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# Riders in the Smog: How Air Pollution Affects Workers in Urban Environments

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**Abstract**

Using large-scale high-granularity data from a food delivery platform and granular pollution and weather information, we study how $PM_{2.5}$ fluctuations affect riders' absenteeism, productivity, and accidents. Exploiting exogenous pollution variation from inverse boundary layer height, we find that higher pollution increases absenteeism for all workers and raises delivery times and accident rates only among (e-)bike riders, who must exert physical effort while working. Affected workers compensate productivity losses by working longer hours. Monetary incentives mitigate the effects on absenteeism but do not offset the decline in productivity and appear to exacerbate accident risk.

**JEL Codes: H4, J28, Q52**

**Keywords: Air Pollution; Food Delivery Riders; Absenteeism; Labor Productivity; Workplace Safety.**

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# 1 Introduction

The impact of air pollution on health and mortality has been widely documented by researchers (Chay and Greenstone, 2003; Currie and Neidell, 2005; Guarnieri and Balmes, 2014; Schlenker and Walker, 2016; Zhang et al., 2017; Deryugina et al., 2019) and public agencies (WHO, 2016; EEA, 2023). Beyond these well-established public health costs, air pollution may also entail far-reaching economic and social consequences. Recent literature has examined how pollution affects labor market outcomes and has shown that fluctuations in air quality can reduce worker productivity (Graff Zivin and Neidell, 2012; Chang et al., 2016; Adhvaryu et al., 2022; Borgschulte et al., 2024) and labor supply (Hanna and Oliva, 2015; Isen et al., 2017; Holub et al., 2020; Hoffmann and Rud, 2024). Yet, despite this growing literature, several important questions remain unanswered, particularly regarding the relative impact of pollution on cognitive and physical abilities, and its simultaneous effects on multiple dimensions of workers' productivity and well-being.

We contribute to this literature by examining the impact of air pollution on the performance, health, and safety of food delivery riders. These workers offer an ideal setting to study the effects of pollution: their exposure is high, their tasks are standardized and their productivity can be measured with precision, and the physical effort required to perform these tasks varies systematically, depending on the mode of transportation that they use. Furthermore, their job entails spending a substantial portion of their working time in traffic, where they are directly exposed to vehicle emissions, a particularly harmful form of air pollution, as highlighted in the literature (Alexander and Schwandt, 2022). Finally, the increasing size of the food delivery sector makes this population a policy-relevant one to study, and one that, with some exceptions (e.g. Papp, 2024), has so far received limited attention. To the best of our knowledge, our study is the first to evaluate the impact of air pollution on food delivery riders.

Using a unique dataset of order- and worker-level records from Just Eat, a leading food delivery platform, we construct high-granularity measures of absenteeism, productivity (measured by delivery speed), and accidents, on the basis of 7.2 million orders fulfilled by 7,915 riders across 24 Italian cities between 2021 and 2023. By combining these data with granular pollution and weather indicators, we assess how fluctuations in air quality affect workers. We further explore heterogeneity in the effects of pollution by vehicle type – (e-)bikes or scooters – to examine whether pollution impairs riders' productivity primarily through physical or cognitive channels. Moreover, we exploit variation in monetary bonuses across cities and days, which can increase total pay by as much as 65%, to investigate whether financial incentives mitigate the adverse impact of pollution on labor outcomes. Finally, we assess whether and how riders attempt to compensate for pollution-induced productivity losses.

Our empirical strategy leverages a rich set of fixed effects, including time, city, and individual (rider) fixed effects, to control for confounding factors. While important, these controls may not fully isolate the causal impact of air pollution, as air quality can be influenced by factors such as road traffic, which also affect absenteeism, safety, and delivery speed. To address these concerns, we adopt an instrumental variable (IV) approach using the inverse planetary boundary layer height (IBLH) as an exogenous source of variation in air pollution. The planetary boundary layer is the lowest part of the atmosphere, where pollutants are trapped. When large-scale air movements compress this layer, pollution becomes more concentrated, worsening air quality. By instrumenting air pollution with the IBLH while flexibly controlling for weather conditions, we isolate variations in air quality driven by atmospheric conditions rather than local economic activity or traffic patterns. Although relatively recent, this approach has been used in environmental economics and public health (Schwartz et al., 2017; Godzinski and Castillo, 2021; Curci et al., 2024) under the assumption that, conditional on weather and seasonality, residual variation in planetary boundary layer height provides exogenous shifts in pollution levels. We show that increases in IBLH are consistently associated with short-term increases, i.e. lasting up to two days, in the levels of air pollution across all cities in our sample. Following the literature, we benchmark our estimates using fine particulate matter ($PM_{2.5}$) as our main pollutant of interest. However, it is worth noting that our instrument affects the concentrations of most other pollutants, and our estimates should consequently be interpreted as the estimated effects of air pollution more generally.

Our findings reveal significant and heterogeneous effects of pollution on riders' performance and safety. A one-standard-deviation increase in $PM_{2.5}$ (10.7 $\mu g/m^3$) increases *absences* by 1.21 percentage points, corresponding to a 6.6% increase, on average. In absolute terms, this effect amounts to 94% of the impact of monetary bonuses and 54% of that of 16 mm of precipitation over 24 hours, corresponding to 4 hours of heavy rain[1]. The result is robust across different specifications and we do not observe significant differences between riders using (e-)bikes and those using motor scooters. In contrast, the impact of air pollution on *delivery speed* is weaker and varies significantly by vehicle type. For riders using (e-)bikes, a one-standard-deviation increase in pollution results in a 0.7% reduction in speed, approximately 25% of the effect of four hours of heavy rain (or 16 mm/day) and 15% of the effect of monetary bonuses. In contrast, no significant effect is observed for scooter riders. These findings suggest that pollution primarily affects the productivity of riders who are required to exert physical effort. We also observe a significant increase in the probability of riders being involved in *accidents*: a one-standard-deviation rise in pollution leads to 4.2 additional accidents per 10,000 shifts for (e-)bike riders, corresponding to 32% of the effect of 4 hours of heavy rain. In line with our findings on delivery speed, this effect is driven by riders using (e-)bikes, highlighting the interaction between physical exertion and exposure to pollution in influencing safety outcomes. Our results are robust to a series of tests, such as leave-one-out analyses, the inclusion of additional controls, changing the functional form of the instrument, and wild bootstrapping to address the limited number of clusters. We also rule out the possibility that pollution affects food delivery demand, which could bias

[1]According to the World Meteorological Association, heavy rain is defined as rates in excess of 4 mm per hour.

our outcomes, by showing that it does not affect *potential orders* (i.e., the sum of completed and canceled orders).

A distinctive feature of our analysis is the presence of *monetary incentives* introduced by the delivery company to increase worker productivity and reduce absenteeism. Beyond assessing the overall effectiveness of these incentives, we examine whether they mitigate or exacerbate the adverse effects of pollution on worker performance. Our results indicate that bonuses are effective in reducing absenteeism, shortening delivery times, and even in lowering reported accident rates. Crucially, we find that while monetary incentives substantially mitigate the effect of pollution on absences, they do not mitigate nor exacerbate its effect on delivery speed, and appear to amplify the effect of pollution on accident rates among (e-)bike riders. This highlights the limitations – and potential unintended consequences – of using financial incentives to address environmentally-driven performance constraints. Our findings suggest that incentives may encourage riders to work under impaired conditions, thereby increasing their vulnerability to pollution-related risks. We show that these results are not driven by the endogeneity of bonus allocation, as the presence of bonuses is not significantly correlated with food delivery demand in our preferred specification.

We then exploit the unprecedented granularity of our data to examine whether workers compensate for increased absenteeism among colleagues and/or their own productivity loss by adjusting labor supply on the intensive margin (i.e., by working longer hours). We find that riders exposed to higher pollution levels tend to work longer hours without increasing their total output – but only among (e-)bicycle riders, whose productivity is directly affected by pollution. Our results suggest a mild decline in total output, indicating that the combined effect of higher absenteeism, lower productivity, and longer working hours is negative. We interpret this as evidence that, in a setting where a substantial share of pay is performance-based, riders attempt to offset their own productivity loss but cannot compensate for their coworkers' absences.

We also examine the temporal dynamics of the effect of air pollution on riders. Our analysis reveals that the effects of $PM_{2.5}$ on absenteeism and productivity are contemporaneous and short-lived: absences respond to pollution levels on the same day and, possibly, the previous day, while delivery speed is affected only by same-day exposure. We find no clear evidence of anticipatory or lagged responses, nor of compensation through increased attendance in subsequent days. With respect to accidents, the results are less precise because of limited statistical power, but suggest a one-day lag between exposure and the manifestation of effects. These findings support the causal interpretation of our estimates.

The literature on the economic effects of air pollution exposure has been expanding rapidly (for a comprehensive review, see Hospido et al., 2023). A growing body of research provides robust evidence that both short-term and prolonged exposure to even moderate levels of pollution negatively affect workers' productivity and earnings (Borgschulte et al., 2024; Leroutier and Ollivier, 2025). These effects have been documented across a wide range of domains, including physically demanding jobs (Graff Zivin and Neidell, 2012; Chang et al., 2016; Adhvaryu et al., 2022), sports performance (Lichter et al., 2017; Mullins, 2018), cognitively intensive tasks (Chang et al., 2019; He et al., 2019; Kahn and Li, 2020; Archsmith et al., 2020; Sarmiento, 2022; Holub and Thies, 2023), and even strategic decision-making games (Künn et al., 2023). Recent studies have also begun to shed light on the detrimental effects of air pollution on workplace safety (Curci et al., 2024; Lavy et al., 2025) and road safety (Sager, 2019).

In the context of labor supply, both long-term (Isen et al., 2017) and short-term (Hanna and Oliva, 2015; Aragón et al., 2017; Holub et al., 2020) exposure to air pollution have been shown to significantly reduce workers' participation in the labor market. A study closely related to our own (Hoffmann and Rud, 2024) investigated the impact of pollution on daily labor supply decisions in Mexico City, and identified a negative, nonlinear relationship between $PM_{2.5}$ levels and same-day labor supply, with particularly strong effects on days characterized by extreme pollution levels.

Our research makes several key contributions to the literature. First, this is the first study to explore the adverse effects of air pollution on food delivery riders – an understudied group of workers, despite their daily and prolonged exposure to road traffic pollution, and one that offers valuable insights into the broader impacts of air pollution on outdoor occupations in urban environments. Second, while previous studies have documented productivity losses in both physically and cognitively demanding tasks, the relative importance of these two dimensions of worker productivity remains unclear. The fact that food delivery is a standardized task that can require different combinations of physical and cognitive effort, depending on the vehicle used by the rider, allows us to show that the impact of air pollution on productivity increases with the level of physical exertion. Third, although the empirical literature has examined the effects of pollution on workers' health, productivity, and, to a lesser extent, safety, these aspects are typically studied in isolation and across different populations and settings, limiting the comparability of findings. Owing to our unique dataset, we are able to examine these dimensions simultaneously for the first time, and to investigate workers' responses on the intensive margin.

The paper proceeds as follows. Section 2 introduces the context of our analysis. Section 3 describes the data in detail, and Section 4 outlines the empirical strategy. Section 5 presents the main results, while Section 6 reports a series of robustness checks. In Section 7, we examine the interaction between pollution and bonuses, dynamic effects and adjustments on the intensive margin of labor supply. Section 8 concludes.

# 2 Context

## 2.1 Food Delivery

Technological advancements, shifting consumer preferences, and the expansion of gig employment have contributed to the growth of the food delivery market in the global economy. The COVID-19 pandemic further accelerated the adoption of online food ordering and delivery services. By 2023, the global online food delivery market was valued at approximately \$254.52 billion, with projections suggesting it will reach \$505.50 billion by 2030 (Grand View Research, 2024). The sector employs millions of workers worldwide, offering flexible job opportunities through gig economy platforms. Additionally, food delivery services have enabled numerous small and medium-sized restaurants to access a wider customer base without the need for extensive in-house delivery infrastructure (Grand View Research, 2024). In Italy, the focus of this research, the market has mirrored this trend, with its value reaching € 1.8 billion in 2023, up from € 360 million in 2018 (The European House Ambrosetti, 2023).

Our study draws on proprietary data from *Just Eat*, a leading company in the Italian food delivery market. *Just Eat* operates in 24 Italian cities.[2] Unlike other platforms, *Just Eat* directly employs its riders under contracts specifying weekly hours (10, 15, 20, 25, or 30). Riders receive a fixed hourly wage (€ 8.75), a piece-rate payment per order (€ 0.25), and tips from customers. On average, riders complete 1.5 orders per hour, and assuming an average tip of € 2 – approximately 10% of the average order value – the variable component of their pay (piece-rate plus tips) accounts for about one-third of their total earnings.

This contractual arrangement is more structured than those typically offered by other gig platforms. Riders are assigned and notified of their shifts in advance, and actual hours worked should match contractual commitments. Despite their contractual obligations, workers fail to show up in 19% of cases. Only a minority of these absences are justified by a medical certificate. This presumably reflects frictions in workers' access to the public health care services, given the predominance of foreign-born riders, as well as some flexibility on the part of the company. Indeed, JustEat typically initiates formal disciplinary proceedings only after a certain number of consecutive unjustified absences. In addition to hindering their career prospects, absences translate into an income loss, as couriers who fail to show up do not receive pay for that shift.

[2] Appendix Figure A.1 illustrates the geographical distribution of our sample.

During scheduled shifts, riders log into an app that provides delivery instructions. Each city also has “captains” who oversee operations, support riders, monitor performance, and ensure compliance with equipment and personnel standards (e.g., backpacks, helmets, and vests) and that deliveries are made by the contracted individual.[3]

To increase productivity, *Just Eat* introduced sizable monetary incentives starting in April 2022. These bonuses, which substantially increased the hourly wage and standard piece-rate payment, are linked to specific performance targets. In general, all bonus schemes rewarded attendance and productivity, with variations in their implementation details over time and across locations. One type of incentive scheme was tied to the number of deliveries per shift, increasing the piece-rate for deliveries above a certain number during particular days or shifts (often during peak times such as dinnertime on weekends or holidays). Another incentive scheme rewarded riders for achieving high attendance and productivity levels in a given month. Riders in affected cities were notified of the implementation of these incentives a few weeks in advance. To provide a better understanding of the magnitude of these additional incentives, workers completing six deliveries in one day could obtain up to €21, or €5.25 per delivery in bonuses. This scheme would thus more than triple the variable part of the wage (including the assumed tips) and represent a 65% increase in total pay. While other schemes were comparatively less generous, these bonuses generally represented a very strong incentive to worker productivity.

## 2.2 Air Quality in Italy

Italy consistently ranks among the most polluted countries in the European Union, with air quality levels exceeding regulatory thresholds set by both the EU and the World Health Organization (WHO)[4]. In 2022, the average Italian citizen would have gained an additional

[3]This structure substantially reduces the likelihood that riders informally subcontract their jobs or work simultaneously for multiple delivery platforms – practices often reported among workers employed under less formal arrangements.

