardized such that the in-sample mean is zero and the standard deviation is one. All estimates include quadratic controls for temperature, precipitation, humidity, and cloud cover.

Table SA5: Main estimates with lagged pollution

	Extensive margin			Intensive margin		
	(1)	(2)	(3)	(4)	(5)	(6)
	EM index	At work	Net login time	IM index	Calls per shift	Average calls per hour
$PM_{2.5}$ ($\mu g/m^3$)						
Day -3	-0.00003	-0.00003	-0.00133	0.00028	0.02480	0.00244
	(0.00031)	(0.00011)	(0.09135)	(0.00048)	(0.03997)	(0.00449)
Day -2	-0.00015	-0.00002	-0.06061	-0.00043	-0.03638	-0.00393
	(0.00036)	(0.00013)	(0.10614)	(0.00084)	(0.07000)	(0.00786)
Day -1	-0.00042	-0.00018	-0.09827	-0.00008	-0.01410	0.00005
	(0.00040)	(0.00017)	(0.11175)	(0.00098)	(0.08543)	(0.00884)
Day 0	0.00085**	0.00030*	0.23174*	-0.00142*	-0.12140*	-0.01298*
	(0.00042)	(0.00017)	(0.11875)	(0.00074)	(0.06474)	(0.00672)
CO (mg/m^3)						
Day -3	0.04187	0.00573	16.11485*	-0.14104**	-11.06428*	-1.39438**
	(0.02989)	(0.01182)	(8.83212)	(0.07063)	(5.93383)	(0.66555)
Day -2	0.02088	0.01403	1.99016	-0.13246	-11.04295	-1.23951
	(0.03177)	(0.01398)	(8.59120)	(0.09135)	(7.68283)	(0.85680)
Day -1	-0.05437	-0.01632	-16.12666	-0.10401	-9.20100	-0.91632
	(0.03948)	(0.01554)	(11.37674)	(0.09654)	(8.51428)	(0.87299)
Day 0	-0.02653	-0.01294	-5.17585	-0.12230**	-10.69905**	-1.09039*
	(0.02623)	(0.00896)	(8.37892)	(0.05764)	(4.73264)	(0.55949)
O_3 ($\mu g/m^3$)						
Day -3	-0.00043	-0.00020	-0.08634	-0.00074	-0.06662	-0.00643
	(0.00048)	(0.00019)	(0.13925)	(0.00110)	(0.09104)	(0.01049)
Day -2	0.00031	0.00000	0.13885	-0.00027	0.00032	-0.00491
	(0.00049)	(0.00021)	(0.13687)	(0.00129)	(0.10836)	(0.01203)
Day -1	-0.00002	0.00005	-0.03868	-0.00158	-0.14546	-0.01326
	(0.00066)	(0.00029)	(0.16268)	(0.00138)	(0.11785)	(0.01283)
Day 0	0.00091	0.00024	0.28454**	-0.00105	-0.06395	-0.01234
	(0.00058)	(0.00026)	(0.14310)	(0.00114)	(0.09722)	(0.01064)
N	109,905	109,905	109,905	77,997	77,997	77,997

Notes: All regressions include worker and date fixed effects. Standard errors clustered by worker and date are reported in parentheses. Index outcomes are standardized such that the in-sample mean is zero and the standard deviation is one. All estimates include quadratic controls for temperature, precipitation, humidity, and cloud cover for days -3, -2, -1 and 0. Fewer observations are available for these analyses due to missing pollution data in lagged days.

