NBER WORKING PAPER SERIES

JOBS IN THE SMOG:
FIRM LOCATION AND WORKERS' EXPOSURE TO POLLUTION IN AFRICAN CITIES

Vittorio Bassi
Matthew E. Kahn
Nancy Lozano Gracia
Tommaso Porzio
Jeanne Sorin

Working Paper 30536
http://www.nber.org/papers/w30536

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
October 2022, Revised April 2026

We gratefully acknowledge financial support from CEGA, IGC, UKRI, PEDL, and USC. We also acknowledge support from the Pollution Management and Environmental Health Program (PMEH) supported under the World Bank's TF0A3415. The PMEH program focuses on providing technical assistance to countries, facilitating pollution management, promoting public awareness, and helping them reduce the negative effects of pollution on health. We thank Bjoern Brey and Tanner Regan for insightful discussions. We also thank Patrick Baylis, Johannes Boehm, Robin Burgess, Victor Couture, Giacomo de Giorgi, Eyal Frank, Simon Franklin, Teevrat Garg, Ed Glaeser, Michael Greenstone, Nina Harari, Jonas Hjort, Koichiro Ito, Kelsey Jack, Namrata Kala, Ryan Kellogg, Gabriel Kreindler, Rob Metcalfe, Melanie Morten, Paulina Oliva, Juan Pablo Rud, Adam Storygard and numerous seminar and conference participants for valuable comments. Kasey Chatterji-Len, Jiong Gao, Jung Hyuk Lee and Leire Sarasola provided excellent research assistance. We also thank everyone at BRAC Uganda and AirQo who made this project possible, in particular Engineer Bainomugisha, Raffaela Muoio, Deo Okure, and Esau Tugume. Ethical approval was received from the Mildmay Research Ethics Committee of Uganda (1106-2018) and USC (UP-20-00923). The RCT is registered on the AEA Registry (AEARCTR-0014162). The findings, interpretations, and conclusions expressed in this paper are entirely those of the authors. They do not necessarily represent the views of the International Bank for Reconstruction and Development/World Bank and its affiliated organizations, or those of the Executive Directors of the World Bank or the governments they represent. We acknowledge the use of Refine.Ink for proof-reading. All errors are our own. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

NBER working papers are circulated for discussion and comment purposes. They have not been peer-reviewed or been subject to the review by the NBER Board of Directors that accompanies official NBER publications.

© 2022 by Vittorio Bassi, Matthew E. Kahn, Nancy Lozano Gracia, Tommaso Porzio, and Jeanne Sorin. All rights reserved. Short sections of text, not to exceed two paragraphs, may be quoted without explicit permission provided that full credit, including © notice, is given to the source.

Jobs in the Smog: Firm Location and Workers' Exposure to Pollution in African Cities
Vittorio Bassi, Matthew E. Kahn, Nancy Lozano Gracia, Tommaso Porzio, and Jeanne Sorin
NBER Working Paper No. 30536
October 2022, Revised April 2026
JEL No. Q4, Q53

ABSTRACT

We show that the organization of production prevalent in Ugandan cities increases workers' exposure to urban pollution. Using new granular spatial data on air pollution and manufacturing firms, we document that small firms cluster along the busiest and most polluted roads because road traffic bundles air pollution with customer access. Even within neighborhoods, cleaner areas exist, yet jobs are in the smog. A spatial equilibrium model rationalizes these patterns, with firms capturing sizable profit gains from polluted locations while workers receive limited compensation for the exposure. Our results imply that the welfare costs of urban air pollution in developing-country cities may be substantially larger than city-level averages suggest.

Vittorio Bassi
University of Southern California
Department of Economics
and NBER
vbassi@usc.edu

Matthew E. Kahn
University of Southern California
Department of Economics
and NBER
kahnme@usc.edu

Nancy Lozano Gracia
The World Bank
nlozano@worldbank.org

Tommaso Porzio
Columbia University
Columbia Business School
and NBER
tommaso.porzio@columbia.edu

Jeanne Sorin
The University of Chicago
jsorin@uchicago.edu

An online appendix is available at http://www.nber.org/data-appendix/w30536

1 Introduction

Cities are engines of economic development. A large literature has shown that urban agglomeration generates demand externalities from the concentration of consumers in dense urban areas, and raises firm productivity and workers' wages through economies of scale, knowledge spillovers, and better matching between firms and workers (Combes and Gobillon, 2015b; Duranton and Puga, 2004). The concentration of consumers is especially valuable for producers in developing-country cities, given that production is dominated by small firms relying on foot traffic and face-to-face interactions to access customers (Lagakos, 2016; Vitali, 2025).

The same features that make cities productive can also generate large costs. In developing countries, urban density often goes hand in hand with congestion, strained infrastructure, unplanned urban development, and greater exposure to pollution (Akbar et al., 2023a; Bryan, Glaeser, and Tsivanidis, 2020; Harari, 2020).

In this paper, we document a previously understudied cost of developing-country cities: the spatial organization of production sorts jobs into the smog. We collect new granular spatial data from urban areas in Uganda to show that small manufacturing firms cluster along the busiest and most polluted roads in the city—not despite the pollution, but because of it. The road traffic that generates pollution is the same traffic that delivers customers. As a result, small firms have strong private incentives to locate precisely where air quality is worst, concentrating employment opportunities in the most polluted parts of the city, even though much cleaner areas exist within just a few hundred meters. A simple spatial model shows that these patterns are consistent with firms and workers optimizing in a world where pollution and customer access are bundled together by road traffic. Our results imply that the costs of urban air pollution in developing-country cities may be substantially larger than city-level averages suggest.

To situate our study, we argue that cities in developing countries feature some of the world's highest pollution levels, driven in part by rapid motorization and poor infrastructure that ultimately lead to traffic congestion.[1] Uganda is no exception: Ugandan cities are today on average as polluted as Chinese cities.

We collect geo-coded $PM_{2.5}$ measurements across urban areas of Uganda using both mobile and stationary monitors. This high-frequency data allows us to document street-by-street variation in pollution within the city and to estimate temporal fluctuations within the day. We combine the pollution data with our own geo-coded survey of more than 1,000 manufacturing firms, collecting measures of productivity (profits, managerial ability), location choices, worker wages, and—for both entrepreneurs and workers—questions on adaptation investments, avoid-

[1]For instance, in Uganda, the setting of our study, between 2013 and 2019 over 800,000 vehicles were added to the country's vehicle fleet. Kreindler (2024) documents rising ownership rates of motor-vehicles in India between 2005-2015. Developing countries tend to import old and used vehicles, which further contributes to generating pollution (Davis and Kahn, 2010).

ance behaviors, and awareness of pollution.[2] We also have access to the geo-coded universe of Ugandan roads. To enable the spatial analysis of our data, we divide our sample area in grid cells of 500 meters × 500 meters (following Ahlfeldt et al., 2015, Michaels et al., 2021) and aggregate the $PM_{2.5}$ measurements and road size information at the grid cell level.[3]

The empirical analysis establishes three core results. First, we document large spatial heterogeneity in air pollution within the city: in the average sub-county (which corresponds to a large neighborhood), grid cells with pollution levels comparable to Dhaka in Bangladesh coexist alongside others with levels comparable to Milan in Italy. The more polluted grid cells are those with major roads. These local spatial differences in pollution are driven by road traffic rather than by the firms themselves: pollution peaks at rush hour, not during peak production times, and is unaffected by controlling for the presence of highly polluting firms in the grid cell. We also address potential concerns about the endogenous placement (or size) of roads with respect to pre-existing polluting activities by showing that our results are robust to focusing on semi-urban sub-counties intersected by large roads connecting major city centers. Importantly, this within-neighborhood variation is invisible in standard satellite data, which has too little local variation to detect it.

Second, despite the availability of cleaner nearby locations, we show that firms sort into the most polluted grid cells: within sub-counties, a 1% increase in pollution is associated with a 0.27% increase in firm density. This sorting is confirmed using the universe of firms from the Uganda Census of Business Establishments, which shows the same pattern holds across the entire country.

Third, we ask why jobs are in the smog and find that this is because road traffic bundles pollution exposure with access to customers. We find that grid cells with major roads, hence more pollution, feature significantly higher profits, even controlling for a rich set of observables: that is, there is a large *profit pollution premium*. We find also a *wage pollution premium* for employees, but it is much smaller: workers only get a small share of the benefits from locating on larger roads.[4] We extensively validate the customer-access mechanism: first, firms near larger roads report more customers and higher prices but no better access to intermediate inputs; second, owners identify customer visibility as the most important reason for their location

[2]We use the terms "entrepreneurs", "owner" and "manager" interchangeably in the paper, since in the great majority of firms this is the same person.

[3]Focusing on grid cells of 500 meters × 500 meters is also justified by the fact that emissions for most traffic pollutants decay to background levels within 570 meters (Karner, Eisinger, and Niemeier, 2010).

[4]We report several robustness checks that suggest that the correlation between pollution and profitability reflects a causal relationship rather than the selection of more productive entrepreneurs (and workers) into more polluted areas. The correlation between profitability and pollution raises the question of what generates heterogeneity in location choice, as not all firms locate in the most polluted areas. While proxies for firm productivity do not predict location choice, we find that locating along the major roads entails a longer commute. Preferences over commuting and other accessibility considerations can then be an explanation for why some firms avoid the major roads. We also discuss the role of land market frictions in explaining why land rental prices do not fully adjust to eliminate the profitability effects.

choice; third, using the Uganda Census of Business Establishments, we show that the sorting onto major roads is strongest for firms and sectors where face-to-face interactions matter most. Remarkably, manufacturing firms in Uganda behave like low-skill services in terms of their location choice: since they are small scale and need to sell face-to-face, they locate near busy roads in the same way in which hairdressers do.[5]

We interpret the evidence through a stylized spatial model in which road traffic simultaneously generates pollution and drives customer flows, entrepreneurs choose where to locate their firms trading off profitability against pollution exposure, and workers search for jobs in a frictional labor market with surplus split through Nash bargaining. The model serves three purposes.