[4]https://www.eea.europa.eu/publications/europes-air-quality-status-2024

nine months of life expectancy if WHO guidelines on fine particulate matter ($PM_{2.5}$) concentrations had been met (Greenstone et al., 2022). For comparison, this value is effectively zero in the United States, the United Kingdom, and Germany. However, air pollution levels in Italy are highly heterogeneous. While much of the country, including the islands and central-southern regions, experiences relatively good air quality, areas such as the Po Valley consistently record some of the highest particulate concentrations in Europe (EEA, 2023). This regional disparity is driven by a combination of geographic, climatic, and industrial factors that contribute to pollution accumulation. Since *Just Eat* operates exclusively in densely populated areas where food delivery services are economically viable, the cities in our sample are all medium-to-large urban centers with high levels of urbanization and pollution. While the air quality within these cities varies, particulate concentrations are systematically higher than the national average, reflecting the broader pattern of pollution distribution across the country.

# 3 Data

## 3.1 Just Eat Data and Outcomes of Interest

Our analysis draws on four interconnected datasets from *Just Eat*, each described in detail below. We link all the datasets using a unique rider identification code.

**Orders.** This dataset encompasses all deliveries carried out by the company from June 2021 to June 2023. It contains rich information on each transaction, including the order date, city, rider identification code, order value (in euros), travel distance, and vehicle type. The dataset records the GPS-calculated distance from the rider's starting point to the restaurant and from the restaurant to the customer, along with key timestamps: when the rider accepts the delivery, picks up the food at the restaurant, and completes the delivery at the customer's location. In our analysis, we focus on the restaurant-to-customer distance and time-to-deliver, as these metrics are independent of the restaurant's efficiency and more accurately reflect the rider's performance. The time-to-deliver captures not only travel speed but also broader dimensions of efficiency, such as optimal route selection, accurate address identification, and locating the customer's name on the doorbell. In our analysis, we focus on the natural logarithm of delivery speed, defined as the optimal GPS-measured distance from the restaurant to the customer divided by the time elapsed between food pickup and delivery.[5]

Additionally, by linking order data with the company's bonus scheme records, we identify whether any monetary bonus was active at the time of delivery.

Descriptive statistics for this dataset are presented in Panel A of Table 1. The dataset includes more than 7.2 million orders, with an average order value of € 20.5. Riders travel an average distance of 1.9 km per delivery at an average speed of 12.4 km/h from the restaurant to the customer. 68% of deliveries are completed by (e-)bike, and 32% by scooter. Finally, 3% of all orders are delivered while a bonus scheme is active.

**Shifts.** This dataset captures all the scheduled shifts for each rider from late August 2021 to June 2023. For every rider-shift, the dataset includes the date, start and end times, and whether rider was present during the scheduled period. The rider identification code allows linking completed orders to their respective shifts. Panel B of Table 1 summarizes this dataset, which covers 1,720,870 shifts with an average duration of 2.6 hours. We define a dummy variable *Absent*, that takes a value of 1 for shifts in which the rider was absent, and 0 when the rider was present.[6] Riders failed to show up for their scheduled shifts 19%

[5]For delivery speed, we winsorize values three interquartile ranges above the third quartile or below the first quartile.

[6]In consultation with the *Just Eat* data managers, we define a rider as absent if both of the following conditions hold: (i) the rider's login duration for the shift is zero minutes, and (ii) the rider completed no deliveries during the shift. This definition ensures that we do not classify those who were in fact present as absent. It is possible for a rider to have a positive login duration but complete no deliveries – for example, if they are in training and shadowing a more experienced rider, or if exceptionally low demand occurs during the shift. At the same time, including the condition of zero deliveries alongside zero login minutes helps mitigate potential errors in the system tracking login duration. In 99.5% of the cases, both conditions are simultaneously met.

of the time, indicating a high absenteeism rate.

**Demographics.** This dataset provides detailed demographic information on riders, including gender, age, nationality, and weekly contracted hours. However, it does not cover the entire population of riders observed in the orders or shifts datasets (a total of 7,915 riders), as it derives from two specific snapshots of *Just Eat*'s rider pool taken in February 2022 and June 2023. Consequently, demographic data are missing for riders whose contracts ended before February 2022, or started after February 2022 and ended before June 2023. Panel C of Table 1 reports that, out of the 2,643 riders for whom demographic data are available, 46% are foreign nationals,[7] 7% are female, and 25% hold a full-time contract of 30 hours per week.

**Accidents.** This dataset covers the period from February 2022 to June 2023 and includes all accidents or events resulting in damage or injury reported by riders, either during their shifts or while commuting to work. Reported incidents include falls, collisions, injuries, and vehicle damage. In total, 2,397 such events are included in the dataset. We define the *Accident* rate as the number of events per 100 shifts in a day. Panel D of Table 1 presents descriptive statistics aggregated at the city-day level, showing that accidents are relatively frequent, with a reported event every 400 shifts.

## 3.2 Air Pollution and Weather Data

In our analysis, we merge the data on riders and orders with data on pollution and weather at the city-day level.

With respect to air pollution, we focus on fine particulate matter ($PM_{2.5}$), a key pollutant because of its small size and harmful health effects. $PM_{2.5}$ can penetrate deep into the lungs and enter the bloodstream, leading to severe cardiovascular, cerebrovascular, and respiratory conditions (Bell et al., 2004; Pope III and Dockery, 2006). Both short- and long-term expo-

[7]The most represented countries of origin are Pakistan (15.8% of all riders), Nigeria (6.38%), Bangladesh (3.29%), Afghanistan (1.85%), and India (1.44%).

Table 1: Descriptive statistics – Food Delivery Company data

| | N | Mean | SD | 10th pct | 90th pct |
|---|---|---|---|---|---|
| *Panel A: Order Level* | | | | | |
| Value of the order (€) | 7156971 | 20.53 | 12.52 | 8.50 | 36.70 |
| Distance (km) | 7156971 | 1.92 | 1.09 | 0.62 | 3.41 |
| Speed (km/h) | 7156971 | 12.39 | 7.82 | 4.80 | 21.48 |
| Bike/E-bike | 7156971 | 0.35 | 0.48 | 0.00 | 1.00 |
| Scooter | 7156971 | 0.32 | 0.47 | 0.00 | 1.00 |
| Bonus | 7156971 | 0.03 | 0.16 | 0.00 | 0.00 |
| *Panel B: Shift Level* | | | | | |
| Absence | 1683046 | 0.19 | 0.39 | 0.00 | 1.00 |
| Shift Hours | 1683046 | 2.72 | 2.95 | 0.00 | 4.15 |
| *Panel C: Rider Level* | | | | | |
| Foreign | 2981 | 0.47 | 0.50 | 0.00 | 1.00 |
| Female | 2981 | 0.07 | 0.26 | 0.00 | 0.00 |
| Contract >= 25 hours | 2981 | 0.25 | 0.43 | 0.00 | 1.00 |
| *Panel D: Day-City Level* | | | | | |
| Accidents (per 100 shifts) | 884691 | 0.26 | 5.21 | 0.00 | 0.00 |

Notes: Panel A presents descriptive statistics for food delivery orders; Panel B displays descriptive statistics for rider shifts; Panel C provides descriptive statistics for rider demographics; Panel D summarizes descriptive statistics for reported accidents.

sure have been linked to increased morbidity and mortality. More broadly, $PM_{2.5}$ is the most widely used indicator of air pollution in research on health and economic outcomes (Deryugina et al., 2019; Deschenes et al., 2020; Hoffmann and Rud, 2024). The PM$_{2.5}$ concentration estimates are sourced from the Copernicus Atmosphere Monitoring Service (CAMS) and are provided at a high spatial resolution of $0.1° \times 0.1°$ (approximately $8km \times 8km$ in the setting). To construct municipality-level daily pollution measures, we compute weighted averages using an inverse-distance weighting method, drawing from the four nearest grid points to each city's residential center.[8]

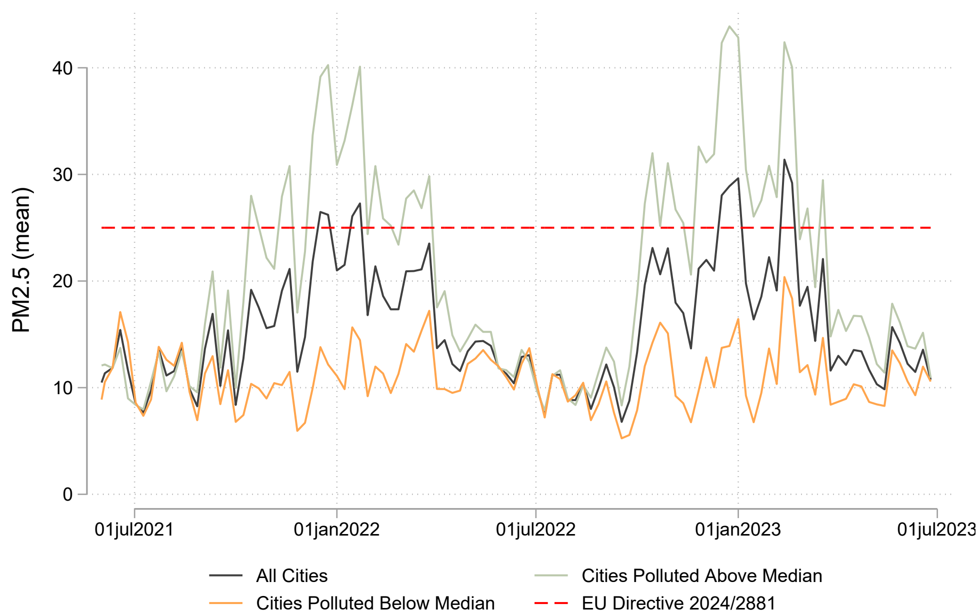
Figure A.2 illustrates the distribution of average daily $PM_{2.5}$ concentrations across the 24 cities included in our sample. The figure highlights substantial heterogeneity in pollution levels across cities, with northern cities experiencing significantly higher concentrations of $PM_{2.5}$ than to those in central and southern Italy do. This spatial variation is consistent

[8]We derive the location of the residential center from Google Maps.

with prior evidence on regional disparities in air quality (EEA, 2023).

In Figure 1, we display the daily fluctuations in $PM_{2.5}$ levels, showing the average concentration for all cities as well as for more and less polluted cities (i.e. above or below the median pollution level). The figure reveals a clear seasonal pattern, with pollution levels peaking during the winter months, which is likely due to increased heating emissions and meteorological conditions. However, even within seasons, there are substantial fluctuations in $PM_{2.5}$ concentrations, reflecting the influence of weather conditions, local emissions, and transboundary pollution. For reference, the figure also indicates the 24-hour $\mathrm{PM}_{2.5}$ limit of 25 $\mu g/m^3$ set by Directive 2024/2881 of the European Parliament for 2030.

Figure 1: Average PM 2.5 over time




The figure shows the evolution of average daily $PM_{2.5}$ concentrations over time for the cities in the sample. It reports the overall average, as well as separate trends for highly polluted and less polluted cities, based on the classification in Figure A.2. The horizontal line indicates the level set for 2030 by Directive 2024/2881 of the European Parliament for daily $PM_{2.5}$ concentrations for reference.

We complement these data with information on the planetary boundary layer height (PBLH), sourced from the Copernicus-ERA5 reanalysis dataset (resolution: $0.25° \times 0.25°$). The PBLH represents the lowest part of the atmosphere, where air pollutants are confined.

From the PBLH data, we construct the inverse planetary boundary layer height (IBLH), which serves as our instrumental variable for air pollution (see Section 4.2).

Weather data, including daily average temperature, wind speed, and precipitation (total precipitation in 24 hours, in mm), are also derived from Copernicus-ERA5. All the variables are aggregated to the municipality level using the same inverse-distance weighting method employed for $PM_{2.5}$.[9]

Table 2 presents descriptive statistics for the air pollution and weather variables.

Table 2: Descriptive statistics – Pollution and Weather

| | N | Mean | SD | 10th pct | 90th pct |
|---|---|---|---|---|---|
| *Panel A: Pollution Data* | | | | | |
| PM2.5 | 18239 | 15.74 | 10.71 | 6.22 | 32.16 |
| IBLH | 18239 | 3.41 | 2.43 | 1.36 | 7.05 |
| PBLH | 18239 | 0.42 | 0.24 | 0.14 | 0.74 |
| *Panel B: Weather Data* | | | | | |
| Rain (mm) | 18239 | 2.35 | 6.01 | 0.00 | 6.83 |
| Wind Speed (km/h) | 18239 | 8.61 | 4.64 | 4.33 | 15.03 |
| Temperature (° C) | 18239 | 16.03 | 7.96 | 5.17 | 26.67 |

This table presents descriptive statistics for pollution and weather variables, calculated as daily averages at the municipality level. Values are derived using inverse-distance weighted averages from the four nearest grid points to each city's residential center. PBLH (km) and IBLH ($km^{-1}$ represent atmospheric boundary layer heights and its inverse.

# 4 Empirical Strategy

## 4.1 Estimating Equation

We aim to assess the relationship between pollution and workers' outcomes by estimating an equation of the form described in equation (1):

[9] For $PM_{2.5}$, IBLH, and wind speed, we winsorize values three interquartile ranges above the third quartile or below the first quartile.

$$y_{imdl} = \alpha_1 \text{PM2.5}_{md} + \textbf{Weather}'_{md}\boldsymbol{\alpha_2} + \alpha_3 \text{Bonus}_{mdl} + \mathbf{X}'_{imd}\boldsymbol{\alpha_4} + \epsilon_{imdl} \tag{1}$$

where $y_{imdl}$ represents the outcome of interest for rider $i$ in municipality $m$ on day $d$ observed at the level $l$, which is either order (when the outcome is speed) or shift (when the outcomes are absences or injuries). The key explanatory variable, $\text{PM2.5}_{md}$, measures the level of air pollution in municipality $m$ on day $d$. $\textbf{Weather}_{md}$ is a vector of local weather conditions in municipality $m$ on day $d$, including daily average temperature (in 20 bins), wind speed, and *Rain* (total daily precipitation, in mm). $\text{Bonus}_{md}$ is a binary variable indicating whether a monetary incentive was offered in municipality $m$ on day $d$. The term $\mathbf{X}_{imd}$ represents a vector of fixed effects. Specifically, we include municipality-by-vehicle, monthly date-by-vehicle, and day-of-the-week fixed effects to account for time-invariant local characteristics and broader temporal patterns.

In our preferred specification, we would ideally include individual (rider-level) fixed effects to identify how a given rider's performance responds to variation in pollution levels. However, given the size and granularity of our dataset, estimating equation (1) with rider fixed effects is computationally challenging.

To estimate individual-level responses while maintaining computational feasibility, we shift from an individual-outcome framework to an analysis aggregated at the municipality-day-vehicle level (mdv). This approach is also conceptually consistent with our empirical strategy, as the key treatment variable ($\text{PM2.5}_{md}$) varies only at the municipality-day level. Accordingly, we aggregate all outcome variables to this level, weighting each cell by the number of underlying observations.

To retain the ability to control for individual heterogeneity despite working with aggregated data, we compute both raw means and mean-residualized outcomes. Specifically, for each outcome, we subtract the individual-specific average (calculated over the full sample period) from each observation prior to aggregation.[10] This residualization effectively controls for time-invariant rider characteristics, as the inclusion of individual fixed effects in a linear framework would do, while preserving computational tractability.

While not mathematically identical to the ideal individual-level regression with rider fixed effects, the aggregate regressions with residualized outcomes can be interpreted as a simplified yet analogous version of our ideal specification. In the Appendix, we replicate our main results using individual-level data and individual fixed effects, and obtain estimates that are virtually identical in both magnitude and statistical significance to those from the aggregate specification (Table A.1).