Table SA6: Main estimates using alternative pollutant measures

	Extensive margin			**Intensive margin**		
	(1)	(2)	(3)	(4)	(5)	(6)
	EM index	At work	Net login time	IM index	Calls per shift	Average calls per hour
Panel A: Pollutant measures from CPCB						
$PM_{2.5}$ ($\mu g/m^3$)	0.00044	0.00016	0.06565	-0.00148***	-0.15007***	-0.01467***
	(0.00032)	(0.00011)	(0.08122)	(0.00056)	(0.04464)	(0.00496)
CO (mg/m^3)	-0.01334	-0.00744	0.74186	-0.20250***	-12.5294***	-1.43640***
	(0.02316)	(0.00884)	(5.60416)	(0.05714)	(3.87134)	(0.42670)
O_3 ($\mu g/m^3$)	0.00065	0.00017	0.38042**	-0.00205**	-0.16146**	-0.02570***
	(0.00062)	(0.00027)	(0.16133)	(0.00101)	(0.07288)	(0.00824)
N	131,278	151,424	151,424	93,877	109,287	109,287
Panel B: $PM_{2.5}$ Measure from Berkeley Earth						
$PM_{2.5}$ ($\mu g/m^3$)	0.00090**	0.00021	0.30053***	-0.00335***	-0.28154***	-0.03104***
	(0.00043)	(0.00018)	(0.10930)	(0.00104)	(0.09078)	(0.00939)
CO (mg/m^3)	-0.00805	-0.00617	-0.35797	-0.23152***	-19.4377***	-2.15202***
	(0.02327)	(0.00969)	(6.17842)	(0.06626)	(5.53128)	(0.62476)
O_3 ($\mu g/m^3$)	0.00045	0.00000	0.20607	-0.00273***	-0.20598**	-0.02785***
	(0.00048)	(0.00020)	(0.12550)	(0.00101)	(0.08671)	(0.00922)
N	117,911	117,911	117,911	83,824	83,824	83,824
Panel C: Pollutant measures winsorized at 99^{th}-Percentile						
$PM_{2.5}$ ($\mu g/m^3$)	0.00035	0.00015	0.08255	-0.00255***	-0.22575***	-0.02237***
	(0.00027)	(0.00011)	(0.07439)	(0.00053)	(0.04561)	(0.00479)
CO (mg/m^3)	-0.00769	-0.00840	1.01243	-0.22999***	-19.2730***	-2.14158***
	(0.02075)	(0.00838)	(5.85093)	(0.06205)	(5.19966)	(0.58371)
O_3 ($\mu g/m^3$)	0.00054	0.00002	0.23673**	-0.00280***	-0.21354***	-0.02841***
	(0.00042)	(0.00018)	(0.11043)	(0.00091)	(0.07729)	(0.00838)
N	131,386	131,386	131,386	93,971	93,971	93,971

Notes: All regressions include worker and date fixed effects. Standard errors clustered by worker and date are reported in parentheses. Indexed outcomes are standardized based on the main sample. Observation counts for estimates for EM and IM indices are therefore limited to observations in the main sample. Panel A is based on pollutant measures directly from the website of the Central Pollution Control Board of India. Panel B replaces the main measure of $PM_{2.5}$ with a gridded measure produced by Berkeley Earth (CO and O_3 measures are those from the main analysis). Panel C repeats the main, concentration-based analysis with each pollutant measure winsorized at the 99^{th} percentile. All estimates include quadratic controls for temperature, precipitation, humidity, and cloud cover.

Table SA7: Main estimates by city

	Extensive margin			Intensive margin		
	(1)	(2)	(3)	(4)	(5)	(6)
	EM index	At work	Net login time	IM index	Calls per shift	Average calls per hour
Hubli						
$PM_{2.5}$ ($\mu g/m3$)	0.00108	0.00088***	0.01994	-0.00212*	-0.19717**	-0.01771*
	(0.00070)	(0.00033)	(0.15801)	(0.00110)	(0.09262)	(0.01028)
CO (mg/m3)	-0.19132*	-0.03135	-70.8539***	-0.24236	-25.28998**	-1.72148
	(0.09791)	(0.03916)	(26.52903)	(0.15524)	(12.01453)	(1.58703)
O_3 ($\mu g/m3$)	0.00243	0.00119	0.47233	0.00342	0.20792	0.04034
	(0.00169)	(0.00073)	(0.43408)	(0.00360)	(0.29315)	(0.03487)
Mumbai						
$PM_{2.5}$ ($\mu g/m3$)	0.00199	0.00005	0.88372	-0.00317	-0.19269	-0.03734
	(0.00226)	(0.00091)	(0.56758)	(0.00436)	(0.36807)	(0.04069)
CO (mg/m3)	-0.04361	-0.02640	-5.73470	-0.55067***	-47.1631***	-5.01836***
	(0.06738)	(0.02797)	(16.99285)	(0.16253)	(13.75228)	(1.51681)
O_3 ($\mu g/m3$)	0.00054	0.00022	0.12552	-0.00232	-0.17624	-0.02355
	(0.00087)	(0.00035)	(0.22343)	(0.00170)	(0.14171)	(0.01626)
Noida						
$PM_{2.5}$ ($\mu g/m3$)	0.00023	-0.00005	0.13373	-0.00468***	-0.40677***	-0.04192***
	(0.00040)	(0.00017)	(0.09993)	(0.00117)	(0.10264)	(0.01045)
CO (mg/m3)	-0.02410	-0.01508	-2.90058	-0.63685***	-52.3905***	-6.03517***
	(0.04352)	(0.01938)	(9.85830)	(0.11537)	(9.78120)	(1.07402)
O_3 ($\mu g/m3$)	-0.00006	-0.00002	-0.01437	-0.00708**	-0.60650**	-0.06447**
	(0.00072)	(0.00031)	(0.18053)	(0.00324)	(0.27986)	(0.02932)
Patna						
$PM_{2.5}$ ($\mu g/m3$)	0.00036	0.00018	0.06908	-0.00177***	-0.15459***	-0.01576***
	(0.00031)	(0.00012)	(0.08969)	(0.00053)	(0.04466)	(0.00499)
CO (mg/m3)	0.03087	-0.00354	16.08248*	-0.05491	-3.89828	-0.58693
	(0.03173)	(0.01334)	(8.71394)	(0.05602)	(4.81015)	(0.51751)
O_3 ($\mu g/m3$)	0.00030	-0.00036	0.33408**	-0.00069	-0.01054	-0.01152
	(0.00061)	(0.00025)	(0.16544)	(0.00076)	(0.06288)	(0.00730)
Udaipur						
$PM_{2.5}$ ($\mu g/m3$)	0.00042	0.00055	-0.10456	-0.00220	-0.21056*	-0.01769
	(0.00102)	(0.00052)	(0.26030)	(0.00141)	(0.12497)	(0.01297)
CO (mg/m3)	-0.14397**	-0.04638*	-40.98255**	0.00350	-0.63496	0.13236
	(0.05930)	(0.02764)	(15.94103)	(0.06270)	(5.22958)	(0.61262)
O_3 ($\mu g/m3$)	0.00319**	0.00256***	0.08326	-0.00108	-0.15006	-0.00364
	(0.00140)	(0.00065)	(0.36611)	(0.00152)	(0.12949)	(0.01455)
N	131,386	131,386	131,386	93,971	93,971	93,971