First, it shows that the sorting of firms into polluted locations and the coexistence of a large profit pollution premium with a modest wage pollution premium can all be rationalized in a simple spatial equilibrium: when traffic is the primary source of demand and workers' bargaining power and perceived pollution costs are limited, firms sort into polluted areas and capture most of the surplus from locating in high-traffic areas while workers receive only limited compensation for their exposure.

Second, we use the model as a measurement framework to quantify the trade-off embedded in the observed spatial allocation. We compare the benefits and costs for firms and workers from the observed allocation relative to a counterfactual in which firms actively avoid pollution within their sub-county, locating in the least polluted grid cell within 1,000 meters of their current location. This exercise should be interpreted as an accounting exercise, as it holds fixed the local relationship between traffic, pollution, profits, and wages. Relative to this counterfactual, the observed sorting raises average annual profits by \$579 and wages by \$29, at the cost of 1.8 months of lost life expectancy—a trade-off that entrepreneurs strongly prefer under reasonable valuations of health gains, but that is flatter for workers given the much lower wage benefits.[6] Reducing pollution exposure in developing-country cities is thus difficult because entrepreneurs face strong private incentives to locate in the midst of the pollution.[7]

Third, we use the model to discuss the implications for firm relocation policies. Our empirical evidence suggests that traffic is driven by broader urban mobility rather than firms

[5]The negative health consequences of working in polluted areas could in principle be reduced through in-place adaptation. In practice, we show that adaptation investments are very limited and, importantly, are no higher in more polluted areas, though firm owners with higher managerial ability do protect workers more through both equipment and organizational practices.

[6]In these calculations, we assume that relocation does not affect the cost of commuting. This is plausible since the relocation would be within the same sub-county and thus would not entail moving far: for instance, actively avoiding polluted areas would entail a move of only about 400–1,100 meters for the average firm. If anything, as entrepreneurs and workers tend to live farther from large roads, any such relocation away from large roads would likely decrease commuting costs.

[7]Survey evidence and an incentivized information experiment show that firm owners broadly perceive the bundling of pollution with road traffic and profitability, although they tend to underestimate pollution levels near their firm and have significant demand for additional information on pollution when it becomes available.

themselves, and that access to demand plays a key role in generating the productivity gains from locating in more polluted areas. As a result, the health gains and profitability losses from relocating a group of firms are likely similar to those in the accounting exercise—which helps explain why such policies are likely to encounter significant resistance from entrepreneurs. The model also speaks to how the trade-off between profitability and pollution exposure may evolve over the development process: as economies develop and firms adopt alternative marketing channels and improve logistics, the link between profitability and pollution may weaken. However, the model also highlights the possibility of path dependence in the spatial organization of economic activity. As agglomeration forces strengthen over the course of development, cities may become locked into high-congestion, high-pollution spatial equilibria—not because polluted locations continue to offer greater exogenous demand, but because past concentration itself generates a self-reinforcing productivity advantage.

Related literature. Our results highlight an important welfare cost of the organization of production in developing-country cities: because firms must locate near customers concentrated along major roads, workers end up systematically exposed to high levels of traffic pollution. In doing so, we contribute to three strands of the literature.

First, and most directly, we contribute to a growing literature on the economics of cities in the developing world. This literature has documented the substantial productivity benefits of urban agglomeration—through better firm-worker matching, input sharing, knowledge spillovers, and demand externalities—and debated how well these benefits extend to cities in low-income countries (Bryan, Glaeser, and Tsivanidis, 2020; Duranton, 2015; Duranton and Puga, 2004). A parallel strand has studied the negative externalities of urban density, including congestion, pollution, poor infrastructure and non-compact city shape (Akbar et al., 2023a,b; Bryan, Glaeser, and Tsivanidis, 2020; Harari, 2020). We contribute by documenting a new and distinct cost of the spatial organization of cities in developing countries: the same forces driving firm agglomeration—road traffic—also concentrate pollution exposure on workers. Critically, the mechanism we uncover—firms sorting into polluted areas because pollution is bundled with customer access—is specific to the organization of production in developing-country cities and has no direct counterpart in the rich-country literature, where firms have broader means of accessing customers and do not face the same trade-off. More broadly, we complement recent work showing that spatial sorting within developing-country cities generates large inequalities in access to jobs and public goods (Balboni et al., 2025; Deffebach et al., 2025; Harari, 2024); we add complementary evidence on how the spatial sorting of firms within the city shapes the exposure to pollution of the workers they employ.[8]

[8] A related paper is Gollin, Kirchberger, and Lagakos (2021), who study the role of air pollution measured from satellite data as a determinant of location choice between rural and urban areas in Africa. We contribute by studying the relationship between local pollution and location choices within city neighborhoods.

Second, we contribute to the classic literature on customer access and agglomeration as drivers of firm location (Combes and Gobillon, 2015a; Ellison, Glaeser, and Kerr, 2010; Glaeser and Xiong, 2017; Marshall, 1920). A growing body of work has focused on demand access for small firms in developing countries, highlighting that information frictions are a critical source of inefficiency (Bassi et al., 2024; Jensen and Miller, 2018; Lagakos, 2016; Pelnik, 2025; Startz, 2025) and that managerial and marketing constraints limit access to new markets (Anderson, Chandy, and Zia, 2018; Hjort, Iyer, and Rochambeau, 2020). As a consequence, small firms tend to sell locally and cluster near their customers. Vitali (2025) shows that consumer information frictions are a key driver of firm agglomeration in our same setting in Kampala, comparable in magnitude to supply-side agglomeration economies. We complement this work by showing that one further and previously unrecognized consequence of firms struggling to reach customers at a distance is their systematic exposure to traffic pollution: the need to locate on congested roads to attract consumers imposes a substantial health cost on the workers employed there.[9]

Third, and more broadly, we contribute to a growing literature at the intersection of environmental and development economics studying the determinants of individuals' pollution exposure in lower- and middle-income countries. This literature has examined demand for clean air and adaptation investments by households (Greenstone, Lee, and Sahai, 2021), avoidance through labor supply decisions (Aragon, Miranda, and Oliva, 2017; Hanna and Oliva, 2015; Hoffmann and Rud, 2024), and migration and residential sorting (Chen, Oliva, and Zhang, 2022; Khanna et al., 2025), including the role of transportation networks in facilitating adaptation (Barwick et al., 2024).[10] We contribute by documenting and explaining how firm location choices concentrate workers in the most polluted parts of developing-country cities, making avoidance strategies difficult.[11]

The rest of the paper is organized as follows. Section 2 discusses the context of our study. Section 3 describes the sample and data sources. Section 4 presents the data construction for the empirical analysis. The main results are then presented in Section 5. Section 6 presents the model and its implications for welfare and policy. Section 7 concludes. Additional details

[9] A related literature has shown that firms respond to environmental regulation by sorting *away* from regulated areas (Greenstone, 2002; Levinson, 1996; Wang, Zhang, and Zhang, 2019) and that flood-affected firms move away from flood-prone areas (Balboni, Boehm, and Waseem, 2024). We contribute by showing how the spatial distribution of within-city pollution indirectly affects the location of non-polluting firms in Ugandan cities, as in this context the pollution disamenity is positively correlated with access to customers.

[10] An established literature has studied these topics in high-income countries, focusing on demand for clean air (Chay and Greenstone, 2005; Currie et al., 2015), adaptation and protective investments (Deschenes, Greenstone, and Shapiro, 2017; Ito and Zhang, 2020), as well as migration away from polluted locations, both across and within cities (Banzhaf and Walsh, 2008; Heblich, Trew, and Zylberberg, 2021; Kahn and Walsh, 2015).

[11] More broadly, we speak to the key question in this literature of why the observed marginal willingness to pay for environmental quality may be low in these contexts (Greenstone and Jack, 2015). Our evidence that firms' location choice is driven primarily by profit maximization rather than air quality considerations is consistent with the explanation that at low income levels, marginal increases in income are valued more than marginal increases in environmental quality.

are in the Online Appendix.

2 Air Pollution and Urbanization in Uganda

In this section, we provide context for our study and show the relevance of our setting for studying exposure to air pollution within African cities.

Air pollution levels in Uganda. Uganda features levels of pollution comparable to China and well above the recommendations of the World Health Organization (WHO): average annual $PM_{2.5}$ concentration was 40.8 micrograms per cubic meter (μ/m^3) in 2018 and 29.1 μ/m^3 in 2019, six to eight times higher than the WHO recommended annual average of 5 μ/m^3 (WHO, 2021).[12] Air pollution disproportionately affects urban areas in Uganda, with $PM_{2.5}$ concentrations 40% higher than in rural areas (WHO, 2016). Appendix Figure B1 also shows that: (i) pollution in Uganda has not been decreasing in recent years; (ii) Uganda exhibits pollution levels and trends that are comparable to other African countries such as Nigeria and Ghana.

Urbanization, motorization and pollution emissions. Road traffic is widely recognized as a common source of $PM_{2.5}$. Like other African countries, Uganda has experienced rapid urbanization and motorization in recent decades. The population of Kampala, the capital city, more than doubled since 1990 and had reached over 1.6 million in 2019 (UBOS, 2021). Urbanization in Uganda has been accompanied by a rapid increase in motorization. The road network in Kampala was built in the 1960s for about 100,000 vehicles per day. Today, about 400,000 vehicles per day use these roads (KCCA, 2014). The growth of a second-hand vehicle fleet (see Appendix Figure B2), together with unpaved roads and limited coordinated land use or transport planning, make motorization one of the main sources of pollution in urban Uganda.[13] The issue is acknowledged by Ugandan policy makers, but no comprehensive solution exists yet.[14]

[12]Source: IQAIR (`https://www.iqair.com/us/world-most-polluted-countries`). "PM" stands for particulate matter and "2.5" refers to the size of the particles (2.5 micrometers). Due to their small size, these fine particles pose the greatest risk to health. For additional details see: `https://www.epa.gov/pm-pollution/particulate-matter-pm-basics`.