This leads us to estimate the following specification:

$$\widetilde{y}_{mdv} = \alpha_1 \text{PM2.5}_{md} + \mathbf{Weather}'_{md}\boldsymbol{\alpha_2} + \alpha_3 \text{Bonus}_{md} + \mathbf{X}'_{mdv}\boldsymbol{\alpha_4} + \epsilon_{mdv} \tag{2}$$

where $\widetilde{y}_{mdv}$ is the residualized mean outcome in municipality $m$ on day $d$ for riders using vehicle $v$ (either (e-)bikes or motor scooters), and $\mathbf{X}_{mdv}$ again includes municipality-by-vehicle, month-by-vehicle, and day-of-week fixed effects. Standard errors are clustered at the municipality level. In Section 6, we show that results are robust to wild bootstrap procedures, which perform well even with few clusters (Cameron et al., 2008).

Despite the extensive set of fixed effects and controls we employ, endogeneity concerns may still arise and must be addressed to establish a causal link between pollution and riders' performance. First, pollution levels may be endogenous because of their strong correlation with road traffic, which is among the main sources of air pollution. Traffic not only generates pollutants but also directly affects riders' performance and safety by increasing the likelihood of accidents and increasing the delivery time, thus confounding the relationship between pollution and productivity.

[10] Since some riders may use more than one type of vehicle, we compute individual-specific averages separately for each vehicle. In other words, we residualize the outcome variables by subtracting individual-by-vehicle fixed effects before aggregating.

Moreover, the behaviors and preferences of residents can simultaneously influence both pollution levels and the demand for food delivery. For example, during holidays, air quality may improve due to reduced traffic, while riders may be more likely to be absent, leading us to underestimate the true effect of air pollution on absences.

These intertwined dynamics complicate the identification of a causal effect of air pollution on labor supply and productivity. The direction of the resulting bias is a priori ambiguous and may vary depending on the context and timing. Recognizing these potential sources of endogeneity is essential for an accurate interpretation of our results and motivates the need for a strategy to isolate the impact of pollution from confounding factors.

## 4.2 Instrumental Variable Approach: Inverse Planetary Boundary Layer Height (IBLH)

To address the endogeneity concerns associated with pollution, we employ an instrumental variable (IV) strategy using the inverse planetary boundary layer height (IBLH). This approach has been previously used in research on the health effects of air pollution (Schwartz et al., 2017; Godzinski and Castillo, 2021; Curci et al., 2024), as it provides exogenous variation in air quality.

The planetary boundary layer is the lowest part of the atmosphere, where pollutants are typically trapped because of limited vertical mixing. When its height (i.e. the PBLH) decreases, pollutants become confined within a smaller atmospheric volume, leading to higher concentrations. Conversely, when PBLH increases, pollutants disperse into a larger volume of air, reducing their concentration. Theoretically, this should lead to an inverse linear relationship between pollution levels and PBLH, which we exploit by using IBLH as an instrument.

The thickness of the planetary boundary layer is influenced primarily by solar heating and atmospheric turbulence, making it highly seasonal. However, it is also subject to exogenous fluctuations driven by upper-atmospheric dynamics and interactions with the Earth's surface. After controlling for geographic location, weather, and seasonality, these variations generate plausibly exogenous shocks to pollution levels, independent of local emission sources such as traffic or industrial activity. We leverage these variations to identify the causal effect of pollution on worker performance.

Table 3 presents the first-stage regression results, which confirm a strong and significant association between higher IBLH and increased $PM_{2.5}$ concentrations. Figure 2 illustrates the dynamic nature of this relationship, showing that pollution is affected by same-day and, to a lesser extent, by previous-day IBLH, indicating its immediate and short-lived impact on pollution levels. Moreover, the figure provides further validation of the temporal exogeneity of the instrument, as future IBLH is not associated with current pollution levels.[11]

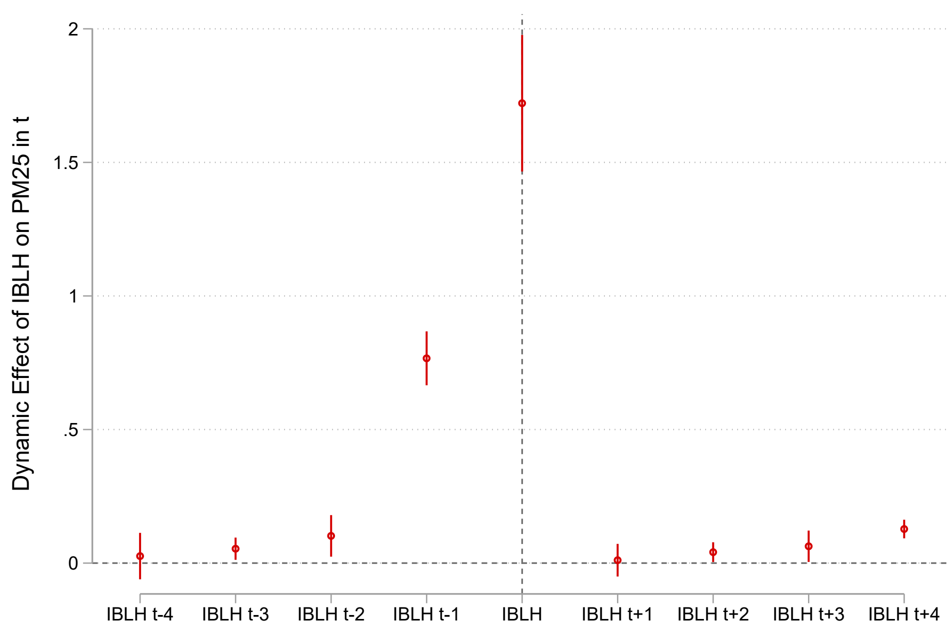
[11]Note that our instrumental variable also affects the concentration of all the main pollutants, not only of $PM_{2.5}$. Thus, while our estimates are based on $PM_{2.5}$, they also encompass the adverse effects of most other pollutants.

Table 3: IBLH and $PM_{2.5}$: First-Stage Estimates

| | $PM_{2.5}$ | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| IBLH | 3.1332*** | 2.8140*** | 2.7349*** | 2.7298*** | 2.4081*** |
| | (0.1514) | (0.1561) | (0.1476) | (0.1474) | (0.1408) |
| F-Stat | 428.31 | 324.92 | 343.4 | 343.02 | 292.65 |
| N | 18239 | 18239 | 18239 | 18239 | 18239 |
| $R^2$: | .51 | .64 | .70 | .70 | .73 |
| Mun FE | - | Y | Y | Y | Y |
| Month FE | - | - | Y | Y | Y |
| DOW | - | - | - | Y | Y |
| Weather | - | - | - | - | Y |
| Mean dep | 15.74 | 15.74 | 15.74 | 15.74 | 15.74 |
| SD dep | 10.71 | 10.71 | 10.71 | 10.71 | 10.71 |
| Mean IBLH | 3.41 | 3.41 | 3.41 | 3.41 | 3.41 |
| SD IBLH | 2.43 | 2.43 | 2.43 | 2.43 | 2.43 |

*Notes.* This table reports the results of the first-stage regression of $PM_{2.5}$ concentrations on the inverse planetary boundary layer height (IBLH) and control variables. Weather controls include daily average temperature (20 bins), wind speed, and precipitation (mm). Standard errors are clustered at the city level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure 2: First stage - Dynamic Effect




The figure shows the estimated coefficients (with 90% confidence intervals) from regressions of $PM_{2.5}$ concentration on multiple leads and lags of the inverse planetary boundary layer height (IBLH). The models include city and time fixed effects (month and day of the week), weather controls (daily average temperature (20 bins), wind speed, and precipitation (mm)) and a dummy variable equal to one on days with monetary incentives in a given city.

To support the credibility of the monotonicity assumption for our instrument, we have replicated the first-stage regression after including an interaction term between municipality fixed effects and IBLH. The results of this test are summarized in Appendix Figure A.3, which shows that the association between IBLH and $PM_{2.5}$ is positive and significant for all cities individually, thus supporting the monotonicity assumption of the instrument. Furthermore, the residual bin plot in Appendix Figure A.4 confirms the linearity of this relationship.

In conclusion, the first-stage regression and supporting analyses establish IBLH as a strong and consistent predictor of air pollution ($PM_{2.5}$), validating its suitability as an instrumental variable in our empirical framework.

# 5 Main Results

## 5.1 Absences

We begin by analyzing the impact of air pollution on riders' absences. Table 4 summarizes the results, with progressively richer sets of controls across columns.

Column (1) presents the OLS estimate from equation (2), controlling for municipality-by-vehicle month-by-vehicle, and day-of-week fixed effects, for weather conditions and bonuses, and using the residualized version of the dependent variable, that accounts for rider fixed effects. The coefficient indicates a positive (marginally not significant at conventional levels) relationship between $PM_{2.5}$ levels and absences. Columns (2)-(5) report the IV estimates, following the methodology described in subsection 4.2. Column (2) includes only month-by-vehicle, city-by-vehicle, and day-of-week fixed effects. In column (3), we residualize the dependent variable to account for unobserved individual heterogeneity. Column (4) adds controls for weather conditions, including rainfall, wind speed, and temperature. Our most complete specification, presented in column (5), further includes a dummy for the presence of monetary incentives.

Table 4: Effect of Air Pollution on Share of Riders Absent in a City on a Given Day

| | OLS | 2SLS | 2SLS | 2SLS | 2SLS | RF |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| PM25 (SD) | 0.0039 | 0.0120* | 0.0085** | 0.0121*** | 0.0121*** | |
| | (0.0026) | (0.0070) | (0.0038) | (0.0042) | (0.0040) | |
| Rain | 0.0013*** | | | 0.0014*** | 0.0014*** | 0.0012*** |
| | (0.0002) | | | (0.0003) | (0.0003) | (0.0002) |
| Bonus | -0.0131*** | | | | -0.0129*** | -0.0131*** |
| | (0.0027) | | | | (0.0027) | (0.0027) |
| IBLH | | | | | | 0.0024** |
| | | | | | | (0.0009) |
| N cells | 32145 | 32145 | 32145 | 32145 | 32145 | 32147 |
| N observations | 1665743 | 1665743 | 1665743 | 1665743 | 1665743 | 1665776 |
| Mean dep. | .18 | .18 | .18 | .18 | .18 | .18 |
| First-stage F | - | 201.05 | 201.05 | 169.48 | 170.26 | - |
| Mun FE | Y | Y | Y | Y | Y | Y |
| Time FE | Y | Y | Y | Y | Y | Y |
| Individual Residuals | Y | - | Y | Y | Y | Y |
| Weather | Y | - | - | Y | Y | Y |

Notes. This table reports the estimated effect of air pollution on rider absences. The dependent variable is the share of absent workers in a city on a given day. Column (1) presents OLS estimates. Columns (2) to (5) report 2SLS estimates using the IBLH as an instrument for air pollution. Column (6) displays the reduced-form estimates. All regressions include fixed effects for city-by-vehicle, monthly date-by-vehicle, and day-of-week. The specification labeled *Individual residuals* uses a residualized version of the dependent variable, obtained by subtracting each riders individual-specific average. Weather controls include daily average temperature (20 bins), wind speed, and precipitation (mm). *Bonus* is a dummy equal to one on days when monetary incentives were in place in a given city. *N cells* refers to the number of day-city-level cells, while *N observations* reflects the actual number of individual observations contributing to the analysis. Standard errors are clustered at the city level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Across specifications, our IV estimates consistently indicate a positive effect of air pollution on worker absences. The estimates in Column (5) suggest that a one-standard-deviation increase in $PM_{2.5}$ raises the probability of absence by 1.21 percentage points, corresponding to 6.6% of its mean. The reduced form estimates, reported in Column (6), are reassuringly in line with these results showing that IBLH has a positive and significant effect on riders' absences.

Beyond the main findings, Table 4 provides additional insights. Rain has a substantial positive effect on absences: an additional 1 mm of rain during a 24 hour period increases absences by 0.14 percentage points. Four hours of heavy rain (16 mm) increases absences by 2.2 percentage points. Column (5) also reveals a strong negative relationship between monetary bonuses and absences, suggesting that financial incentives promote attendance.[12] For comparison, the estimated effect of a one-standard-deviation increase in pollution on absences is approximately 54% times the effect of 4 hours of heavy rain and approximately 94% of the estimated effect of monetary incentives.

In Table 5 we display the same results, distinguishing between different modes of transportation. Specifically, Panel A reports the coefficients for riders using (e-)bikes, while Panel B focuses on those using scooters. The findings indicate that the effects of pollution on absences are positive and statistically significant for both (e-)bike and scooter users, with no significant differences between the two groups.

## 5.2 Productivity: delivery speed

Table 6 presents the estimated effects of air pollution on riders' speed: Panel A reports the results for all vehicle types, while Panels B and C focus on (e-)bike and scooter riders.

Overall, air pollution seems to have a negative effect on the rider average speed, although estimates are mostly imprecise and not statistically significant at conventional levels. How-

[12] We discuss the caveats to the causal interpretation of this estimate in Section 7.1

Table 5: Effect of Air Pollution on Share Absent – By Vehicle

| | | | | | | |
|---|---|---|---|---|---|---|
| | *Panel A: (E-)Bike* | | | | | |
| | OLS | 2SLS | 2SLS | 2SLS | 2SLS | RF |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| PM25 (SD) | 0.0046 | 0.0118 | 0.0098** | 0.0130** | 0.0130** | |
| | (0.0028) | (0.0076) | (0.0041) | (0.0051) | (0.0048) | |
| Rain | 0.0014*** | | | 0.0015*** | 0.0015*** | 0.0013*** |
| | (0.0003) | | | (0.0004) | (0.0003) | (0.0003) |
| Bonus | -0.0177*** | | | | -0.0174*** | -0.0178*** |
| | (0.0039) | | | | (0.0039) | (0.0038) |
| IBLH | | | | | | 0.0027** |
| | | | | | | (0.0011) |
| N cells | 16071 | 16071 | 16071 | 16071 | 16071 | 16072 |
| N observations | 1085292 | 1085292 | 1085292 | 1085292 | 1085292 | 1085311 |
| Mean dep. | .19 | .19 | .19 | .19 | .19 | .19 |
| First-stage F | - | 227.75 | 227.75 | 262.59 | 266.68 | - |
| | *Panel B: Scooter* | | | | | |
| | OLS | 2SLS | 2SLS | 2SLS | 2SLS | RF |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| PM25 (SD) | 0.0021 | 0.0124* | 0.0056 | 0.0103*** | 0.0103*** | |
| | (0.0024) | (0.0061) | (0.0034) | (0.0031) | (0.0030) | |
| Rain | 0.0010*** | | | 0.0011*** | 0.0011*** | 0.0010*** |
| | (0.0002) | | | (0.0002) | (0.0002) | (0.0002) |
| Bonus | -0.0054 | | | | -0.0054 | -0.0053 |
| | (0.0033) | | | | (0.0034) | (0.0034) |
| IBLH | | | | | | 0.0018*** |
| | | | | | | (0.0005) |
| N cells | 16074 | 16074 | 16074 | 16074 | 16074 | 16075 |
| N observations | 580451 | 580451 | 580451 | 580451 | 580451 | 580465 |
| Mean dep. | .17 | .17 | .17 | .17 | .17 | .17 |
| First-stage F | - | 179.59 | 179.59 | 111.45 | 111.44 | - |
| Mun FE | Y | Y | Y | Y | Y | Y |
| Time FE | Y | Y | Y | Y | Y | Y |
| Individual Residuals | Y | - | Y | Y | Y | Y |
| Weather | Y | - | - | Y | Y | Y |