Notes: All regressions include worker and date fixed effects. Standard errors clustered by worker and date are reported in parentheses. Estimates in each column are from a single regression. City-specific estimates are obtained by interacting city indicators with pollutant variables. Index outcomes are standardized such that the in-sample mean is zero and the standard deviation is one. All estimates include quadratic controls for temperature, precipitation, humidity, and cloud cover.

Table SA8: Estimates for Figure 1

	(1) EM index	(2) IM index
$PM_{2.5}$ 1-2 SDs	-0.014	-0.041
	(0.037)	(0.074)
$PM_{2.5}$ 2-3 SDs	0.033	-0.394***
	(0.037)	(0.091)
$PM_{2.5}$ 3-4 SDs	0.035	-0.464***
	(0.055)	(0.122)
$PM_{2.5}$ >4 SDs	0.056	-0.455***
	(0.081)	(0.143)
CO 1-2 SDs	0.010	-0.171**
	(0.031)	(0.067)
CO 2-3 SDs	-0.040	-0.230**
	(0.038)	(0.091)
CO 3-4 SDs	0.007	-0.285**
	(0.043)	(0.127)
CO >4 SDs	-0.010	-0.649***
	(0.063)	(0.164)
O_3 1-2 SDs	0.005	-0.064
	(0.023)	(0.044)
O_3 2-3 SDs	0.040	-0.180**
	(0.039)	(0.072)
O_3 3-4 SDs	0.031	-0.259***
	(0.038)	(0.080)
O_3 >4 SDs	-0.087	-0.329***
	(0.064)	(0.125)
N	131,386	93,971

Notes: Reports the regressions that are used to create Figure 1. All regressions include worker and date fixed effects. Standard errors clustered by worker and date are reported in parentheses. Index outcomes are standardized such that the in-sample mean is zero and the standard deviation is one. Pollutants are measured in standard deviations relative to *zero pollution levels.* All estimates include quadratic controls for temperature, precipitation, humidity, and cloud cover.

Table SA9: Estimates for Figure 2

	(1)
	IM index
$PM_{2.5}$ 50-100 $\mu g/m^3$	-0.091
	(0.059)
$PM_{2.5}$ 100-150 $\mu g/m^3$	-0.215**
	(0.086)
$PM_{2.5}$ 150-200 $\mu g/m^3$	-0.404***
	(0.100)
$PM_{2.5}$ >200 $\mu g/m^3$	-0.551***
	(0.136)
CO 0.5-1.0 mg/m^3	-0.210***
	(0.080)
CO 1.0-1.5 mg/m^3	-0.278***
	(0.095)
CO 1.5-2.0 mg/m^3	-0.364***
	(0.114)
CO >2.0 mg/m^3	-0.532***
	(0.134)
O_3 30-60 $\mu g/m^3$	-0.052
	(0.046)
O_3 60-90 $\mu g/m^3$	-0.163**
	(0.073)
O_3 90-120 $\mu g/m^3$	-0.242***
	(0.078)
O_3 >120 $\mu g/m^3$	-0.279**
	(0.117)
N	93,971

Notes: Reports the results used to construct Figure 2. All regressions include worker and date fixed effects. Standard errors clustered by worker and date are reported in parentheses. The outcome is standardized such that the in-sample mean is zero and the standard deviation is one. All estimates include quadratic controls for temperature, precipitation, humidity, and cloud cover.