[13]The Ministry of Works and Transport reports that petrol and diesel vehicles are 15.4 and 16.4 years old on average, respectively (Source: `http://www.airqualityandmobility.org/PCFV/EAC_Workshop/Ugandasinitiativecleanervehicles.pdf`). Kirenga et al. (2015) emphasize the role of unpaved roads in driving up $PM_{2.5}$ concentrations in Kampala and Jinja, two Ugandan cities.

[14]In 2018, a ban on imports of motor vehicles older than 15 years was enacted, significantly lowering the average age of newly registered vehicles, as shown in Appendix Figure B3. While this policy was effective, the average age of newly registered vehicles still remained high at over 7 years in 2018. A Bus Rapid Transit (BRT) project for Kampala, with pre-feasibility studies completed in 2010, is still pending.

3 Sampling Strategy, Data, and Descriptives

The extent to which the high levels of traffic-related air pollution described in Section 2 translate into health impacts ultimately depends on individuals' exposure. Our goal in this paper is to study the role of the spatial organization of production in mediating workers' exposure to pollution in urban Uganda. Towards this goal, we need to build a specific data infrastructure. First, we need data on pollution within cities to document the spatial variation in pollution levels at a granular level. Second, we need data on the road network and on firm location to examine how firm location choices within the city determine exposure to traffic and pollution. Third, we need firm- and worker-level survey data to study the economic benefits and costs associated with different locations, as well as potential adaptation strategies and perceptions of pollution.

3.1 Sampling Strategy

We collected $PM_{2.5}$ measurements and a novel firm survey in a representative sample of urban and semi-urban areas across three of the four macro-regions of Uganda: Central, Western, and Eastern regions. The pollution measurements and the firm survey are both geo-located and were collected in the same areas and at the same time, which allows us to combine them for the analysis.

Our sampling units are sub-counties, which typically correspond to large neighborhoods of a city.[15] A sample of 52 sub-counties in 25 separate districts was randomly extracted for our study, stratifying by population and by whether the sub-county is in the broader Kampala area.[16]

3.2 Pollution Measurements

We create a unique database of $PM_{2.5}$ measures with geo-coordinates and time stamps that we collected in partnership with AirQo.[17]

Stationary and mobile measurements. Pollution measurements come from two distinct types of monitors, which we refer to as *stationary* and *mobile*. The former were attached to fixed locations (e.g., lamp posts) within our sampled sub-counties. The latter were attached to the front of motorcycle taxis (boda-bodas) circulating on the streets within our sampled

[15] For a sense of scale, the median sub-county in our sample spans 4.7 square miles and has 22,500 individuals.

[16] Appendix Figure B4 shows the final sample of sub-counties.

[17] AirQo (https://www.airqo.net/) was founded in 2015 at Makerere University and works to improve air quality data in Uganda. AirQo develops and deploys low-cost air quality monitors across Ugandan cities.

areas.[18]

Our budget allowed us to place 33 separate stationary monitors in distinct sub-counties for a period of roughly 8 months, from January to August 2019, covering 24 out of the 25 districts in our sample. The stationary monitors were active 24 hours a day.[19] The average number of $PM_{2.5}$ measurements by monitor-day-hour is 41 (median 45), for a total of 3,179,575 measurements across all stationary monitors and days in the dataset.

In addition, we used 10 mobile monitors placed on motorcycle taxis for roughly 4 months, from February to May 2019. These mobile monitors were deployed in 32 of our 52 sampled sub-counties. The partner taxi drivers were instructed to keep the monitors on at all times and to drive through all the streets of the sampled sub-counties. The mobile monitors produced an average of 30 (median 31) measurements an hour for a total of 119,011 data points in our sampled sub-counties.[20]

By moving across space, the mobile monitors allow us to measure the spatial variation in pollution at a granular level within the city. By being fixed in one location, stationary monitors allow us to precisely measure the time variation in pollution. In Section 4, we describe how we use both types of measurements in our empirical approach.

Sanity checks and descriptives. In the left panel of Figure 1, we report average $PM_{2.5}$ readings by hour of the day, from both stationary and mobile monitors. The figure shows that: (i) the two types of measurements track each other closely, which reassures us about the quality of our data; (ii) average levels of $PM_{2.5}$ are high in our sample, oscillating between 30-90 μ/m^3, which lines up well with the average of 29.1 and 40.8 $\mu g/m^3$ for Uganda reported by IQAIR in 2018 and 2019, respectively, and mentioned in Section 2;[21] (iii) there is a strong cyclicality in pollution within the day with peaks at rush-hour in both mornings and evenings, which suggests that road traffic is a main source of pollution in these urban areas—something we explore and confirm further in Section 5. This hourly pattern is robust: we reach the same conclusion if we use the stationary or mobile readings, and if we use the average or the median readings, as shown in Appendix Figure B7.[22] While pollution peaks in the morning and evening, average

[18]Appendix Figure B5 shows pictures of a stationary and mobile monitor. Okure et al. (2022) summarizes the technical details of monitors and processes used for data collection.

[19]Stationary monitors were installed close to the ground between 2.5 and 4 meter high to ensure that captured pollution levels are reflective of population exposure.

[20]In those sub-counties where the stationary and mobile monitors overlap, all active mobile monitors were within proximity of a stationary monitor. The median distance between a mobile pollution measurement and the closest stationary monitor is 2.345km and 95% of measurements are within 7km from a stationary monitor.

[21]These numbers are also consistent with measurements of $PM_{2.5}$ in Kampala between 2018 and 2021 by Atuyambe et al. (2024), averaging at 39 $\mu g/m^3$.

[22]Appendix Figure B8 shows that the average $PM_{2.5}$ readings of mobile and stationary monitors in the same sub-county are positively correlated (the correlation is 0.86, significant at the 1% level), which further reassures us about the internal validity of our measurements. Of course, we expect the correlation of the pollution readings from stationary and mobile monitors within sub-counties to be less than one as the mobile monitors

levels of pollution are still much higher than WHO standards even at those times when pollution tends to be lowest, such as in the early afternoon.

3.3 Firm Survey

The second data source is a novel firm survey that we conducted. The survey took place in all our target 52 sub-counties between September 2018 and July 2019 and was implemented by our partner NGO, BRAC. The survey is described in detail in Bassi et al. (2022). Here we summarize the key elements of the sampling and survey design, and then focus on those aspects that were specifically designed for this study.[23] We followed up again with our sample in early 2022 with a phone survey, to collect additional information on entrepreneurs' perceptions of pollution and access to customers, and to run an information experiment. This section describes this additional survey as well.

Firm sampling. Our survey targeted three prominent sectors in manufacturing: carpentry, metal fabrication and grain milling. Together, these sectors cover approximately 33% of manufacturing employment (UBOS, 2011). We conducted a door-to-door listing of all the firms in our three sectors, identifying close to 3,000 firms. For each firm in the listing, we recorded their GPS coordinates, so that we virtually have geo-coded data on the universe of firms in our sampled sub-counties and sectors.[24] We then randomly selected about 1,000 firms from our listing to be included in the initial survey, oversampling firms with five or more employees. In firms selected for the survey, we interviewed the owner and all the employees working on the main product.[25]

Survey design. Our baseline survey was designed to study firm performance and employment, firm location choices, adaptation to pollution and awareness of pollution as a problem, as well as the role of managerial ability.

On *firm performance and employment*, we collected information on revenues, profits, inputs, number of employees, wages, as well as other owner and worker characteristics (e.g., education,

were potentially hundreds of meters away from the stationary monitors at times.

[23] Bassi et al. (2022) study the role of the rental market for mechanization and productivity. The two studies were always intended to produce two independent papers, as reflected in the design of our initial survey, which had separate sections on (i) mechanization and (ii) firm location choice, pollution perceptions and adaptation.

[24] Appendix Figure B6 plots the firms in the listing in one of the study sub-counties.

[25] More precisely, as discussed in Bassi et al. (2022), for each of the three sectors we pre-specified one "core product" commonly produced in that sector (e.g., doors in carpentry). If a firm produced the core product, we interviewed all employees working on that product. If a firm did not produce the core product, we interviewed all employees working on the main product of the firm. Compliance with the survey was high at over 90% and all the results from our survey are appropriately weighted to reflect our sampling strategy. See Bassi et al. (2022) for more details.

age, experience etc.) including measures of workers' time use at the firm.[26] On *firm location*, we asked the reasons behind the owner's location choice, including detailed information on how firms access customers. We also collected information on the size of the business premises and their rental value as well as on how far owners and employees live from the firm and how they commute to work. On *adaptation to pollution*, we asked detailed questions about: (i) investments made by the firm owner to protect workers from pollution, such as providing masks; (ii) organizational strategies to protect workers from pollution, such as allowing flexibility in commuting times to avoid exposure to traffic pollution at rush hour. In addition, we included multiple questions to measure *employees' awareness of pollution* as a problem for their own health and in general for society. To measure *managerial ability*, we follow McKenzie and Woodruff (2017), and create a standardized index by aggregating a range of questions about business practices.[27]

Follow-up survey and information experiment. We followed up with our sample of firms in early 2022 with a phone survey in order to: (i) test the firm owners' awareness of pollution and profitability in their neighborhood (by comparing their perceptions to the measurements from the initial survey); (ii) collect additional information on the perceived *benefits and costs of locating in different parts of the city*, and on *entrepreneurs' awareness of pollution* as a problem for their own health and for employee productivity; (iii) implement an *information experiment*, which is described in more detail in Section 5 and Appendix Section A.6. We were able to successfully interview about 68% of the target sample of firms.[28]

The nature of production makes firm location relevant for workplace exposure. Appendix Table B1 reports basic descriptives for the 1,027 firms in our survey sample and their employees, to characterize the nature of production in this setting. These firms are well-established businesses which are representative of the typical manufacturing jobs in urban East Africa. The average firm has been active for 10 years and has about five employees. Average monthly profits are $244, while employees make about $71 dollar per month (for comparison, GDP per capita was around $60 per month at the time of the study). Importantly, employees spend close to 10 hours per day at the firm on average (and the standard deviation is only 1.6 hours) and work primarily outdoors: 64% of firms produce only outside or mostly outside, and only 16% of firms produce entirely inside. This confirms that the location choice of firms is an

[26] See Bassi et al. (2024) for more details on the measurement of time use.