Notes. This table reports the estimated effect of air pollution on rider absences. Panel A focuses on riders using (e-)bikes, while Panel B on those using scooters. The dependent variable is the share of absent workers in a city on a given day. Column (1) presents OLS estimates. Columns (2) to (5) report 2SLS estimates using the IBLH as an instrument for air pollution. Column (6) displays the reduced-form estimates. All regressions include fixed effects for city-by-vehicle, monthly date-by-vehicle, and day-of-week. Weather controls: daily average temperature (20 bins), wind speed, and precipitation (mm). *Bonus* is a dummy equal to one on days when monetary incentives were in place in a given city. *N cells* refers to the number of day-city-level cells, while *N observations* reflects the actual number of individual observations contributing to the analysis. Standard errors are clustered at the city level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

## Table 6: Effect of Air Pollution on Delivery Speed

| | *Panel A: All Vehicles* | | | | | |
|---|---|---|---|---|---|---|
| | OLS | 2SLS | 2SLS | 2SLS | 2SLS | RF |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| PM25 (SD) | -0.0030* | -0.0071 | -0.0043 | -0.0046 | -0.0051 | |
| | (0.0015) | (0.0044) | (0.0041) | (0.0039) | (0.0032) | |
| Rain | -0.0019*** | | | -0.0020*** | -0.0019*** | -0.0019*** |
| | (0.0001) | | | (0.0001) | (0.0001) | (0.0001) |
| Bonus | 0.0444*** | | | | 0.0444*** | 0.0444*** |
| | (0.0043) | | | | (0.0043) | (0.0043) |
| IBLH | | | | | | -0.0010 |
| | | | | | | (0.0007) |
| N cells | 34574 | 34574 | 34574 | 34574 | 34574 | 34576 |
| N observations | 6905933 | 6905933 | 6905933 | 6905933 | 6905933 | 6906102 |
| Mean dep. | 11.69 | 11.69 | 11.69 | 11.69 | 11.69 | 11.69 |
| First-stage F | - | 249.94 | 249.94 | 206.45 | 206.94 | - |
| | *Panel B: (E-)Bike* | | | | | |
| | OLS | 2SLS | 2SLS | 2SLS | 2SLS | RF |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| PM25 (SD) | -0.0035** | -0.0095** | -0.0067 | -0.0065* | -0.0072** | |
| | (0.0014) | (0.0043) | (0.0041) | (0.0036) | (0.0031) | |
| Rain | -0.0018*** | | | -0.0019*** | -0.0018*** | -0.0017*** |
| | (0.0001) | | | (0.0001) | (0.0001) | (0.0002) |
| Bonus | 0.0471*** | | | | 0.0472*** | 0.0472*** |
| | (0.0039) | | | | (0.0040) | (0.0040) |
| IBLH | | | | | | -0.0015** |
| | | | | | | (0.0007) |
| N cells | 17328 | 17328 | 17328 | 17328 | 17328 | 17329 |
| N observations | 4687984 | 4687984 | 4687984 | 4687984 | 4687984 | 4688093 |
| Mean dep. | 9.85 | 9.85 | 9.85 | 9.85 | 9.85 | 9.85 |
| First-stage F | - | 290.25 | 290.25 | 295.55 | 298.7 | - |
| | *Panel C: Scooter* | | | | | |
| | OLS | 2SLS | 2SLS | 2SLS | 2SLS | RF |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| PM25 (SD) | -0.0018 | -0.0011 | 0.0015 | 0.0005 | 0.0004 | |
| | (0.0027) | (0.0061) | (0.0052) | (0.0054) | (0.0047) | |
| Rain | -0.0022*** | | | -0.0022*** | -0.0022*** | -0.0022*** |
| | (0.0001) | | | (0.0001) | (0.0001) | (0.0001) |
| Bonus | 0.0399*** | | | | 0.0399*** | 0.0399*** |
| | (0.0062) | | | | (0.0062) | (0.0062) |
| IBLH | | | | | | 0.0001 |
| | | | | | | (0.0008) |
| N cells | 17246 | 17246 | 17246 | 17246 | 17246 | 17247 |
| N observations | 2217949 | 2217949 | 2217949 | 2217949 | 2217949 | 2218009 |
| Mean dep. | 15.56 | 15.56 | 15.56 | 15.56 | 15.56 | 15.56 |
| First-stage F | - | 197.8 | 197.8 | 132.7 | 133.25 | - |
| Mun FE | Y | Y | Y | Y | Y | Y |
| Time FE | Y | Y | Y | Y | Y | Y |
| Individual Residuals | Y | - | Y | Y | Y | Y |
| Weather | Y | - | - | Y | Y | Y |

Notes. This table reports 2SLS estimates of the effect of air pollution on riders' speed (in ln). Panel A looks at all the riders in the sample, while Panel B and C distinguish between riders using (e-)bikes and scooters. Column (1) presents OLS estimates. Columns (2) to (5) report 2SLS estimates using the IBLH as an instrument for air pollution. Column (6) displays the reduced-form estimates. All regressions include fixed effects for city-by-vehicle, monthly date-by-vehicle, and day-of-week. Weather controls: daily average temperature (20 bins), wind speed, and precipitation (mm). *Bonus* is a dummy equal to one on days when monetary incentives were in place in a given city. *N cells* refers to the number of day-city-level cells, while *N observations* reflects the actual number of individual observations contributing to the analysis. Mean dep. represents the average value of the dependent variable in its original (non-logarithmic) form. Standard errors are clustered at the city level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

ever, when we disaggregate the results by the type of vehicle used by the riders, a more nuanced pattern emerges. Specifically, as we show in Panel B of Table 6, both OLS and IV estimates point toward a negative and statistically significant effect of $PM_{2.5}$ on the speed of riders using (e-)bikes: our preferred specification (Column (5)) suggests that a one standard deviation increase in $PM_{2.5}$ leads to a 0.72% reduction in the speed of (e-)bicycle riders (equivalent to -5.3% of a standard deviation[13]). This effect is approximately 15% of the impact of monetary incentives (in absolute terms) and 25% of the estimated effect of 4 hours of heavy rain. In contrast, the effect on scooter riders is small and statistically insignificant (Panel C). These results are confirmed in the reduced form (Column (6)). Note that these estimates are based on the selected sample of individuals who attended work despite pollution (see section 5.1). Assuming positive selection into work – meaning that less healthy or more pollution-sensitive riders are disproportionately likely to skip shifts on polluted days – our estimates should be interpreted as a lower bound of the causal effect of pollution on the performance of the average rider. In other words, stronger effects would be expected in contexts where workers have stronger incentives to attend work despite being adversely affected by air pollution.

In both panels of Table 6, the coefficients related to rain and monetary bonuses are precisely estimated and align with expectations: adverse weather conditions slow down riders, whereas financial incentives increase their speed.

The stronger impact on riders using (e-)bikes is likely attributable to their greater physical exertion and direct exposure to air pollution, relative to those of scooter riders. Fine particulate matter like $PM_{2.5}$ can impair respiratory function and reduce physical performance - effects that are particularly detrimental for cyclists who rely on sustained physical effort to maintain speed.

[13]The standard deviation is computed on the dataset aggregated at the city-day level.

### 5.3 Accidents

Table 7 reports the estimated effect of air pollution on the frequency of accidents involving delivery riders (computed as the number of events per 100 shifts in the day). Panel A presents the results for all the vehicles. The estimates from our preferred specification (Column (5)) imply that a one standard deviation increase in the $PM_{2.5}$ concentration leads to approximately 3.6 additional accidents per 10,000 rider-days – an increase of approximately 13% relative to the mean.

Panels B and C disaggregate the analysis by mode of transportation, revealing substantial heterogeneity in the effects. Among riders using (e-)bikes (Panel B), the impact of pollution on accident risk is both positive and precisely estimated. In our most comprehensive model, a one standard deviation increase in $PM_{2.5}$ raises the accident rate by approximately 4.3 incidents per 10,000 rider-days. Given a baseline mean of 29 daily accidents per 10,000 rider-days, this corresponds to a relative increase of approximately 15%. In contrast, in our preferred specification we find no significant effect of pollution on incidents among scooter users (Panel C), with smaller and generally statistically insignificant estimates across all IV specifications.[14]

Although the estimates for this outcome are less precise and display greater variability across specification – likely due to the relative rarity of such events – these results point toward a significant positive impact of air pollution on accidents, which appears to be more pronounced for (e-)bike riders.

Consistent with expectations, we also find that accidents are more frequent on rainy days for both types of vehicles. Additionally, the presence of monetary incentives is associated with a lower incidence of accidents among riders who use (e-)bikes. On the one hand, the lack of a positive effect of monetary incentives on the accident rate suggests that bonuses do not endanger riders by encouraging reckless driving. On the other hand, the fact that

[14] Note that the OLS estimate is positive and marginally significant for scooter riders, while still smaller in magnitude than for (e-)bike riders.

## Table 7: Effect of Air Pollution on Accident Rate

*Panel A: All Vehicles*

| | OLS (1) | 2SLS (2) | 2SLS (3) | 2SLS (4) | 2SLS (5) | RF (6) |
|---|---|---|---|---|---|---|
| PM25 (SD) | 0.0296* | -0.0032 | 0.0065 | 0.0352** | 0.0361** | |
| | (0.0148) | (0.0261) | (0.0239) | (0.0167) | (0.0170) | |
| Rain | 0.0106*** | | | 0.0108*** | 0.0107*** | 0.0103*** |
| | (0.0018) | | | (0.0018) | (0.0019) | (0.0018) |
| Bonus | -0.0799*** | | | | -0.0802*** | -0.0789*** |
| | (0.0271) | | | | (0.0270) | (0.0268) |
| IBLH | | | | | | 0.0070* |
| | | | | | | (0.0035) |
| N cells | 25419 | 25419 | 25419 | 25419 | 25419 | 25421 |
| N observations | 865076 | 865076 | 865076 | 865076 | 865076 | 865101 |
| Mean dep. | .27 | .27 | .27 | .27 | .27 | .27 |
| First-stage F | - | 287.15 | 287.15 | 229.11 | 229.75 | - |

*Panel B: (E-)Bike*

| | OLS (1) | 2SLS (2) | 2SLS (3) | 2SLS (4) | 2SLS (5) | RF (6) |
|---|---|---|---|---|---|---|
| PM25 (SD) | 0.0304 | 0.0189 | 0.0312 | 0.0412* | 0.0430** | |
| | (0.0193) | (0.0248) | (0.0222) | (0.0202) | (0.0202) | |
| Rain | 0.0079*** | | | 0.0082*** | 0.0080*** | 0.0076** |
| | (0.0027) | | | (0.0028) | (0.0028) | (0.0027) |
| Bonus | -0.1107*** | | | | -0.1115*** | -0.1096*** |
| | (0.0364) | | | | (0.0359) | (0.0361) |
| IBLH | | | | | | 0.0088** |
| | | | | | | (0.0042) |
| N cells | 12708 | 12708 | 12708 | 12708 | 12708 | 12709 |
| N observations | 544481 | 544481 | 544481 | 544481 | 544481 | 544495 |
| Mean dep. | .29 | .29 | .29 | .29 | .29 | .29 |
| First-stage F | - | 363.68 | 363.68 | 368.2 | 367.65 | - |

*Panel C: Scooter*

| | OLS (1) | 2SLS (2) | 2SLS (3) | 2SLS (4) | 2SLS (5) | RF (6) |
|---|---|---|---|---|---|---|
| PM25 (SD) | 0.0238* | -0.0502 | -0.0462* | 0.0154 | 0.0153 | |
| | (0.0132) | (0.0293) | (0.0268) | (0.0266) | (0.0270) | |
| Rain | 0.0145*** | | | 0.0144*** | 0.0144*** | 0.0143*** |
| | (0.0020) | | | (0.0020) | (0.0020) | (0.0020) |
| Bonus | -0.0355 | | | | -0.0353 | -0.0348 |
| | (0.0268) | | | | (0.0271) | (0.0268) |
| IBLH | | | | | | 0.0027 |
| | | | | | | (0.0048) |
| N cells | 12711 | 12711 | 12711 | 12711 | 12711 | 12712 |
| N observations | 320595 | 320595 | 320595 | 320595 | 320595 | 320606 |
| Mean dep. | .24 | .24 | .24 | .24 | .24 | .24 |
| First-stage F | - | 216.26 | 216.26 | 142.87 | 144.59 | - |
| Mun FE | Y | Y | Y | Y | Y | Y |
| Time FE | Y | Y | Y | Y | Y | Y |
| Individual Residuals | Y | - | Y | Y | Y | Y |
| Weather | Y | - | - | Y | Y | Y |

Notes. This table reports the effect of air pollution on the number of reported accidents per 100 shifts. Panel A looks at all the riders in the sample, while Panel B and C distinguish between riders using (e-)bikes and scooters. Column (1) presents OLS estimates. Columns (2) to (5) report 2SLS estimates using the IBLH as an instrument for air pollution. Column (6) displays the reduced-form estimates. All regressions include fixed effects for city-by-vehicle, monthly date-by-vehicle, and day-of-week. Weather controls: average temperature (20 bins), wind speed, and precipitation (mm). *Bonus* is a dummy equal to one on days when monetary incentives were in place in a given city. *N cells* refers to the number of day-city-level cells, while *N observations* reflects the actual number of individual observations contributing to the analysis. Standard errors are clustered at the city level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

bonuses *reduce* the number of reported accidents suggests that the accidents that do not prevent riders from working may be reported when bonuses are absent, but not reported when they are present and the opportunity cost of reporting is greater.

Once again, the effects of pollution are stronger for workers using (e-)bikes and are smaller and generally not significant among those using motor scooters. This pattern likely reflects the greater physical effort required to cycle in polluted conditions, which may lead to increased fatigue and, in turn, a higher risk of accidents. This interpretation aligns with our findings on delivery speed and reinforces the idea that the negative effects of air pollution are more pronounced when physical exertion is involved.

# 6 Robustness Tests

In this section, we assess the robustness of our findings through several complementary analyses.

First, in Table A.1, we show that our main estimates remain virtually unchanged when the effects are estimated using shift- or order-level data with rider-level fixed effects (as in Equation 1), rather than municipality-level aggregates of residualized variables (as in Equation 2). As expected, the results are nearly identical, confirming that our use of aggregate measures for practical reasons does not affect our conclusions.

Second, we test the sensitivity of our results to more saturated model specifications and alternative functional forms of the primary instrument. Figures A.5, A.6, and A.7 visually summarize the results for worker absences, delivery speed, and accidents, respectively. Our estimates remain stable when we augment the preferred specification with interactions between day-of-week and municipality fixed effects (*D.O.W. by Mun.*), which capture local weekly variation, as well as municipality-specific linear time trends (*D.O.W. and L.T. by Mun.*). We also experiment with transformed versions of the IBLH, including binned instruments (10 quantile bins), which capture possible nonlinearities in the first stage, and interactions between IBLH and municipality fixed effects to allow the effect of IBLH on air pollution to vary by city. Our results are extremely robust across these different model specifications, with the only exception being the estimated effect of air pollution on accidents for scooter riders, which becomes marginally statistically significant in one specification (although it remains smaller in magnitude that the estimated effect for (e-)bike riders).