[27] The exact construction of the index is detailed in Appendix A.1. We validate the index in Bassi et al. (2022), where we show that it is a strong predictor of revenues per worker.

[28] Appendix Table B4 reports the predictors of attrition and, reassuringly, shows that the index of managerial ability, being located near major roads, and treatment assignment for the information experiment are all insignificant predictors of attrition. Whenever data from this follow-up survey is used in any of the tables or figures of the paper, this is explicitly stated in the corresponding notes.

important determinant of workers' exposure to outdoors' levels of air pollution.

3.4 Road Network Data

We supplement the pollution measures and firm survey with data on the network of Ugandan roads published by the World Food Program (WFP). The WFP data distinguishes between five road types in Uganda: *track/trail*, *tertiary roads*, *secondary roads*, *primary roads*, and *highways*.[29] As the dataset is geo-referenced, we can match roads with both the pollution and firm survey data. We create an ordinal measure of road size, so that *track/trail* is assigned the value 1, and *highways* is assigned the value 5. We use these values when calculating summary statistics within a geographical area. For example, the median road size of a geographical area containing one *track/trail* (1), one *secondary road* (3) and one *primary road* (4), will be 3.[30]

4 Data Construction

In this section we develop the empirical framework that enables us to characterize the joint spatial distribution of pollution and economic activity within the city, by transforming the data described in Section 3 to make it amenable to a spatial empirical analysis. To do so, we first residualize the pollution measurements to remove temporal variation and extract a measure of average local pollution. We then project the firm-level, road-level and pollution variables on small geographic units (i.e., grid cells) generating a "location-level" dataset that we use in the empirical analysis of the next sections.

4.1 Recovering Residual Spatial Variation in $PM_{2.5}$

As described in Section 3, we collected measures of $PM_{2.5}$ from both stationary and mobile monitors. To construct measures of spatial variation in pollution within the city, we leverage our mobile monitors. As the mobile monitors were attached to motorcycle taxis, the location of the mobile measurements might be systematically related to time trends in pollution (e.g., taxi drivers might be more likely to drive through some specific neighborhoods at the time of

[29]The World Food Program data follows the United Nations Spatial Data Infrastructure (UNSDI) for Transport standards. Source: `https://geonode.wfp.org/layers/ogcserver.gis.wfp.org:geonode:uga_trs_roads_osm/metadata_detail`. The WFP classification is a mapping of the 18 Open Street Map (OSM) highway tag into seven categories (the five categories mentioned above, as well as Residential and Path/Footway, which are absent from the Uganda road shape-file). Details of the mapping can be found on the WFP website.

[30]We define a "road" as a road segment not intersected by any other road. Each road intersection marks the extremity of the intersecting roads, as illustrated in Appendix Figure B9. Appendix Table B5 presents summary statistics about the number of kilometers per road type and the corresponding share of total kilometers, both for the country as a whole and for our sample. Our sample of 52 sub-counties contains 2,754km of roads in total, or about 2% of Ugandan roads, and roads are larger in our sample than in the rest of the country. This reflects our sampling strategy where rural areas (which likely have smaller roads) were excluded by design.

day when traffic, hence pollution, is highest or lowest). To address this potential concern of non-random spatial location of the mobile monitors across hours of the day and days of the year, we net out hour and date fixed effects using the readings from the stationary monitors.[31]

We run the following regression using the readings from all our stationary monitors k in order to recover hour b_h and date c_d fixed effects:

$$ln(PM2.5)_{k,h,d} = a + b_h + c_d + \lambda_k + \epsilon_{k,h,d} \tag{1}$$

where $ln(PM2.5_{k,h,d})$ is the log of the $PM_{2.5}$ reading from monitor k recorded on calendar date d and hour h. We include stationary monitor fixed effects λ_k since we do not have a balanced panel. We then net out these time fixed effects from the readings of our mobile monitors. To do so, we compute the pollution residuals $e_{\hat{m,h,d}}$ as the log of the raw measurements from our mobile monitors at GPS coordinates m at time h of date d, net of the hour and calendar date fixed effects estimated from the stationary monitors:

$$\hat{e}_{m,h,d} = ln(PM2.5)_{m,h,d} - (\hat{a} + \hat{b_h} + \hat{c_d}). \tag{2}$$

$\hat{e}_{m,h,d}$ captures residual pollution variation across locations conditional on a particular hour of the day and a particular calendar date. As such, this allows us to isolate systematic *spatial* variation in pollution within the city. As $\hat{e}_{m,h,d}$ is the result of estimation, we always bootstrap standard errors in any regressions involving this measure of residual pollution, as described in more detail in the next section.

4.2 Grid-Cell Approach

We adopt a grid-cell approach to create neighborhood-level measures of firm density, pollution, and road size. The administrative unit below sub-counties are parishes. Our 52 sub-counties comprise 179 sampled parishes. Following Ahlfeldt et al. (2015), Carozzi and Roth (2023) and Michaels et al. (2021), we split parishes in our sample into grid cells of $500m \times 500m$, drawing grid cells on all selected parishes.[32] Each road, pollution measure, and firm are attributed to a cell using their geo-coordinates.[33]

[31] While stationary monitors are useful for recovering the *time* variation in pollution, we cannot rely on them to recover the *spatial* variation in pollution within sub-county without making very strong assumptions on the decay of pollution with distance from the stationary monitor. In fact, we decided to use both stationary and mobile monitors precisely to be able to document both the spatial and temporal variation in pollution at a granular level. Sullivan and Krupnick (2018) discuss the unreliability of using only stationary monitors. In using the stationary monitors to identify time fixed effects across all the sub-counties in our study, we are assuming that time trends do not vary spatially across the sub-counties in our sample.

[32] We show that our results are robust to alternative ways of building the grid cells in Figures 6 and B12.

[33] 18% of firms interviewed in the survey fall slightly outside the boundaries of the corresponding sampled sub-counties, often by just a few meters. We still include these firms in our estimation sample by adding grid cells containing these firms, in addition to the grid cells in our sampled sub-counties. In the estimation we

We then compute the following variables for each grid cell: (i) the average residual pollution $\hat{e}^{c}_{m,h,d}$ for all the observations m recorded within cell c, constructed as described above; (ii) the median road size in the cell, where each road dummy is associated an ordinal number, as described in Section 3.4; (iii) the firm density, computed by dividing the number of firms in the cell by the cell area in km^2. To compute (iii) we use our comprehensive initial firm listing which covers *all* firms (not only those that we eventually selected for the survey).[34]

Figure 2 illustrates how our sampled parishes are split into grid cells, and shows that, in this specific sub-county, firms are clustered close to major roads and that such roads are more polluted. The figure thus summarizes well one of our key results: firm density is higher in more polluted grid cells with larger roads.[35] Next, we show that this pattern holds in general, study the motives leading firms to locate along major roads, and discuss the consequences for workers' exposure to pollution.

5 Empirical Analysis and Results

We build on the data structure described in Sections 3 and 4 to establish our three core empirical results. First, we uncover large spatial differences in air pollution within the city, which makes avoidance possible *in principle* as the pollution is concentrated near major roads. Second, we show that the firms sort to the polluted locations, so that there is lack of avoidance *in practice*. Finally, we study the returns from being located in high-exposure areas for firm owners and workers, to understand *why* the jobs are in the smog. We show that access to customers is a primary driver of location choice.

5.1 Spatial Distribution of Air Pollution within Cities

We describe the extent of local spatial heterogeneity in air pollution and its drivers.

Local spatial variation in air pollution. Panel (a) of Figure 3 displays the distribution of the maximum decrease in $PM_{2.5}$ levels that could be achieved by moving (i) 500 meters, (ii) 1,000 meters and (iii) 2,000 meters away from each grid cell in our data.[36]

control for a dummy for whether the firm falls in this category. Our results are robust to dropping these firms.

[34]When computing firm density, we take into account that all grid cells are not exactly $500m \times 500m$. This may happen because grid cells overlapping two adjacent parishes are split at the parish level, and because parishes are not of rectangular shape. A histogram of grid cell areas can be found in Appendix Figure B10. Besides, in regressions including grid-level variables, we control for whether the grid cell has an area of less than 0.25 km^2 (dummy), as well as for grid cell size (linear control).

[35]Appendix Figure B11 shows the disaggregated pollution measurements and how these result in the grid cell level averages shown in Figure 2.

[36]To compute this distribution, we first net out the temporal variation from our individual measurements to create residuals $e_{\hat{m},h,d}$, as explained in Section 4.1. We then average these residuals at the grid cell c level $e^{c}_{\hat{\hat{m}},h,d}$. To transform our residuals from log to levels, we add the log average air pollution measured by our monitors,

The figure shows substantial local spatial heterogeneity in air pollution. It is common for high-pollution grid cells to be just next to low-pollution locations: for instance, firms (or households) located in 25% of grid cells would experience a reduction of about 23 μ/m^3 of average $PM_{2.5}$ or more by moving away only 500 meters (in other words moving to the neighboring grid cell), which is greater than the reduction in air pollution of going from Beijing to Milan. Slightly longer moves would achieve even bigger reductions in pollution: individuals in a quarter of the grid cells could achieve a reduction of average $PM_{2.5}$ levels of at least 40 μ/m^3 by moving 2,000 meters, similar to the difference in pollution levels between Jakarta and Paris. We learn that there are parts of the city that feature relatively low levels of average pollution: in principle, firm owners could avoid significant exposure for themselves and their workers through their choice of where to locate the firm, even within neighborhoods.

Pollution is higher near larger roads. We next show that air pollution is concentrated near large roads. We run the following regression for grid cell j in sub-county s in region r:

$$ResidPollution_{j,s,r} = \alpha_0 + \alpha_1 MedianRoad_j + \delta_s + \theta log(dist)_{j,r} + \nu_{j,s,r}, \tag{3}$$

where $ResidPollution_{j,s,r}$ is the average residual (log) pollution in the grid cell, calculated as discussed in Section 4.1. $MedianRoad_j$ is the median road size in the grid cell. δ_s are sub-county fixed effects. This ensures that we compare grid cells with different road sizes *within* the same neighborhood. In addition, we include log distance to the main city in the region, $log(dist)_{j,r}$, to control for the fact that areas closer to the city center may have higher economic activity, leading to both more pollution and larger roads.[37] We use bootstrap standard errors to account for the uncertainty and sampling error due to the fact that $ResidPollution_{j,s,r}$ is itself the result of estimation.[38] Our coefficient of interest is α_1, which should be positive if

before taking the exponential:

$$\tilde{\text{poll}}_c^{\,\text{r}} = \exp\left(\bar{\hat{\mathcal{E}}}_{m,h,d} + \log \bar{\text{poll}}_{\text{measured}}\right)$$

$\tilde{\text{poll}}_c^{\,\text{r}}$ is the average pollution measurement for grid cell c, netted out of time fixed effects (and recentered at the average pollution level in our data). For each "starting" grid cell c in our data, we find the corresponding grid cell c' that leads to the maximum decrease in $\tilde{\text{poll}}_c^{\,\text{r}}$ by moving at most 500m, 1,000m or 2,000m from grid cell c (where we use centroids of the grid cells to calculate distance), and then record the difference in $\tilde{\text{poll}}_c^{\,\text{r}}$ between c and c'. We repeat this procedure using as "starting" grid cells c all the grid cells in our data, and plot the resulting grid cell level distribution of the maximum decrease in $\tilde{\text{poll}}_c^{\,\text{r}}$ in Panel (a) of Figure 3.

[37] We do not have data on road quality. To the extent that larger roads are of higher quality and road quality reduces pollution (by reducing congestion), then our estimates of the correlation between road size and pollution understate the true effect.

[38] To implement the bootstrap, we first take random draws (with replacement) of the pollution readings from the stationary monitors to predict the time fixed effects. We then take random draws (with replacement) of the pollution readings from the mobile monitors, which we residualize from the time fixed effects recovered in the previous step. Last, we aggregate our (resampled) pollution residuals to create $ResidPollution_{j,s,r}$ by taking the average at the grid cell level, and then estimate equation 3. We repeat these three steps 400 times. This approach takes into account the spatial correlation in our raw pollution measurements. Note that we effectively bootstrap the entire data transformation procedure described in Section 4.1 to create $ResidPollution_{j,s,r}$.

areas closer to larger roads are more polluted.

The results are in Table 1: column 1 shows that an increase in median road size in the cell of one unit is associated with an increase in residual pollution of about 7%, a result significant at the 1% level. Including sub-county fixed effects barely affects the results (as can be seen comparing columns 1 and 2), thus confirming that there is a strong relationship between road size and local air pollution *within* neighborhoods of a city. In columns 3 and 4, we check robustness to conducting the analysis at the level of the individual pollution measurement (rather than the grid cell), by replacing the median road size in the cell with the size of the road closest to the individual pollution measurement. Reassuringly, the results are similar.[39]

To better gauge the extent to which local heterogeneity in air pollution is driven by heterogeneity in road size, in panel (b) of Figure 3 we draw an analogous distribution to panel (a), but exploiting only heterogeneity in *predicted* air pollution levels from equation 3 and restricting each candidate move to within the starting grid cell's own sub-county. Naturally, the extent of the within-sub-county dispersion is reduced, as we are only focusing on the component of $PM_{2.5}$ that is explained by road size, but the local spatial heterogeneity remains substantial.[40]

Robustness. Appendix Figure B12 shows that the result that larger roads are more polluted is robust to a battery of robustness tests where we (i) vary the granularity of the spatial fixed effects; (ii) change the definition of road size at the grid cell level; (iii) calculate average residual pollution in the grid cell only using data during peak production times (i.e., 10am-3pm), as this is the period most relevant for workers' exposure at the firm premises; and (iv) change the starting point used to divide sub-counties into grid cells. The 39 point estimates of α_1 reported in the figure all fall between 0.05 and 0.10, and are all significant at the 5% level.

The importance of granular data. We have shown that our key result that large roads are more polluted is robust to changing the granularity of the spatial fixed effects and to adding different controls. We now show that our results instead are *not* robust to aggregating our data to a higher level of spatial granularity or to using publicly available satellite data to measure pollution. This analysis shows that our data are essential for uncovering the patterns we document in this paper.

First, we show that increasing the size of the grid cells leads to a decrease in the correlation between road size and pollution. In Figure 4, Panel (a), we report the estimate and confidence

[39] In columns 3 and 4 of Table 1, 4,887 pollution observations (corresponding to 8% of the sample) are dropped because the size of their closest road was not available as they are more than 100m away from the closest road.

[40] In panel (b) we predict pollution in each grid cell using the estimated elasticity of pollution residuals with respect to median road size in the grid cell, estimated in Table 1, column 1. Because this elasticity is estimated in a specification with sub-county fixed effects, predicted pollution differences across sub-counties are not separately identified by the regression; accordingly, in panel (b) we restrict each grid cell's candidate "destination" cell to lie within the same sub-county. Appendix A.5 describes the construction of predicted grid-level pollution in more details.

interval for α_1 from equation 3, when incrementally varying the size of the grid cells from $200m \times 200m$ to $4km \times 4km$: when using $4km \times 4km$ grid cells, the correlation is roughly *half* of the one in our preferred specification with $500m \times 500m$ cells.

Second, we show that our key correlation would not be detected using satellite data. We retrieve $PM_{2.5}$ satellite estimates from van Donkelaar et al. (2021) for our sampled areas.[41] This data comes at the resolution of approximately $1100m \times 1100m$ grid cells. Panel (a) shows that when estimating equation 3 using the satellite data to measure pollution, this produces an estimate of α_1 that is very close to *zero* and precisely estimated. Notice that this is not due to the size of the grid cells *per se*: as shown in Panel (a), when using $1000m \times 1000m$ grid cells with our own pollution data, we find that $\hat{\alpha_1}$ is around 0.06 and statistically significant at the 1% level.

Satellite data produce results that are so different because the imputation process used to generate the data leaves very little local variation. We show this in Figure 5. Panel (a) shows that, when we average both our data and the satellite data at the sub-county level, we find a positive and strong correlation between the two. In Panel (b), we instead remove sub-county fixed effects from both our data and the satellite data, and report the residual correlation between the two, at the level of the grid cell. Strikingly, now the correlation is very close to zero. This is due to the fact that, within sub-counties, there is very little variation left in the satellite data.

Why are large roads more polluted? The role of road traffic. So far, we have established that large roads are more polluted. We now study why this positive correlation arises. We focus on a plausible potential explanation: the role of road traffic. To do so, we conduct several tests to confirm that the results in Table 1 are due to traffic being higher on larger roads, rather than to two main alternative explanations. The first is that polluting firms may sort on major roads, so that pollution is higher on larger roads because of the presence of polluting firms. The second is that larger roads may be built in areas that are more polluted to begin with (e.g., areas with higher population density and economic activity), in which case equation 3 would capture reverse causality and the endogenous placement (or size) of roads.

As a first test, if pollution was originating mostly from the firms themselves rather than traffic, we would expect pollution to be highest at peak production times rather than at rush hour. We find the opposite. In the right panel of Figure 1, we overlay the average hourly levels of $PM_{2.5}$ in our data with the share of workers at the firm premises by hour of the day (from our time use data): while pollution peaks between 6-9am and 7-9pm—times corresponding to rush hour in Uganda—, production peaks between 10am and 3pm.[42] We further confirm that

[41] van Donkelaar et al. (2021) combine Aerosol Optical Depth retrievals from the NASA MODIS, MISR, and Sea WIFS instruments to estimate $PM_{2.5}$ levels.

[42] We conduct one further test in Appendix Figure B14: we split the stationary monitors by whether they

pollution originates mostly from road traffic in panel (a) of Appendix Figure B13, where we use traffic slowdowns data from GoogleMaps (available for Kampala) to show that the evening peak in pollution tracks closely the evening peak in traffic.[43]

One concern with the previous analysis is that this is based on the firms in our sample, which are small and operate in sectors that likely produce low levels of $PM_{2.5}$.[44] Pollution near large roads may be higher because more highly polluting firms in other sectors sort near these roads. We address this concern directly by estimating a version of equation 3 where we control for the presence of firms in highly polluting sectors in the grid cell. To do so, we leverage the latest available Census of Business Establishments from 2010, which covers the universe of firms in Uganda, with information on GPS coordinates and sector. We classify all firms in the census into high- vs low-polluting based on the U.S. EPA's Toxics Release Inventory (TRI).[45] Appendix Table B3 shows that controlling for the presence of such highly polluting firms barely affects the coefficient on road size in equation 3.

Finally, to further address the concern of endogenous placement (or size) of roads with respect to pre-existing polluting activities, we repeat the analysis focusing only on primary roads outside major urban areas. The logic is that as primary roads tend to connect major city centers, the location of primary roads is plausibly exogenous to the pre-existing economic activity (and therefore the $PM_{2.5}$ emissions) of the places *in between* the city centers connected by these primary roads. Appendix Table B2 replicates the results in Table 1 but only focusing on primary roads in areas outside Kampala. We first consider all parishes outside Kampala, and then progressively restrict the sample to parishes with lower population density, to narrow in the analysis to semi-urban areas located in between the city centers connected by the primary roads. Reassuringly, we find that grid cells with a primary road have pollution levels 17-20% higher than other grid cells without primary roads in the same sub-county, and the estimate is stable when restricting the sample to more semi-urban parishes.

Taken together, these results support the interpretation that the higher pollution along larger roads is due primarily to higher road traffic. As the average firm in our sample is small

fall in a grid cell with at least one firm, or whether they have no firms nearby. If firms are a major source of pollution themselves, we would expect the cyclicality in pollution emissions throughout the day to be different in these two areas. The cyclicality, instead, is almost identical, and this remains true when we restrict the sample to grid cells with at least one road.