Third, we investigate whether the results are driven by specific municipalities by re-estimating our preferred specification iteratively, excluding one municipality at a time. Figure A.8 presents these leave-one-out results for absences. We conduct analogous analyses for delivery speed and accidents, restricting the sample to riders using (e-)bikes – the subgroup for which we observe the strongest effects. The corresponding results are shown in Figures A.9 and A.10. Our point estimates are generally robust to the exclusion of individual cities, with the partial exception of Milan and Turin (the second and third most represented cities in our sample), whose exclusion leads to a decrease and an increase in the estimated effect on speed, respectively, without affecting our main conclusions.

Fourth, we address concerns about the limited number of clusters in our sample (24 clusters, corresponding to the 24 municipalities) by implementing a wild bootstrap procedure (Cameron et al., 2008) clustered at the municipality level. The results are reported in Table A.2. Again, the significance of all our estimates is robust to this procedure.

As air pollution has also been linked to economic activity (Leroutier and Ollivier, 2025) and even to demand for food delivery (Chu et al., 2020), one final concern is that air pollution may affect the demand for food delivery and, through this channel, influence our outcomes. We rule out this possibility by showing that, in our setting, the estimated effect of air pollution on *potential orders* (i.e., the sum of completed and canceled orders) is very small and not statistically significant in our preferred specification. We report the details and results of this analysis in Appendix C.

# 7 Additional results

## 7.1 Interaction between Pollution and Economic Incentives

The analyses presented thus far demonstrate the impact of pollution on our three main outcomes: absences, delivery speed, and accidents. Additionally, we document a strong association between monetary incentives and rider performance. Specifically, monetary bonuses significantly reduce the likelihood of absences (Column (5), Table 4) and accidents (Column (5), Table 7), while increasing delivery speed (Column (5), Table 6).

Beyond assessing the effectiveness of bonuses, a key question concerns the interaction between pollution and economic incentives. This analysis is relevant for two main reasons. First, it may shed light on the mechanisms through which pollution affects performance: if pollution reduces productivity by generating discomfort, which can be counteracted through increased effort, then bonuses might attenuate its negative effects. Second, it may uncover hidden costs of financial incentives. If bonuses encourage riders to work despite exposure to adverse environmental conditions, they may increase risks to health and well-being – which manifest in the short term through higher accident rates, and in the medium term through cumulative health impacts.

In Table 8, we display results from the estimation of a version of equation (2) augmented with the interactions between $Bonus_{md}$ and $PM2.5_{md}$ and between $Bonus_{md}$ and $Rain$. Columns (1)–(3) show the results for our coefficients of interest when the outcome variable is absenteeism. The interaction term between air pollution and the dummy variable indicating the presence of a bonus in a given city-day is negative and statistically significant for riders who use (e-)bikes (Column (2)). This finding indicates that monetary incentives can substantially mitigate the adverse effect of pollution on attendance for this group of workers. These results align with the idea that economic incentives can serve as a powerful counterbalance to external deterrents to the labor supply, such as environmental hardships.

However, for delivery speed (Columns (4)–(6)), economic incentives do not appear to mit-

Table 8: Effect of Air Pollution on Riders' Outcomes - Interaction with Economic Incentives

| | Share Absent | | | Delivery Speed (ln) | | | Accident Rate | | |
|---|---|---|---|---|---|---|---|---|---|
| | All | (E-)Bike | Scooter | All | (E-)Bike | Scooter | All | (E-)Bike | Scooter |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| PM25 (SD) | 0.0130*** | 0.0143*** | 0.0099*** | -0.0055 | -0.0077 | 0.0005 | -0.0059 | -0.0026 | -0.0145 |
| | (0.0041) | (0.0049) | (0.0033) | (0.0046) | (0.0049) | (0.0055) | (0.0345) | (0.0383) | (0.0453) |
| Bonus | -0.0107*** | -0.0150*** | -0.0034 | 0.0447*** | 0.0490*** | 0.0366*** | -0.1354** | -0.1815** | -0.0611* |
| | (0.0026) | (0.0034) | (0.0035) | (0.0056) | (0.0057) | (0.0078) | (0.0522) | (0.0680) | (0.0345) |
| Bonus × PM25 (SD) | -0.0051* | -0.0067** | 0.0007 | 0.0019 | 0.0005 | 0.0022 | 0.1458** | 0.1597** | 0.0999 |
| | (0.0029) | (0.0032) | (0.0047) | (0.0080) | (0.0100) | (0.0064) | (0.0616) | (0.0664) | (0.0782) |
| Rain | 0.0014*** | 0.0014*** | 0.0012*** | -0.0018*** | -0.0017*** | -0.0021*** | 0.0092*** | 0.0073** | 0.0119*** |
| | (0.0003) | (0.0004) | (0.0001) | (0.0001) | (0.0001) | (0.0002) | (0.0024) | (0.0033) | (0.0029) |
| Bonus × Rain | 0.0000 | 0.0004 | -0.0004 | -0.0007** | -0.0008** | -0.0007 | 0.0063** | 0.0039 | 0.0099** |
| | (0.0003) | (0.0003) | (0.0003) | (0.0003) | (0.0003) | (0.0005) | (0.0030) | (0.0037) | (0.0045) |
| N cells | 32145 | 16071 | 16074 | 34574 | 17328 | 17246 | 25419 | 12708 | 12711 |
| N observations | 1665743 | 1085292 | 580451 | 6905933 | 4687984 | 2217949 | 865076 | 544481 | 320595 |
| Mean dep. | .18 | .19 | .17 | 11.69 | 9.85 | 15.56 | .27 | .29 | .24 |
| Mun FE | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Time FE | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Individual Residuals | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Weather | Y | Y | Y | Y | Y | Y | Y | Y | Y |

Notes. This table reports 2SLS estimates of the impact of air pollution, monetary incentives, and their interaction on rider absences, delivery speed, and accidents. Air pollution and its interaction with bonuses are instrumented using IBLH and its interaction with the same variable. All regressions focus on the residualized version of the dependent variable, constructed by subtracting each riders individual-specific average, and include fixed effects for city-by-vehicle, monthly date-by-vehicle, and day-of-week, and weather controls (average temperature in 20 bins, wind speed, and precipitation). *Bonus* is a dummy equal to one on days when monetary incentives were in place in a given city. *N cells* refers to the number of day-city-level cells, while *N observations* reflects the actual number of individual observations contributing to the analysis. Standard errors are clustered at the city level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

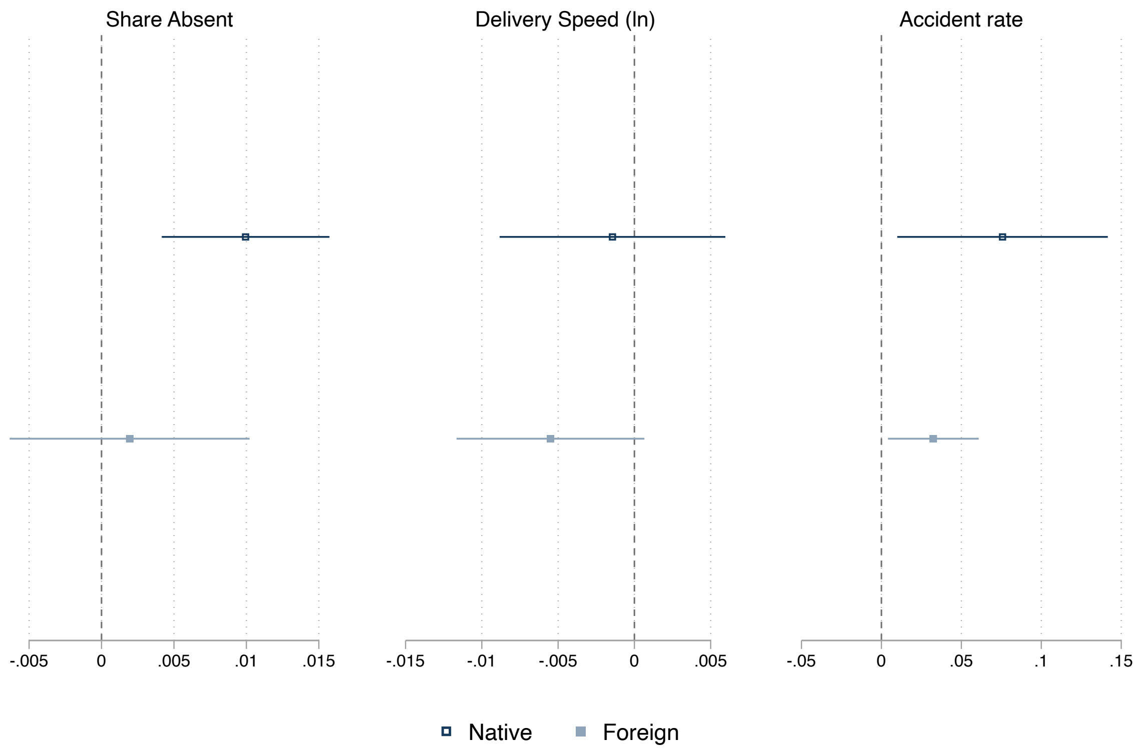
igate or exacerbate the effects of pollution. Specifically, while delivery speed is significantly higher when bonuses are present, for (e-)bike riders – the group most affected by pollution – the interaction term between bonuses and pollution is indistinguishable from zero. This suggests that pollution hampers physical performance, likely through increased fatigue, in a way that financial incentives cannot easily counteract.

The results for accidents (Columns (7)–(9)) further indicate that the presence of bonuses under high pollution levels may not benefit either workers or firms. While economic incentives reduce the likelihood of accidents in the absence of pollution (see also 5.3), they increase it as pollution rises, particularly for (e-)bike riders. The greater effort induced by bonuses may backfire when riders experience the physical consequences of exposure to pollution. In other words, by incentivizing riders to work when their conditions are impaired, bonuses may increase their vulnerability to the adverse effects of poor air quality.

A potential caveat to the causal interpretation of these estimates is that the company's decision to introduce monetary incentives may be influenced by observed productivity or demand. For instance, if bonuses are implemented in response to declining productivity, this could create a spurious negative correlation between bonuses and performance, biasing the estimated effects downward. Conversely, if bonuses are introduced during periods of unexpectedly high demand, the direction of bias becomes less predictable. According to the company, however, bonuses are primarily introduced to increase productivity when the *predicted* demand is high (e.g., on weekends or during the summer months). Importantly, these decisions are not based on real-time demand fluctuations, but are instead planned in advance on the basis of the company's forecasts of expected demand in a given city and period. Therefore, controlling for day-of-week, seasonality, and city fixed effects – variables that are likely used in the firm's internal demand forecasting – should be sufficient to address potential endogeneity. In support of this, in Section C of the Appendix, we show that in our preferred specification, which includes a rich set of time and municipality fixed effects, bonuses are not significantly associated with *actual* demand levels. This evidence substantially mitigates concerns about the endogeneity of monetary incentives and reinforces the causal interpretation of the estimated bonus effects.

The results presented in this section suggest that air pollution may or may not induce workers to be absent from work, depending on their incentives to attend work. Hence, it is reasonable to expect that more financially constrained workers are less likely to respond to air pollution through higher absenteeism, as the stakes are always higher for this category. Since we lack explicit information on the financial conditions of riders, we test for this possibility by investigating possible heterogeneous effects of air pollution for foreign-born and native workers. There are a series of reasons to believe that foreign riders are more likely to have their food delivery job as their main source of income. For instance, foreign workers are significantly older and more likely to have a full-time work contract. In Figure 3, we plot the estimated effects of air pollution on the main outcomes of interest for foreign and native riders, computed in separate regressions. We find that absenteeism for native workers is substantially more responsive to air pollution, with the estimated effect of air pollution on absences indistinguishable from zero for foreign riders.

Figure 3: Heterogeneous Effects: Coefficient Plot




This figure presents 2SLS estimates of the effect of air pollution on rider absences, delivery speed, and accidents for foreign-born and native workers in separate regressions. $PM_{2.5}$ is instrumented using IBLH. The analysis is restricted to the subset of riders for whom demographic information is available (2,981 riders). All regressions include the full set of controls and fixed effects used in the main specification. Dots represent point estimates, and lines indicate 90% confidence intervals.

## 7.2 Workers' Compensation on the Intensive Margin

In this section, we exploit the unique level of detail in our data to investigate whether workers compensate for their colleagues' absences and/or their own productivity losses by increasing their labor supply on the intensive margin. Specifically, within the limits imposed by their scheduled work shifts, workers may compensate for their reduced productivity due to air pollution along two dimensions that we can directly measure and examine using our dataset: first, by taking on *marginal* deliveries, i.e., orders assigned to them toward the end of their shift; second, by taking shorter breaks between deliveries, i.e., reducing their order acceptance time.

There are two main reasons why we might expect workers to increase their labor supply when pollution levels are high. First, given the increase in absenteeism and the lack of an effect on demand, the individual workload increases. Second, since the piece-rate component constitutes a substantial share of riders' income, any decrease in productivity would result in income losses unless it is offset by longer working hours. Existing evidence on the wage elasticity of labor supply in settings similar to ours shows that workers increase work time or effort in response to wage decreases. This result is explained by a model of reference-dependent preferences, whereby workers set a daily target for themselves, in terms of income or deliveries, and adjust labor supply accordingly (Goette et al., 2004; Fehr and Goette, 2007; Camerer et al., 1997).

These results contrast with the predictions of a neoclassical model, whereby workers substitute labor supply across days to work more on days when wages and productivity are higher. In addition, labor supply would be negatively correlated with pollution if workers are physically weakened by higher levels of air pollution, reducing their willingness to remain active for extended hours, or encouraging them to take longer breaks, thus exacerbating the overall negative impact of pollution on labor supply.

The presence of these competing predictions highlights the importance of empirically investigating riders' response to higher pollution on the intensive margin of labor supply. The results are presented in Table 9, where we apply our preferred specification to a range of outcomes related to riders' effort during a shift. We report estimates for all riders (Panel A) and by vehicle type (Panels B and C).