[43]Panel (a) of Appendix Figure B13 shows that our traffic data cannot explain the high levels of pollution at night and the early morning peak in pollution. This can be because of the role of temperature in mediating the effect of traffic on pollution: the environmental literature has established that lower temperatures at night and especially in the early morning before sunrise trap pollutants close to the ground, leading to increased levels of pollution (Alaran et al., 2024; Chen, Oliva, and Zhang, 2022). Indeed, in panel (b) of Appendix Figure B13 we use temperature data to show that the early morning peak in pollution happens right after when temperature is the lowest.

[44]For instance, only about 4% of firms use generators, which could be potential sources of pollution.

[45]In practice, we map the ISIC Rev 4 code of each firm in the Uganda census to its corresponding NAISC code, used in the EPA's TRI to flag polluting industries.

and reports only about four customers per day, this suggests that most of the traffic is due to cars driving down the road for other reasons (such as commuting), rather than to customers driving to the firms located along the roads.[46]

5.2 No Avoidance: Firms Locate Near Large and Polluted Roads

Next, we study firm location within the city by looking at the correlation between firm density and the presence of large roads. Since we have shown that major roads are more polluted, these results are informative of whether firms sort into more polluted areas. We run a grid-level regression similar to equation 3 but with firm density on the left hand side. We also verify the correlation between firm density and pollution directly by replacing the median road size in the cell with the average residual pollution in the cell. The results are in Table 2.

On the extensive margin, columns 1 and 2 show that cells with larger roads (column 1) and more pollution (column 2) are more likely to have at least one firm. On the intensive margin, column 3 shows that an increase in median road size of one unit is associated with an increase in firm density of 13%. Further, column 4 shows that a 1% increase in pollution is associated with a 0.27% increase in firm density. In column 7, we show that this result is robust to running the regression at the level of the individual pollution measurement.[47] Notice again that in all these specifications we are controlling for sub-county fixed effects and distance from the center of the major city in the region. Therefore, these results show that even within the city—and in fact within neighborhoods—firms sort into the more polluted areas with better road access, thus implying that most jobs are in the highly polluted locations.[48] Finally, in columns 5 and 6 we add the average managerial ability index in the cell as a regressor, and find that the sorting pattern does *not* vary significantly by this firm characteristic, as the coefficient on the index is positive but small in magnitude and not significant.[49]

[46]Notice that if small firms cluster on major roads and this creates agglomeration externalities that increase traffic (e.g., demand externalities leading to more customers driving to the firm cluster) then this would only refine the interpretation of our results. The key result that firms choose to locate in areas with high pollution since road traffic bundles pollution and demand would be unaffected. Any policy counterfactuals, however, would vary, as changing the firms' location choice would also change the geographical distribution of traffic and demand. We return to this point in the model.

[47]In column 7, the dependent variable log(firm density) is defined as the log of the sum of the inverse squared distances between each pollution measurement and all the firms in the data, so that the firm density measure is specific to each pollution measurement.

[48]Notice that while pollution peaks during early morning and late evening, it is still much higher than EPA standards during peak production times (Figure 1). As discussed above, our finding that larger roads are more polluted is true even if we restrict the pollution data to only peak production times (Appendix Figure B12).

[49]As a result of the sorting in polluted areas, the median employee works in a neighborhood with $PM_{2.5}$ levels of about 56 $\mu g/m^3$, even though much cleaner locations are available nearby (Figure 3). The negative health consequences of working in polluted areas could in principle be reduced through in-place adaptation. We study this in Appendix A.3, where we show that: (i) there is little in-place adaptation overall, so that adaptation is unlikely to meaningfully reduce actual exposure to pollution for workers in this context; (ii) adaptation is not higher in more polluted areas, confirming that the reason why wages are only marginally higher near larger

Evidence from the Uganda Census of Business Establishments. We replicate the analysis using the universe of firms in Uganda from the 2010 Census of Business Establishments. We extend our grid cell approach to all sub-counties in the entire country, and for each grid cell we calculate the median road size as well as firm density by sector and firm size. We then run specifications based on equation 3 with these firm density measures from the census as dependent variables and clustering standard errors at the sub-county level. The results are reported in Table 3. For comparison, column 1 reports the sorting regression using as sample the manufacturing firms in our own survey, so this is the same specification as column 3 of Table 2, but restricting to firms in carpentry and metal fabrication.[50] The sorting regression for manufacturing using the census is in column 2: the coefficient is remarkably similar to column 1. This is reassuring as it shows that the sorting results in Table 2 apply to the entire population of firms in these two sectors. The rest of the table examines heterogeneity by firm size and sector. In short, the sorting on larger roads is particularly pronounced among smaller firms and those operating in retail and low-skill services (such as hairdressing).[51] As face-to-face interactions with customers are more important for smaller firms and firms in these sectors, this already suggests that visibility to customers may be an important driver of the sorting pattern—something we return to and expand upon in the next section.

5.3 Returns from Locating Near Large and Polluted Roads

We have established that *jobs are in the smog*. We now study why firms locate near large and polluted roads—that is, *why* the jobs are in the smog. To do so, first, we show that locations near large roads feature higher profitability and wages. Second, we discuss what generates these economic returns, and present evidence consistent with larger roads providing access to customers.

5.3.1 Why Do Firms Sort to Polluted Areas? Returns for Owners and Workers

At first, the observed location choice of firms and workers may seem puzzling, as it exposes them to substantial ambient air pollution. In this section, we show that locating near larger roads provides higher profits for firm owners and higher wages for workers, so that the observed sorting is consistent with optimization. To do so, we study the cross-sectional relationship between proximity to large roads and measures of profitability, wages, rental cost and other input costs, conditioning on a rich set of controls. This approach relies on the assumption that

roads is not that workers receive more protection from air pollution; (iii) higher ability managers protect their workers more, but the overall level of protective investments remains low even at these better managed firms.

[50] Grain-milling is classified under agriculture in the firm census.

[51] Column 4 shows that agricultural firms sort *away* from large roads. This is expected given that land is more expensive along large roads (see Table 4).

any residual unobserved firm and worker characteristics correlated with firm productivity do not also predict location choice within sub-counties. Although this may sound like a strong assumption, we provide evidence in its favor later in this section. There we also verify that reverse causality concerns about the endogenous placement (or size) or roads with respect to the location of more productive firms are not first order.[52]

Profit premium for firm owners. We estimate the following regression for firm i in grid cell j in sub-county s and region r:

$$y_{i,j,s,r} = \beta_0 + \beta_1 MedianRoad_j + \beta_2 ManScore_i + \lambda_{l(i)} + \delta_s + \eta log(dist)_{j,r} + \upsilon_{i,j,s,r}, \quad (4)$$

where $y_{i,j,s,r}$ is the outcome of firm i, such as log profit. We regress this on the median road size in the cell and the firm-level standardized index of managerial ability $ManScore_i$, controlling for sector fixed effects $\lambda_{l(i)}$, sub-county fixed effects and distance from the major city in the region, as in equation 3. Standard errors are adjusted for spatial correlation.[53]

Our main coefficient of interest is β_1, which would be positive if firms located near major roads are more profitable. The results are in Table 4. Columns 1-2 show that there are clear profitability benefits from locating near large roads: in column 1 we do not control for our index of managerial ability, and the results show that increasing median road size by one unit (e.g., moving from a secondary to a primary road) is associated with an increase in profits of 17%, a result significant at the 1% level. Column 2 shows that adding the managerial ability index as a control barely affects $\hat{\beta}_1$, even though the index is a very strong predictor of profits. As long as observable and unobservable determinants of profitability are correlated, this result already suggests that any scope for selection on unobservables to bias our results is limited (we return to this assumption below).

These results confirm that there are direct and large profitability benefits for firms of being located on busy roads with high traffic (and high pollution): we call this the *profit pollution premium*, to emphasize that profits are higher in polluted areas. In Appendix Table B6, we show that we reach similar conclusions if we replace median road size in the grid cell with average residual pollution in the cell on the right hand side.[54]

[52]The ideal experiment would be to exogenously induce firms to move (e.g., by paying them to move) or manipulate where roads are built, but these are both difficult interventions to implement in practice. Naturally, it is also difficult to observe firms moving across locations as those moves are rare: only 6% of firms in our data moved in the year before the survey.

[53]Specifically, we use Spatial Heteroskedastic and Autocorrelation Consistent (SHAC) standard errors (Conley, 1999; Kelejian and Prucha, 2007), using the routine developed by Hsiang (2010). When including sub-county fixed effects, we first demean both left- and right-hand side variables.

[54]The number of observations is lower in Table B6 than Table 4 because, as described in Section 3.2, information on pollution is available in 32 of our 52 sampled sub-counties, while road size is available in all

Wage premium for workers. We compare the profit pollution premium with the corresponding wage premium for working along larger and more polluted roads—i.e., the *wage pollution premium*. To do so, we estimate equation 4, but at the worker level and with monthly wages on the left hand side. Column 3 of Table 4 shows that employees working near larger roads earn higher wages, after controlling for a rich set of worker controls. However, the magnitude is relatively small: increasing median road size by one unit is associated with an increase in wages of 2.5%, a result at the margin of statistical significance. Notably, the magnitude of this coefficient is smaller than the one in columns 1 and 2 for firm owner's profits.[55]

Working along large roads may benefit workers' careers also in other ways. For instance, the higher density of firms and jobs may increase the returns to experience or education, or make it easier to eventually start a firm. Our evidence shows this is not the case: in Appendix Table B7, we find no evidence of differential returns to experience or skills on larger roads, and Appendix Table B8 shows that firm owners near larger roads are no more likely to have been employees in the past, or to have received training.

5.3.2 Why Are There Profit Premia on Large and Polluted Roads?

We explore potential mechanisms for the estimated profit pollution premium, by studying how access to customers, access to other inputs, and land rental values vary near large roads. We then conclude the section by returning to the discussion on identification, and present several robustness checks to alleviate concerns that the estimated premia might reflect sorting on unobservable productivity or reverse causality.

Large roads provide access to customers. To study the role of access to demand, we asked firms how many customers they typically have on a good and a bad day. We create the average of the answers to these two questions, and use this as dependent variable in column 4 of Table 4. We find that firms located near larger roads report significantly more customers. Column 5 shows that output prices are also higher, consistent with higher demand. Finally, in column 6 the dependent variable is a standardized index of output quality: this shows that the higher prices do not reflect higher quality products, although the estimates are noisy.[56]

In Table 5 we offer further support to the interpretation that large roads provide access to customers. First, Panel A shows that firms typically sell their products to final consumers face-to-face, and do not market their products widely. While only 7% of firms spend any money

sub-counties.

[55] In Appendix Table B6, column 7, we find a small negative point estimate when replacing median road size with average residual pollution in the grid cell, but given the size of the standard error we cannot reject a small positive effect.

[56] The index is based on assessments by enumerators of the quality of finished products at the firm. The index is missing for firms that did not have a finished product available at the firm premises on the day of the interview. See Bassi et al. (2022) for more details.

on marketing, common strategies to communicate quality and gain visibility to customers are talking to the customer directly and having products on display at the firm. This suggests that firms lack the means to attract customers to their location. Therefore, by locating on large roads, firms can gain visibility to potential customers driving down the road.[57]

Our survey also directly corroborates the idea that firms locate in the more polluted areas of the city to access customers. We asked firm owners about the benefits, if any, for a firm to be located near a major road. Panel B shows that gaining visibility to new customers is *by far* the most important perceived benefit, and much more important than other benefits such as interacting with other firms or accessing suppliers. Finally, we asked all firms that relocated or considered relocating in the previous year the reasons for their location choice. Panel D of Table 5 shows that access to customers is the most important reason driving location choice, with more than half of the firms reporting this among the top three reasons; in contrast, avoidance of air pollution is not a major reason for location choice, with less than 10% of firms reporting it among their top choices.[58]

Finally, linking back to the results on sorting in the firm census in Table 3, we highlight how those support the interpretation of access to demand as a primary driver of location choice: the fact that the sorting near larger roads is less prevalent among larger firms is consistent with larger firms being better able to invest in marketing and separate production and retail activities, thus breaking the "bundling" of customer demand and pollution generated by large roads. In addition, the fact that the sorting on large roads is stronger in customer-facing sectors such as retail and low-skill services provides further evidence on the role of the demand channel in driving location choice. Remarkably, manufacturing firms in low-income countries behave like low-skill services in terms of their location choice: since they are small scale and need to sell face-to-face, they locate on the "high-street" in the same way in which hairdressers do.

Large roads do not provide better access to intermediate inputs. In columns 7-8 of Table 4, we focus on the relationship between large roads and access to intermediates. In column 7, we use detailed data on the price paid by the firm for a series of pre-specified intermediate inputs, to show that there is no correlation between the log of intermediate input prices and large roads. In column 8, we combine several questions about how each intermediate input is accessed, to create a standardized index of input accessibility: again, there is no relationship with being located near large roads.[59] The profitability premium of large roads is thus *not*

[57] In line with this, Appendix Figure B15 shows that lack of demand is the main perceived constraint to growth in our survey.

[58] We asked firms to rank a list of 18 possible reasons. To limit the number of rows in the table, we report the three most common options selected by firm owners, and then the options related to pollution, for comparability. Appendix Figure B16 reports the distribution of all 18 possible reasons for location choice. Access to customers is clearly the primary reason.

[59] The regressions in columns 7 and 8 are at the firm $\times$ intermediate input level. We include fixed effects for the different types of intermediates, and control for the quantity purchased of each type of intermediate input.

due to cheaper or easier access to intermediates. These null results support the claim that the benefits of locating on larger roads stem from better customer access rather than from a general improvement in transit connectivity with suppliers.

Net profitability benefits of large roads despite higher rental prices. Finally, in column 9 of Table 4, we focus on the relationship between road size and rental prices.[60] Increasing median road size by one unit leads to an increase in rental expenditure of about 11%: prime locations are more expensive. Consistent with this, Panel C of Table 5 shows that firm owners report high rents as the main perceived drawback of locating near major roads. Despite the higher wage and rental cost, the impact of roads on profitability is on net positive (as shown in columns 1-2). This is expected given that the wage differential is small, and rental expenditures are only a small share of overall firm costs.[61]

Why are the profitability benefits not eroded away by higher rents? There are at least three mechanisms that can explain why the land market does not capture all the increase in profitability from locating near larger roads. While distinguishing between these is beyond the scope of this paper, we present evidence that these mechanisms may be at play.

First, we document that busy areas are associated with disamenities that would lower their attractiveness, and in turn their equilibrium rent. In Appendix Table A8, we show that firm owners are at least somewhat aware of the productivity and health costs of air pollution, and perceive areas with more road traffic as being more polluted. In addition to air pollution, another disamenity of these profitable locations is their distance to the owner's home: Appendix Table B10 shows that owners whose firm is located on larger roads face a longer commute.[62]

A second explanation for the partial passthrough of profits into rents is rooted in failures

In Appendix Table B9, we show that the null relationship in column 8 holds for all individual components of the input accessibility index.

[60] We use our survey questions about the rental value and the size of the business premises. This information is available for those firm owners who rent the business premises (rather than owning or using them free of charge), which is about 2/3 of the sample.

[61] In our sample, the rental expenditures of the median (average) firm is 5% (11%) of this firm's monthly revenues, among firms renting their premises.

[62] We can perform a back of the envelope calculation to get a sense of the magnitude of the commuting disamenity: assuming that individuals can walk at 5 km/h or drive at 20 km/h on average, the estimates from column 1 of Table B10 imply that increasing road size by one unit leads to an increase in monthly time spent commuting of 100 minutes if walking, or 25 minutes if driving (notice that 43% of firm owners typically walk to work). Repeating the calculation for workers shows this disamenity is even larger for them (Appendix Table B11): moving to a road one unit larger would increase monthly commuting time by 125 minutes if walking, or 31 minutes if driving. If we value the extra commuting time at the average hourly wage (i.e., hourly equivalent of the monthly wage of \$71, see Table B1), then moving to a road one unit larger would imply an increase in monthly commuting cost of \$1.19 if walking. While this is a non-negligible extra average commuting cost, it is still small relative to the estimated monthly wage premium of working near a road one unit larger, which is \$1.775 (this is given by the elasticity of monthly wage to road size estimated in column 3 of Table 4, (0.025), times the average monthly wage (\$71)).

in the land market. Bird and Venables (2020) argue that in Kampala, the coexistence of four land tenure systems leads to significant land tenure-specific frictions and show that distortions are even larger on *Mailo* land—which a significant share of our sampled areas in Kampala fall into—in part because of a rent cap far below market rates for some tenants. Analogously, in Kampala, Sorin (2025) finds that properties on different land tenure regimes sell and rent at different rates.

A third potential explanation is that some firm owners may be (partially) unaware of the profitability benefits of larger and more polluted roads, and may therefore avoid these areas, lowering pressure on rents. While our data shows that on average firm owners perceive a positive correlation between road size, pollution and profitability (see Table A8), some firm owners may not be aware of these correlations (or at least not of their true magnitude). Pelnik (2025) provides direct evidence that firm owners in the same context have imperfect information on the spatial distribution of profitability across neighborhoods of the city.

Identifying assumptions and robustness. We conduct several tests to support the assumption of no selection on large roads based on unobservable productivity.

First, we show that there is no evidence of selection on *observable* proxies for productivity. In Appendix A.2 we show that: (i) there is no statistical correlation between road size and several firm owner and employee characteristics, such as firm owners' managerial ability, age, education and gender, as well as employees' age, education, training and gender, thus suggesting that selection on unobservable productivity is also unlikely, to the extent that observable and unobservable productivity are related;[63] (ii) the profitability results of locating near larger roads are robust to the bounding exercise proposed by Oster (2019) to account for selection on unobservables; (iii) the returns from locating near larger roads are not stronger for higher ability managers, thus justifying the lack of strong sorting based on managerial ability.[64]

Second, Figure 6 shows that the results of equation 4 are robust to a large battery of robustness tests regarding: (i) the level of the spatial fixed effects (orange estimates); (ii) the definition of road size at the grid cell level (pink estimates); (iii) adding different combinations of firm level covariates (green estimates); (iv) restricting the sample to areas outside Kampala and less urban areas (black estimates); and (v) varying the starting point to divide sub-counties into grid cells. The results are remarkably stable across the 75 specifications reported in the figure. The results in (iii) help rule out some plausible alternative explanations for the profit

[63]The lack of correlation between large roads and output quality as well as input prices/accessibility documented in Table 4 is in line with these results, and further alleviates concerns of selection on unobservable productivity.

[64]This lack of correlation between observable proxies for productivity and location choice raises the question of which firm characteristics do predict locating along major roads. As discussed above, the results in Appendix Table B10 are consistent with heterogeneity in taste for commuting being an important explanation for why some entrepreneurs locate further from the large roads and closer to home.

premia of being located on larger roads. First, as we control for capital stock, this rules out that entrepreneurs with easier access to capital are better able to sort on larger roads (where rent is more expensive) and therefore that the profitability premia reflect their higher capital stock rather than access to customers. Second, firms producing customized products may have stronger incentives to locate on larger roads if their business model relies more on face-to-face interactions with customers. Controlling for the extent of customization in production (proxied by the share of sales made to order) alleviates concerns of selection on returns, whereby the profit premia may capture the differential profitability of firms relying on customized production. Third, firm owners that employ family members or friends may value differently the pollution-profitability trade-off, as they might internalize to a greater extent the pollution exposure of their workers, thus leading these types of firms (which may be more or less profitable) to avoid the polluted areas. Our estimates are robust to controlling for whether the firm employs family members or friends of the owner, thus confirming that the profit premia do not reflect the differential sorting of these firms near large roads. Overall, the results in Figure 6 further support the claim that selection based on productivity or other firm characteristics is unlikely to explain our results.[65]

Finally, we address potential concerns related to the location (or size) of roads being endogenous to firm location. We follow a similar approach as we did for addressing the endogeneity of roads to pre-existing sources of air pollution (see Appendix Table B2, columns 1-3)—that is, we focus on comparing grid cells with and without primary roads in areas outside major city centers. The results (in Appendix Table B2, columns 4-6) show that, reassuringly, we still find positive and large profit premia on primary roads outside Kampala, and this remains true even when further restricting the sample to parishes with lower population density, in order to better proxy for semi-urban areas in between the city centers connected by the primary roads.