Specifically, in Columns (1) and (2), we test whether the total hours worked and the number of deliveries completed by riders, respectively, respond to air pollution. Column (3) investigates the average acceptance time (i.e., the time elapsed between receiving an order request and accepting the delivery). Column (4) examines the effect of pollution on the total workforce. Finally, in Columns (5) and (6), we investigate cumulative hours and delivery at

Table 9: Effect of Air Pollution on Additional Outcomes

| | *Panel A: All Vehicles* | | | | | |
|---|---|---|---|---|---|---|
| | Workers' output | | | Total output | | |
| | Hours Worked | Daily Deliveries | Acceptance Time | Tot Day Workers | Tot Day Hours Worked | Tot Day Deliveries |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| PM25 (SD) | 0.0509** | 0.0321 | 0.0872 | -1.1183* | -2.0446 | -5.4498 |
| | (0.0223) | (0.0303) | (0.2141) | (0.6333) | (1.7610) | (3.5228) |
| N cells | 34575 | 34575 | 34575 | 34575 | 34575 | 34575 |
| N observations | 1116000 | 1116000 | 6905934 | 34575 | 34575 | 34575 |
| Mean dep. | 4.36 | 6.57 | 24.13 | 64.38 | 280.69 | 422.79 |
| First-stage F | 198.71 | 198.71 | 206.94 | 283.59 | 283.59 | 283.59 |
| Weights | Workers | Workers | Orders | None | None | None |
| | *Panel B: (E-)Bike* | | | | | |
| | Hours Worked | Daily Deliveries | Acceptance Time | Tot Day Workers | Tot Day Hours Worked | Tot Day Deliveries |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| PM25 (SD) | 0.0593** | 0.0360 | 0.2034 | -1.9005 | -3.0599 | -8.8864 |
| | (0.0222) | (0.0314) | (0.1795) | (1.1151) | (2.9730) | (6.1243) |
| N cells | 17329 | 17329 | 17329 | 17329 | 17329 | 17329 |
| N observations | 770611 | 770611 | 4687985 | 17329 | 17329 | 17329 |
| Mean dep. | 4.28 | 6.45 | 24.69 | 44.47 | 190.32 | 286.83 |
| First-stage F | 291.13 | 291.13 | 298.7 | 285.32 | 285.32 | 285.32 |
| Weights | Workers | Workers | Orders | None | None | None |
| | *Panel C: Scooter* | | | | | |
| | Hours Worked | Daily Deliveries | Acceptance Time | Tot Day Workers | Tot Day Hours Worked | Tot Day Deliveries |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| PM25 (SD) | 0.0259 | 0.0173 | -0.2458 | -0.3309 | -1.0104 | -1.9666 |
| | (0.0367) | (0.0416) | (0.3793) | (0.2755) | (1.1395) | (1.8185) |
| N cells | 17246 | 17246 | 17246 | 17246 | 17246 | 17246 |
| N observations | 345389 | 345389 | 2217949 | 17246 | 17246 | 17246 |
| Mean dep. | 4.54 | 6.83 | 22.96 | 20.03 | 90.91 | 136.77 |
| First-stage F | 129.89 | 129.89 | 133.25 | 281.4 | 281.4 | 281.4 |
| Weights | Workers | Workers | Orders | None | None | None |
| Mun FE | Y | Y | Y | Y | Y | Y |
| Time FE | Y | Y | Y | Y | Y | Y |
| Individual Residuals | Y | Y | Y | Y | Y | Y |
| Weather | Y | Y | Y | Y | Y | Y |

*Notes.* This table reports the estimated effect of $PM_{2.5}$ concentrations on various measures of workers labor supply and output. Columns (1) to (3) report rider-level outcomes: total hours worked, number of deliveries completed, and average acceptance time (in seconds). Column (4) reports the number of active riders per city-day. Columns (5) and (6) aggregate total hours worked and total number of deliveries completed at the city-day level. Each panel reports results separately for all vehicles (Panel A), (e-)bike riders (Panel B), and scooter riders (Panel C). All regressions report 2SLS estimates using the IBLH as an instrument for $PM_{2.5}$. All regressions include fixed effects for city-by-vehicle, monthly date-by-vehicle and day-of-week, along with flexible weather controls. Regression weights reflect the unit of analysis: observations are weighted by the corresponding number of workers in Columns (1) and (2), by the corresponding number of orders in Column (3), and not weighted in Columns (5) and (6). Standard errors are clustered at the city level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

the municipality-day level (i.e., we replicate the analysis in Columns (1) and (2) looking at municipality aggregates instead of worker-level aggregates) to investigate the net effect on total production.

The results in Column (1) indicate that riders who show up for their shifts work longer hours when pollution is higher. This effect is driven by (e-)bike riders; for scooter riders, the estimated effect is smaller and not statistically significant. Hence, the increase in hours worked appears limited to those who experience a productivity loss. These results suggests that riders are not increasing their labor supply to compensate for absent colleagues (which would imply a similar response among scooter riders), but rather to offset their own reduced productivity. Specifically, we estimate a 1.39% increase in hours worked for (e-)bike riders, which is not too far from the observed decline in productivity for this group. The results in Column (2) suggest that the increase in hours worked fully compensates for the productivity decline: the net effect on the total number of deliveries completed is small and statistically insignificant. These results are consistent with workers having set themselves a target in terms of the number of deliveries in a shift, and increasing work time to reach that target on days when pollution slows them down.

We do not observe any significant change in acceptance time (Column (3)), suggesting that workers do not offset lower productivity by shortening their breaks.[15] This result is plausible, given that the average acceptance time is only 24 seconds, with more than 90% of orders accepted within one minute. As such, there is limited room for meaningful adjustment in this dimension.

Finally, when we examine outcomes at the municipality-day level – total number of riders (Column 4), total hours worked (Column 5), and total deliveries completed (Column 6) – we observe nonnegligible (although imprecisely measured) reductions in all three measures. For all groups, the point estimates of the reduction in the total workforce are perfectly compatible

[15] In this setting, workers are assigned deliveries directly by the company and are required to accept them. Hence, longer acceptance time does not imply the risk of losing the delivery.

with the estimated increases in absences, suggesting that the company does not anticipate the increased absenteeism, and thus does not compensate for these absences by scheduling more workers. Although only the reduction in the total workforce is statistically significant at conventional levels, the point estimates are economically meaningful and consistent with our earlier findings: riders compensate for their own productivity losses, but not for their colleagues' absences, resulting in a net decline in total daily output ($p = 0.135$).

### 7.3 Dynamic Effect

In this section, we examine the dynamic relationship between air quality and our three main outcomes of interest: absences, delivery speed, and accidents. To do so, we extend our preferred specification by including one lead and two lags of $PM_{2.5}$, which we instrument with the corresponding leads and lags of IBLH. To ensure consistency, we also include leads and lags of the control variables (temperature, precipitation, wind speed, and monetary incentives). In addition to strengthening the causal interpretation of our estimates, this test may also shed light on the dynamic effect of air pollution.

The results are summarized in Figure 4. The positive and negative associations between air pollution and absences and productivity discussed in Section 5 mostly appear to be contemporaneous and short-lived. Although not statistically significant, the association between absences and air pollution on the previous day is comparable in magnitude to the contemporaneous relationship between absences and same-day pollution. This pattern suggests that prior-day exposure may influence attendance decisions, which is more consistent with a health-based mechanism than with riders strategically avoiding excessive exposure to air pollution. By contrast, if absences were driven *exclusively* by avoidance behavior, they should respond primarily to same-day pollution, since prior-day pollution exposure cannot be avoided.[16] This is not entirely surprising given that our identification relies on short-

[16]Estimates for other lags and leads are not statistically significant, with the exception of a small positive association between delivery speed in $t$ and air quality in $t+1$, likely due to collinearity

term fluctuations in atmospheric conditions, which are largely unobservable to workers and therefore unlikely to be anticipated. Overall, the dynamic profile of the estimated effects, together with the nature of the identifying variation, suggests that the observed increase in absenteeism is more likely a direct consequence of health deterioration among workers rather than a conscious attempt by riders to avoid excessive exposure to air pollution.

Unlike previous studies that have found temporal reallocation of labor in response to pollution (Hoffmann and Rud, 2024), we do not detect evidence of compensatory behavior, such as reduced absenteeism, in the days following high pollution exposure. This different result may be due to the fact that riders, whose shifts are scheduled in advance, enjoy less flexibility in adjusting their work hours than self-employed workers.

Finally, when we examine accident rates, we observe a positive and statistically significant association between accidents in $t$ and pollution in $t-1$. This may suggest some delayed effects of pollution on safety and support the health-based channel behind the effect of pollution on absences.

Although the limited statistical precision and the high degree of collinearity between pollution concentrations in consecutive days suggest that caution should be taken when interpreting these results, these estimates point toward a contemporaneous and short-lived effect of PM on all outcomes, with outcomes responding to same-day or, at most, previous-day exposure.

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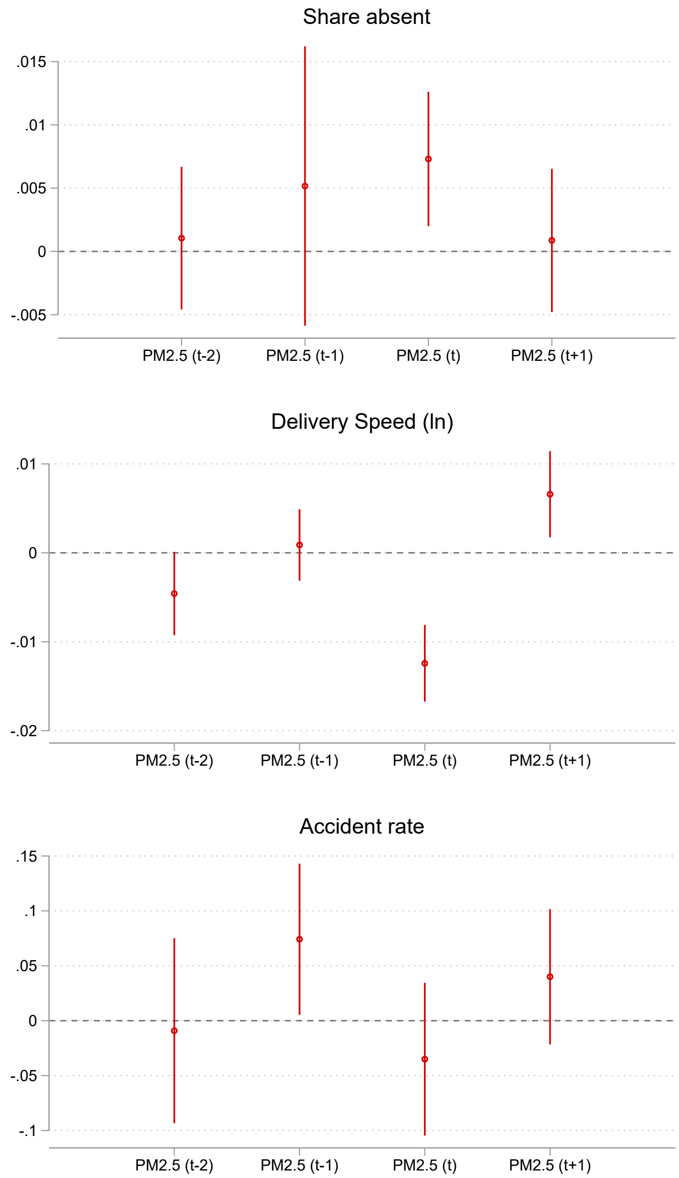
across adjacent pollution measures.

Figure 4: Dynamic Effects




This figure shows the dynamic effects of air pollution on absenteeism, delivery speed, and accidents, using 2SLS estimates from our preferred specification. It plots the estimated coefficients for the association between outcomes measured on day $t$ and $PM_{2.5}$ levels from day $t-2$ to $t+1$. For delivery speed, the analysis is restricted to (e-)bike riders. Dots represent point estimates; lines indicate 90% confidence intervals.

# 8 Concluding Remarks

This paper investigates the impact of air pollution on the health, safety, and productivity of food delivery riders. We leverage unique high-granularity data from *Just Eat*, which cover over 7 million deliveries across 24 Italian cities between June 2021 and June 2023. Using an instrumental variable strategy based on the IBLH, we identify the causal effects of fluctuations in $PM_{2.5}$ on absenteeism, delivery speed, and accident rates.

We find that a one-standard-deviation increase in $PM_{2.5}$ (10.7 $\mu g/m^3$) leads to a 1.21 percentage point increase in rider absences, or 6.6% relative to the mean. Among (e-)bike riders, pollution reduces delivery speed by 0.7% and increases the likelihood of accidents by 4.3 per 10,000 shifts. No significant effects are detected for scooter riders. Taken together, these results highlight the role of physical effort in shaping the adverse effects of pollution on outdoor workers in urban environments.

As previously discussed, this is the first study to jointly assess the impact of air pollution on both workers' absenteeism and their productivity, enabling a direct comparison of the relative importance of these two channels in shaping the overall effect of pollution on total output. According to our estimates, a 1-SD increase in air pollution reduces the effective workforce by 1.4% and lowers productivity by 0.4%.[17] In the absence of any compensatory behavior on the intensive margin, this would lead to a total output loss of 1.8%, with absenteeism accounting for 78% of this reduction.[18]

Our study is also the first to investigate the behavioral response of workers on the intensive margin. Our results indicate that workers offset declines in individual productivity by increasing their working time, such that the net reduction in output – measured by the total number of completed deliveries – amounts to 1.3%, perfectly aligning with the contraction in workforce size. This suggests that, in our setting, the impact of air pollution on produc-

[17] Assuming no effect for the 33% of riders using motor scooters.

[18] For (e-)bike riders, our estimates suggest that a 1-SD increase in pollution leads to a 1.5% reduction in the workforce, a 0.7% reduction in productivity, and a 2.2% reduction in production, with increased absences responsible for 68% of this decrease.

tivity operates almost entirely through absenteeism, while the direct productivity effect is relatively minor and, in a setting where a substantial share of workers' pay is output-related, fully offset by workers' compensating behavior. This behavioral pattern is consistent with workers having a daily target in terms of number of deliveries, and adjusting their work time on the margin to reach it when air pollution negatively affects their speed. Although the specific characteristics of our study population warrant caution in generalizing these estimates to other occupations or labor markets, our findings offer broader insight into the relative contributions of absenteeism and productivity losses to the economic cost of pollution.

Our results indicate that pollution causes a deterioration in workers' well-being through multiple channels. First, given the importance of the variable pay, increased absenteeism leads to a significant income loss – a loss that, in this context, is not offset on subsequent days. Second, income loss is only the visible part of the broader costs of air pollution in terms of workers' well-being. In fact, absenteeism is at least partly driven by deteriorating health, which is a cost per se. Furthermore, some groups (e.g., foreign workers) may be less able to take time off because of tighter financial constraints and suffer adverse health effects from exposure to pollution, even if this does not immediately impact their absences and their income. Moreover, when workers compensate for lost productivity by working longer hours, this requires increased effort and comes at the expense of reduced leisure time. Finally, air pollution exposure undermines well-being by increasing the likelihood of workplace accidents.

Our analysis also provides valuable insights into how monetary incentives can mitigate the adverse effects of pollution. While financial bonuses effectively reduce the effect of air pollution on absenteeism, they fail to offset the productivity slowdown caused by pollution for (e-)bike riders. These findings suggest that, while incentives can mitigate the effect of air pollution on absences, they are less effective at counteracting the physical strain and fatigue induced by prolonged exposure to poor air quality. Moreover, economic incentives have unintended negative consequences on the risk of accidents, when applied on high-pollution days. This suggests that economic incentives may incentivize riders to work even when their physical and cognitive conditions are impaired by poor air quality, increasing their vulnerability to the adverse effects of pollution.

These findings have important policy implications. First, they emphasize the need to strengthen protective measures for workers who face constant exposure to environmental hazards, and vehicle emissions in particular. Stricter emission standards and the promotion of cleaner transportation options could significantly enhance the working conditions of delivery riders and other vulnerable labor groups. Employers and policy-makers could also consider providing safety equipment, such as air filtration masks, and implementing more frequent rest breaks to help mitigate the adverse health and performance impacts of pollution.

Second, our results show that financial incentives can be limited and even risky when pollution is high. This calls for long-term policies to improve urban air quality through stricter emission controls.

Finally, the heterogeneous effects observed across vehicle types point to the importance of tailoring policy interventions to the specific working conditions and physical demands of different groups of workers. (E-)bike riders, who exert greater physical effort, appear more vulnerable to pollution effects and may require targeted support measures. By accounting for these differences, policy-makers can design more effective strategies to safeguard worker health and maintain productivity.

While our findings offer novel insights into the multiple ways in which air pollution affects workers' productivity and well-being, some limitations are worth noting. First, although our empirical strategy is well-suited for capturing the effects of short-term fluctuations in air quality, it does not allow us to assess the consequences of long-term exposure.

Second, as with most observational studies, we lack data on individual exposure levels and on possible defensive behaviors. Our estimates therefore reflect the effects of changes in average air quality across areas, not the biological impacts of personal exposure or the effectiveness of mitigation strategies such as wearing masks. While this limits our ability to assess health mechanisms directly, it also makes our results particularly relevant for policy, which typically targets ambient air quality rather than individual exposure.

Finally, the prevalence of young male workers in our sample restricts the scope for heterogeneous effects analysis to the comparison of riders using different vehicles and between native and foreign-born individuals, partially limiting the general validity of our findings for more heterogeneous workers' populations in terms of gender and age. Further research should aim to address these limitations.

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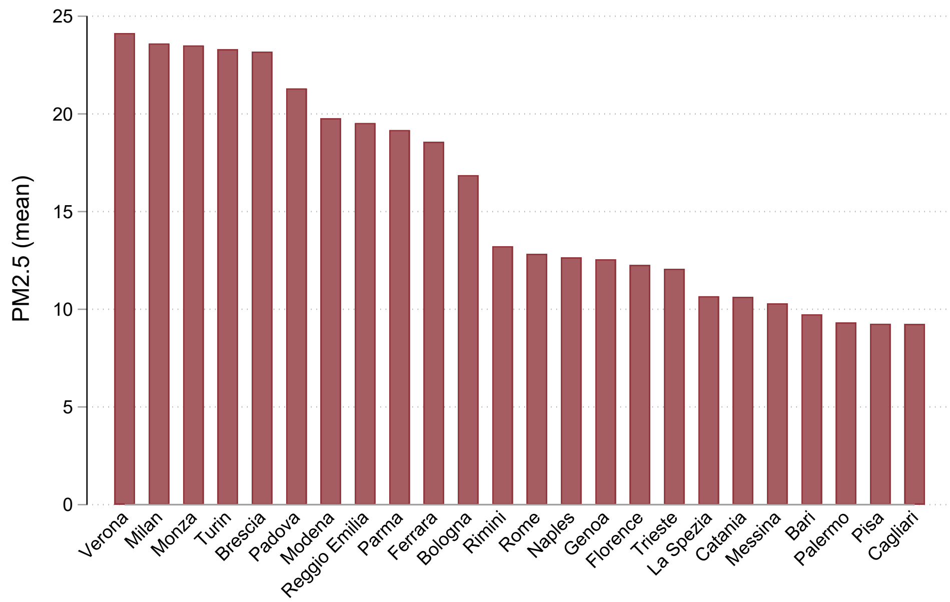
# A Appendix Figures

Figure A.1: Geographical distribution of cities in the sample

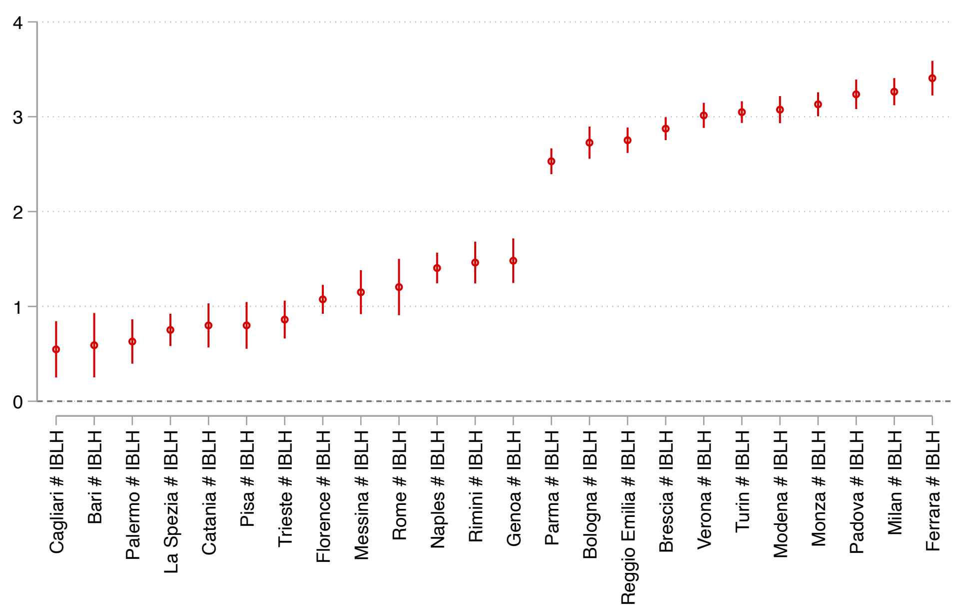
The figure displays the geographical distribution of cities in Italy where *Just Eat* operated during the analysis period. Each point represents a city included in our dataset.

Figure A.2: Average PM 2.5 by City



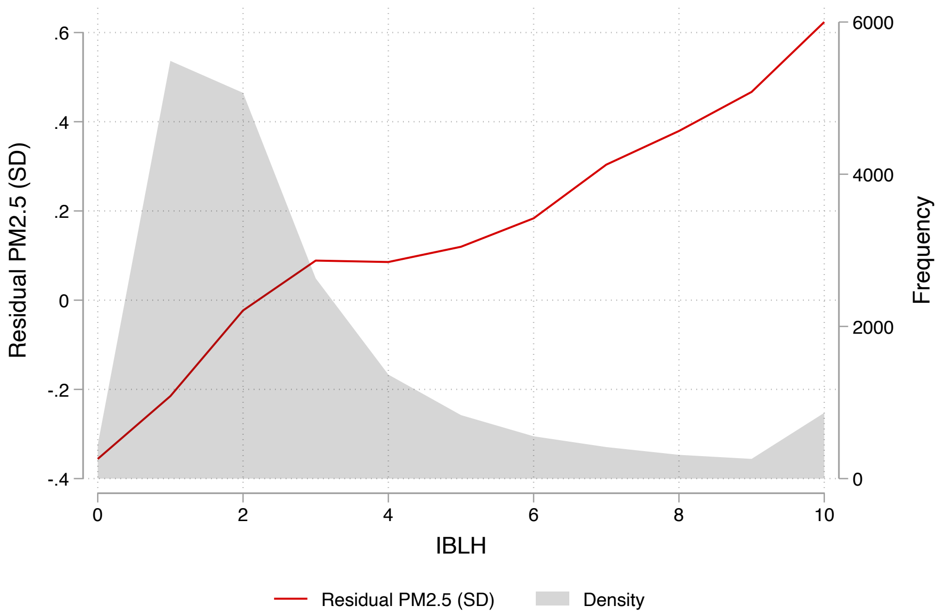

The figure shows the distribution of average daily $PM_{2.5}$ concentrations across the 24 cities in the sample. Each bar represents the mean pollution level for a given city over the study period.

Figure A.3: IBLH and $PM_{2.5}$: First-Stage Estimates by City



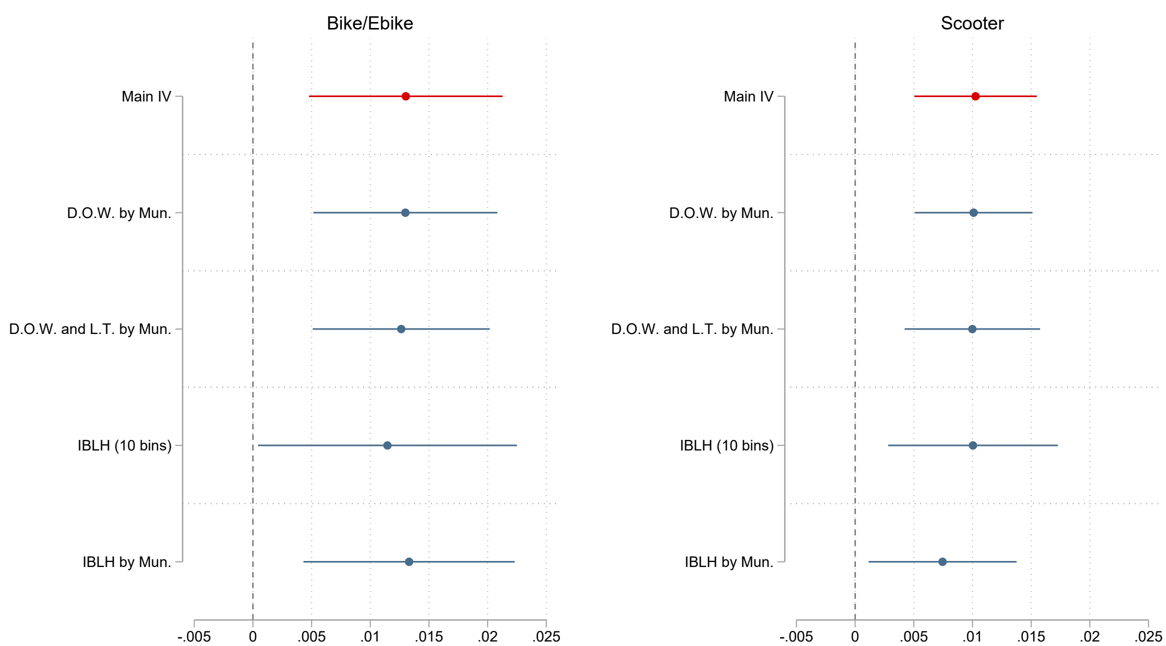

The figure displays estimated coefficients and the associated 90% confidence intervals from a pooled regression of $PM_{2.5}$ concentration on the interaction between municipality-level fixed-effects and the inverse planetary boundary layer height (IBLH). The regression includes city and time fixed effects (monthly date and day-of-week) as well as weather controls: daily average temperature (20 bins), wind speed, and precipitation (mm).

Figure A.4: First Stage: Residuals Plot



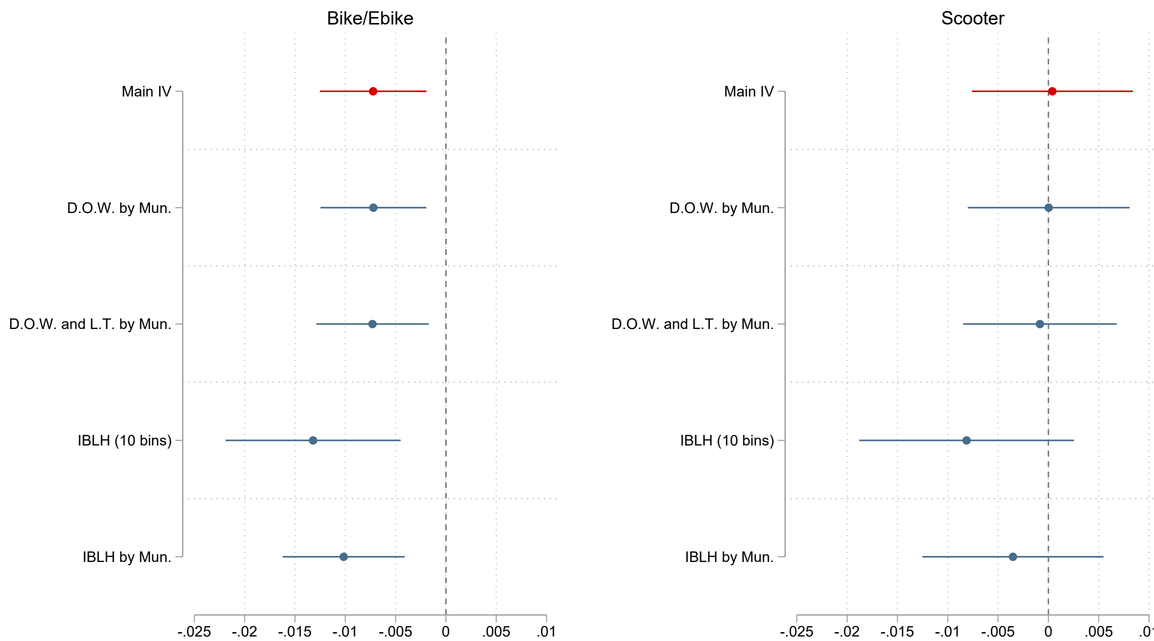

The figure shows the relationship between the inverse planetary boundary layer height (IBLH) binned at its integer values and the average values of the residual $PM_{2.5}$ concentrations computed using our most saturated specification. The gray area represents the number of observations in the corresponding bin.

Figure A.5: Different model specifications: Share Absent



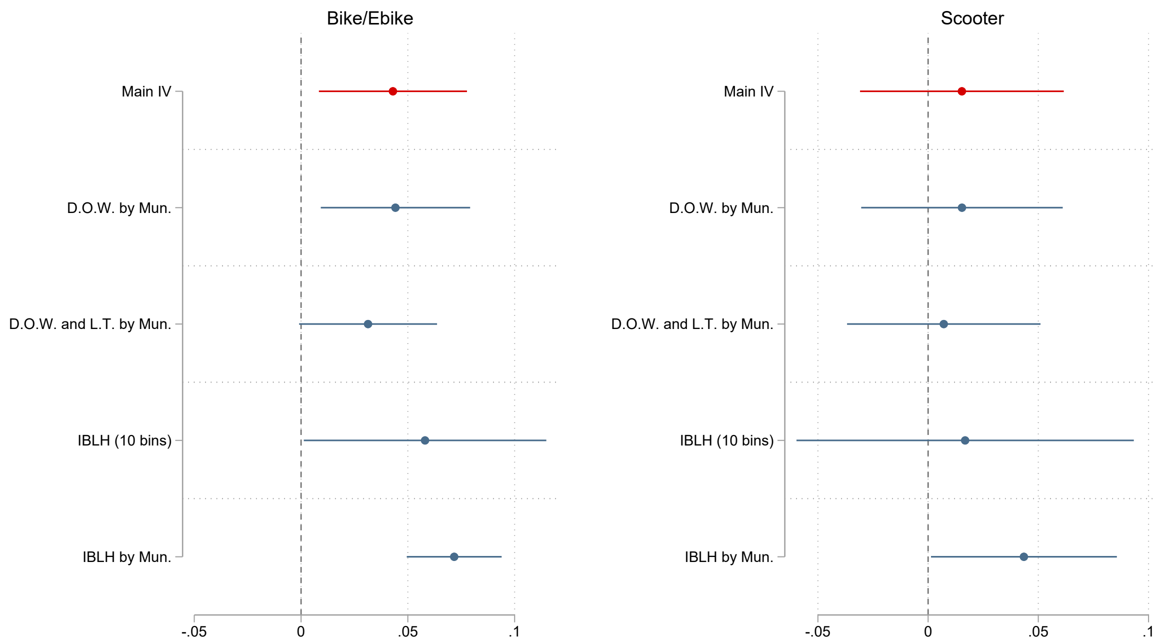

This figure reports the estimated effect of air pollution on riders' absences across increasingly saturated specifications. *Main IV* corresponds to our preferred 2SLS specification. *D.O.W. by Mun.* adds interactions between day-of-week and municipality fixed effects, while *D.O.W. and L.T. by Mun.* further includes municipality-specific linear time trends. *IBLH (10 bins)* replaces the continuous instrument with a binned version based on the deciles of the IBLH distribution. *IBLH by Mun.* interacts the continuous IBLH instrument with municipality fixed effects. Dots represent point estimates; lines indicate 90% confidence intervals.

Figure A.6: Different model specifications: Delivery Speed



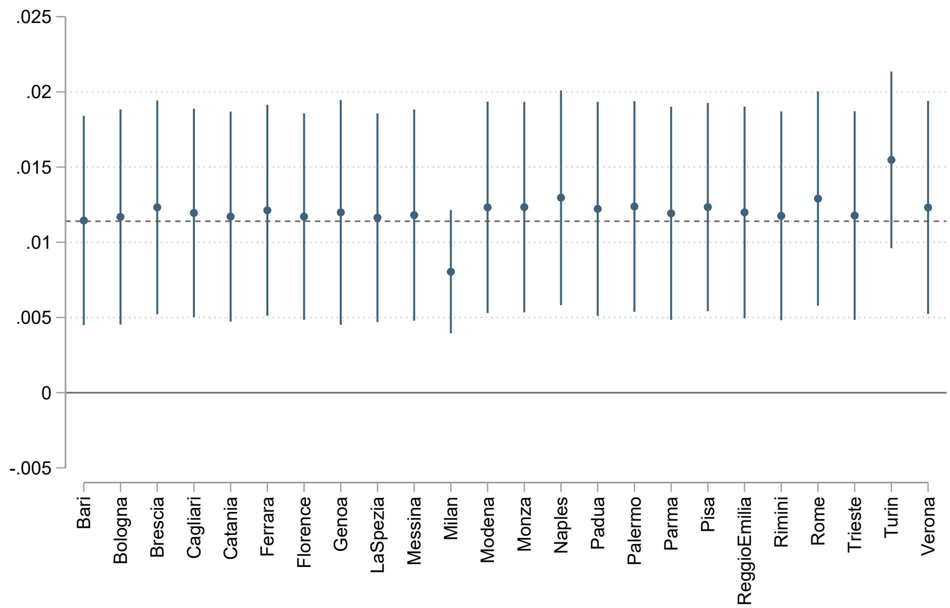

This figure reports the estimated effect of air pollution on riders' speed across increasingly saturated specifications. *Main IV* corresponds to our preferred 2SLS specification. *D.O.W. by Mun.* adds interactions between day-of-week and municipality fixed effects, while *D.O.W. and L.T. by Mun.* further includes municipality-specific linear time trends. *IBLH (10 bins)* replaces the continuous instrument with a binned version based on the deciles of the IBLH distribution. *IBLH by Mun.* interacts the continuous IBLH instrument with municipality fixed effects. Dots represent point estimates; lines indicate 90% confidence intervals.

Figure A.7: Different model specifications: Accident Rate



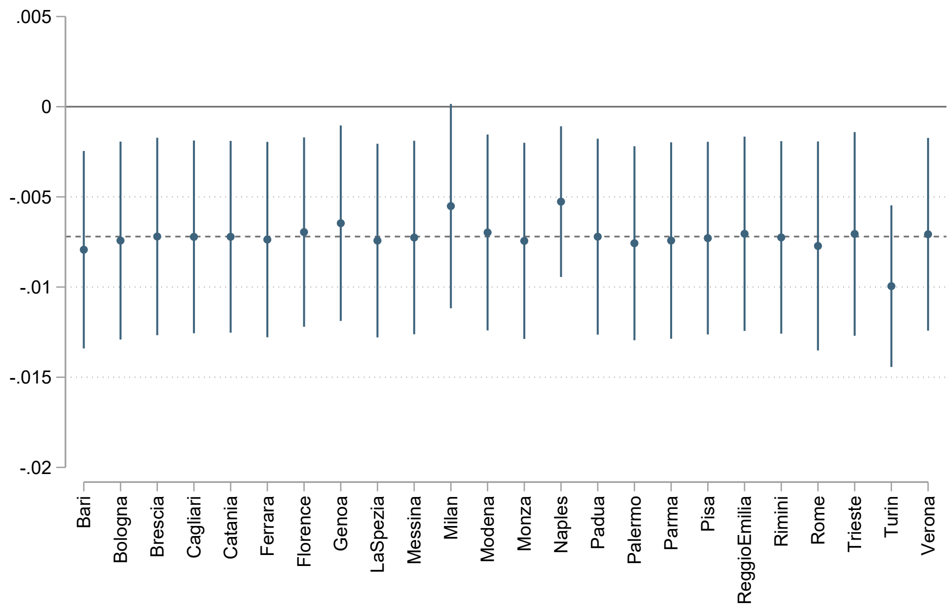

This figure reports the estimated effect of air pollution on riders' accidents across increasingly saturated specifications. *Main IV* corresponds to our preferred 2SLS specification. *D.O.W. by Mun.* adds interactions between day-of-week and municipality fixed effects, while *D.O.W. and L.T. by Mun.* further includes municipality-specific linear time trends. *IBLH (10 bins)* replaces the continuous instrument with a binned version based on the deciles of the IBLH distribution. *IBLH by Mun.* interacts the continuous IBLH instrument with municipality fixed effects. Dots represent point estimates; lines indicate 90% confidence intervals.

Figure A.8: Leave-One-Out Analysis: Share Absent



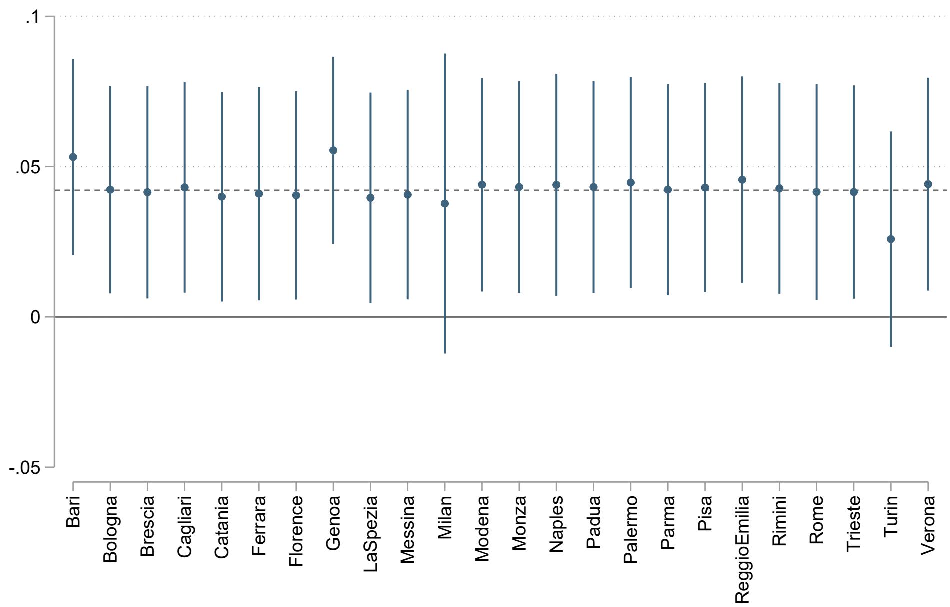

This figure presents a leave-one-out sensitivity analysis of the estimated effect of air pollution on rider absences. We iteratively re-estimate our preferred 2SLS specification (Column (5), Table 4) excluding one municipality at a time. Each dot represents the estimated coefficient when one city is omitted, with the corresponding city indicated on the horizontal axis. Vertical lines denote 90% confidence intervals. The dashed line marks the baseline estimate from the full sample.

Figure A.9: Leave-One-Out Analysis: Delivery Speed




This figure presents a leave-one-out sensitivity analysis of the estimated effect of air pollution on rider speed. We iteratively re-estimate our preferred 2SLS specification (Column (5), Table 6) excluding one municipality at a time. The analysis is restricted to riders using (e-)bikes. Each dot represents the estimated coefficient when one city is omitted, with the corresponding city indicated on the horizontal axis. Vertical lines denote 90% confidence intervals. The dashed line marks the baseline estimate from the full sample.

Figure A.10: Leave-One-Out Analysis: Accident Rate




This figure presents a leave-one-out sensitivity analysis of the estimated effect of air pollution on accidents. We iteratively re-estimate our preferred 2SLS specification (Column (5), Table 7) excluding one municipality at a time. The analysis is restricted to riders using (e-)bikes. Each dot represents the estimated coefficient when one city is omitted, with the corresponding city indicated on the horizontal axis. Vertical lines denote 90% confidence intervals. The dashed line marks the baseline estimate from the full sample.

# B Appendix Tables

Table A.1: Replication of main results on individual data

| | All (1) | (E-)Bike (2) | Motor (3) |
|---|---|---|---|
| | *Panel A: Absent (0/1)* | | |
| PM25 (SD) | 0.0122*** | 0.0133** | 0.0099*** |
| | (0.0040) | (0.0048) | (0.0031) |
| Rain (mm) | 0.0014*** | 0.0015*** | 0.0011*** |
| | (0.0002) | (0.0003) | (0.0002) |
| bonus | -0.0110*** | -0.0156*** | -0.0037 |
| | (0.0030) | (0.0043) | (0.0040) |
| Observations | 1,665,727 | 1,085,280 | 580,447 |
| | *Panel B: Speed (ln)* | | |
| PM25 (SD) | -0.0051 | -0.0069* | -0.0003 |
| | (0.0037) | (0.0035) | (0.0052) |
| Rain (mm) | -0.0019*** | -0.0018*** | -0.0021*** |
| | (0.0001) | (0.0001) | (0.0001) |
| bonus | 0.0689*** | 0.0633*** | 0.0819*** |
| | (0.0156) | (0.0171) | (0.0128) |
| Observations | 6,738,898 | 4,571,487 | 2,167,411 |
| | *Panel C: Accidents* | | |
| PM25 (SD) | 0.0418* | 0.0512** | 0.0168 |
| | (0.0208) | (0.0244) | (0.0289) |
| Rain (mm) | 0.0103*** | 0.0076*** | 0.0142*** |
| | (0.0017) | (0.0025) | (0.0020) |
| bonus | -0.1048** | -0.1445*** | -0.0464 |
| | (0.0408) | (0.0506) | (0.0341) |
| Observations | 884,629 | 558,712 | 325,917 |

Notes. This table reports the 2SLS estimated of the effect of air pollution on rider absences, on delivery speed, and on accidents, using individual-level data instead of municipality-day aggregate measures. In Panel A, the unit of observation is a rider-shift, the dependent variable takes value 1 if the rider was absent for that shift. In Panel B, the unit of observation is a rider-order, the dependent variable is the natural logarithm of the delivery speed for in that order. In panel C, the unit of observation is a rider-shift, the dependent is the number of accidents reported by the rider for that shift. PM25 is instrumented with IBLH. All regressions include fixed effects for rider-by-vehicle, municipality-by-vehicle, monthly date-by-vehicle, and day-of-week, and weather controls for daily average temperature (20 bins), wind speed, and precipitation (mm). *Bonus* is a dummy equal to one on days when monetary incentives were in place in a given city. Standard errors are clustered at the city level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.2: Effect of Air Pollution on Riders' Outcomes - Wild Bootstrap

| | Share Absent | | | Delivery Speed (ln) | | | Accident Rate | | |
|---|---|---|---|---|---|---|---|---|---|
| | All | (E-)Bike | Scooter | All | (E-)Bike | Scooter | All | (E-)Bike | Scooter |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| PM25 (SD) | 0.0121*** | 0.0130** | 0.0103*** | -0.0051 | -0.0072** | 0.0004 | 0.0361** | 0.0430** | 0.0153 |
| | (0.0040) | (0.0048) | (0.0030) | (0.0032) | (0.0031) | (0.0047) | (0.0170) | (0.0202) | (0.0270) |
| N cells | 32145 | 16071 | 16074 | 34574 | 17328 | 17246 | 25419 | 12708 | 12711 |
| N observations | 1665743 | 1085292 | 580451 | 6905933 | 4687984 | 2217949 | 865076 | 544481 | 320595 |
| Mean dep. | .18 | .19 | .17 | 11.69 | 9.85 | 15.56 | .27 | .29 | .24 |
| Conventional pvalue | .006 | .013 | .003 | .124 | .028 | .933 | .045 | .045 | .575 |
| Bootstrap pvalue | .001 | .002 | .003 | .212 | .072 | .923 | .099 | .137 | .58 |

Notes. This table reports 2SLS estimates of the effect of air pollution on absenteeism, delivery speed, and accident rate, instrumenting $PM_{2.5}$ with the IBLH. For each coefficient, we report both the conventional *p*-value and the *p*-value from a wild bootstrap procedure clustered at the municipality level. All regressions focus on the residualized version of the dependent variable, constructed by subtracting each riders individual-specific average, and include fixed effects for city-by-vehicle, monthly date-by-vehicle, and day-of-week, weather controls (average temperature in 20 bins, wind speed, and precipitation), and a dummy for monetary incentives. N cells refers to the number of day-city-level cells, while N observations reflects the number of individual observations.

# C Appendix: Effect on Demand

While our main analysis documents a robust causal effect of air pollution on delivery outcomes using an instrumental variable (IV) strategy, an important remaining concern is whether pollution also affects customer demand. If pollution leads to a change in food delivery demand, for instance by inducing more people to stay at home, this could indirectly influence our outcomes of interest–particularly delivery volume and speed.

The primary order variable used in our analysis captures only completed (fulfilled) orders and does not reflect latent or unmet demand. To more accurately measure underlying demand, we leverage an alternative indicator provided by *Just Eat*: *potential orders*. This variable aggregates all fulfilled orders, canceled orders (whether by customers or restaurants), and orders lost because of temporary service closures. These closures occur either through *autoclosing*, triggered when demand exceeds available courier capacity, or *manual closing*, implemented during adverse weather conditions for safety reasons.

Table A.3 presents the results. Once we control for weather conditions and the presence of monetary incentives, we find no meaningful relationship between $PM_{2.5}$ and potential orders. The estimated coefficients are very small in relative terms and statistically insignificant, suggesting that air pollution has no discernible effect on customer demand.

These findings reinforce our main interpretation: the observed effects of air pollution on rider absences, delivery speed, and accidents are not mediated by changes in demand but reflect direct effects on workers' health, productivity, and safety.

Additionally, the results help address concerns regarding the potential endogeneity of monetary incentives. Specifically, if bonuses were introduced to increase worker productivity during periods of unusually high demand, this would complicate the interpretation of their estimated effects and their interaction with air pollution (Section 7.1). The results in Table A.3 alleviate this concern by indicating that controlling for time and day of the week is sufficient to ensure that, in our preferred specification, they can be considered exogenous to the level of demand for food delivery.

Table A.3: Effect of Air Pollution on Potential Orders

| | Potential Orders | | |
|---|---|---|---|
| | 2SLS | 2SLS | 2SLS |
| | (1) | (2) | (3) |
| PM25 (SD) | -7.1647* | -5.8341* | -6.0811 |
| | (3.7423) | (3.3780) | (3.6310) |
| Rain | | -0.3054 | -0.3249 |
| | | (0.3598) | (0.3599) |
| Bonus | | | 8.3387 |
| | | | (11.3399) |
| Mun FE | Y | Y | Y |
| Time FE | Y | Y | Y |
| Weather | - | Y | Y |
| Mean dep. | 246.07 | 246.07 | 246.07 |
| First-stage F | 332.51 | 267.15 | 265.07 |

Notes. This table reports the effect of air pollution on potential orders. 2SLS estimates using the Inverse Planetary Boundary Layer Height (IBLH) as an instrument for air pollution. All regressions include city and time fixed effects (monthly date and day-of-week). Weather controls: average temperature (20 bins), wind speed, and precipitation (mm). *Bonus* is a dummy equal to one on days when monetary incentives were in place in a given city. Standard errors are clustered at the city level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.