Summary. In this section, we have documented that although air pollution is highly heterogeneous within Ugandan cities, firm owners choose to locate along large and polluted roads to access customers, thus increasing profits but leading to substantial exposure to pollution for themselves and their workers. Uncovering these facts leveraging novel granular pollution and survey data is a key contribution of the paper.

6 Stylized Framework, Interpretation, and Discussion

We introduce a stylized framework with three purposes. First, the framework shows that the empirical findings can be rationalized through a standard spatial model under intuitive condi-

[65] In Figure 4, Panel (b), we show that the estimates from equation 4 become smaller and lose significance as we increase the size of the grid-cells, thus highlighting the importance of our granular data not only to study the determinants of local variation in air pollution, but also the determinants of local profitability differences.

tions. Second, it provides an organizing framework to quantify the benefits, net of pollution exposure, of the current spatial distribution of firms for workers and firm owners. Third, it allows us to discuss to what extent our empirical results can inform firm relocation policies.

6.1 Model Environment

We consider a one-period economy partitioned into many locations $j \in \mathbb{J}$.

Traffic. Road traffic in location j is given by a linear combination of τ_j and n_j:

$$t_j(n_j) = (1-\nu)\tau_j + \nu n_j,$$

where τ_j is an exogenous traffic shifter—which may capture local features such as the existing road network—and n_j is the (endogenous) mass of firms in location j. The parameter ν modulates the extent to which firms themselves generate traffic, for example because they attract customers. Traffic translates into pollution through a "unit conversion" constant ψ:

$$p_j = \psi t_j,$$

which determines the spatial distribution of air pollution.[66]

Agents and Utility Functions. The economy is inhabited by a mass Π of entrepreneurs and a mass Ω of workers. Entrepreneurs and workers have linear utility, given respectively by

$$u_\pi(\pi, p_j) = \pi - \kappa_\pi p_j$$
$$u_w(w, p_j) = w - \kappa_w p_j,$$

where π and w denote profits and wages, and $\kappa_\pi p_j$ and $\kappa_w p_j$ are the perceived pollution costs in location j.[67] The constants κ_π and κ_w capture the possibility that entrepreneurs and workers may value (or perceive) pollution differently.

Labor Market. Entrepreneurs choose a location j, as described below, and post vacancies to meet with workers. Workers search for jobs in a frictional labor market with random search

[66] As discussed in Section 5, in this context it is realistic to assume that pollution is largely determined by traffic.

[67] A natural question is whether entrepreneurs and workers are aware of the spatial distribution of pollution. In Appendix A.6 we use our own survey data to show that individuals broadly perceive spatial differences in pollution correctly, thus supporting the assumption made here.

across locations and one-to-one matching.[68] Workers move to the location where they are matched with an entrepreneur and therefore work where they find a job.

Matches follow a standard constant-returns matching function $M(\Pi, \Omega) = \Pi^{\lambda}\Omega^{1-\lambda}$. This implies that the probability that a vacancy is filled and that a worker finds a job are

$$\begin{aligned} \theta &= \frac{M(\Pi,\Omega)}{\Pi} = \left(\frac{\Omega}{\Pi}\right)^{1-\lambda}, \\ \vartheta &= \frac{M(\Pi,\Omega)}{\Omega} = \left(\frac{\Pi}{\Omega}\right)^{\lambda}. \end{aligned}$$

Because θ is common across locations, it affects location choice by scaling the profitability component of the trade-off uniformly across locations.

A filled job—i.e., a match in location j between an entrepreneur and a worker—produces output according to a location-specific revenue productivity

$$D_j\left(n_j\right) = (1-\eta)t_j\left(n_j\right) + \eta n_j, \tag{5}$$

which increases both with traffic, because traffic brings customers, and with the mass of firms through standard agglomeration forces, with η modulating the relative importance of the two.

Profits and Wages. The surplus of a filled job is split according to Nash bargaining, where workers' bargaining power is β.

These assumptions imply that wages and profits in location j are

$$\begin{aligned} w_j\left(n_j\right) &= \kappa_w p_j\left(n_j\right) + \beta\left(D_j\left(n_j\right) - \kappa_w p_j\left(n_j\right)\right), \\ \pi_j(n_j) &= (1-\beta)\left(D_j\left(n_j\right) - \kappa_w p_j\left(n_j\right)\right). \end{aligned}$$

Entrepreneurs therefore internalize both the productivity benefits of locating in busy areas and the associated pollution costs, both for themselves and for workers, since higher pollution exposure is reflected in wages through compensating differentials.

Firm Location Choice. Entrepreneurs choose a location before matching takes place, trading off expected profitability and exposure to pollution. Conditional on locating in j, an entrepreneur incurs the pollution cost of that location regardless of whether the vacancy is

[68] Following Diamond (1982), Mortensen (1982), and Pissarides (1985), or more recently Heise and Porzio (2022).

ultimately filled. If the vacancy is filled, she earns profits $\pi_j(n_j)$; if it is not filled, she earns zero profits. Letting ε_{ij} denote an idiosyncratic extreme-value preference shock for location j, the ex-ante expected utility from locating in j is therefore

$$U_{ij} = \theta\pi_j(n_j) - \kappa_\pi p_j(n_j) + \varepsilon_{ij}.$$

The share of entrepreneurs choosing location j is then given by

$$\mu_j(n_j) = \frac{\exp\left((\theta\pi_j(n_j) - \kappa_\pi p_j(n_j))/\sigma\right)}{\sum_{k\in\mathbb{J}} \exp\left((\theta\pi_k(n_k) - \kappa_\pi p_k(n_k))/\sigma\right)},$$

where σ governs the dispersion of idiosyncratic location preferences.

Equilibrium. An equilibrium is given by a distribution of firms across locations that is consistent with entrepreneurs' optimal location choices. Since profits depend on the distribution of firms across locations, the model may admit multiple fixed points.

Definition 1 (Spatial Equilibrium)**.** *A spatial equilibrium is a distribution of firms* $\{n_j\}_{j\in\mathbb{J}}$ *such that*

$$\sum_{j\in\mathbb{J}} n_j = \Pi$$

and, for every location $j \in \mathbb{J}$*,*

$$n_j = \Pi \frac{\exp\left((\theta\pi_j(n_j) - \kappa_\pi p_j(n_j))/\sigma\right)}{\sum_{k\in\mathbb{J}} \exp\left((\theta\pi_k(n_k) - \kappa_\pi p_k(n_k))/\sigma\right)}.$$

6.2 Characterization and Interpretation of the Empirical Results

We next characterize the solution of the model and show that, under plausible parameter combinations, the equilibrium described above can rationalize two central empirical findings: the sorting of entrepreneurs toward polluted locations and the coexistence of large profit pollution premia with modest wage pollution premia.

For clarity we focus on the case of two locations, indexed by h and l, with $\tau_h > \tau_l$. The intuition extends directly to multiple locations.

Characterization. The linear structure of the model allows us to express entrepreneurial location payoffs in a simple form. Proofs of the Lemmas are in Appendix B.

Lemma 1 (Entrepreneurial Payoff)**.** *The expected utility of an entrepreneur locating in* j *can be written as*

$$v_j = A_\tau \tau_j + A_n n_j,$$

where

$$\begin{aligned} A_\tau &= (1-\nu)\Big[\theta(1-\beta)(1-\eta) - \psi\big(\theta(1-\beta)\kappa_w + \kappa_\pi\big)\Big], \\ A_n &= \theta(1-\beta)\big[\eta + \nu(1-\eta)\big] - \psi\nu\big(\theta(1-\beta)\kappa_w + \kappa_\pi\big). \end{aligned}$$

The coefficient A_τ captures the fundamental attractiveness of locations with higher exogenous traffic once profitability is scaled by the probability of filling a vacancy. Higher traffic increases demand but also raises pollution exposure, which directly lowers entrepreneurial utility and indirectly increases wages through compensating differentials.

The coefficient A_n captures endogenous forces generated by the presence of other firms. When $A_n > 0$, productivity benefits from clustering dominate pollution costs, generating agglomeration forces. When $A_n < 0$, congestion forces dominate.

Lemma 2 (Uniqueness)**.** *If*

$$\frac{\Pi A_n}{2\sigma} < 1,$$

the spatial equilibrium is unique.

This condition states that equilibrium is unique when preference shocks are sufficiently large relative to endogenous agglomeration forces.

Lemma 3 (Sorting to Traffic)**.** *Define*

$$\eta^* = 1 - \psi\kappa_w - \frac{\psi\kappa_\pi}{\theta(1-\beta)}.$$

If equilibrium is unique, entrepreneurs sort toward the high-τ location if and only if $\eta < \eta^*$.

When η is small, traffic is the primary driver of demand. Locations with higher exogenous traffic therefore generate higher revenues, making them attractive despite higher pollution levels. When η is sufficiently large, the productivity advantage of traffic weakens while pollution costs remain, making high-traffic locations less attractive. Finally, a lower vacancy-filling probability θ makes sorting toward high-traffic locations less likely, because it reduces the expected profitability advantage of those locations while leaving the pollution disamenity unchanged.

Lemma 4 (Sorting and Pollution)**.** *Let $\tau_h > \tau_l$ and suppose equilibrium is unique. If entrepreneurs sort toward the high-τ location, then that location necessarily exhibits higher pollution. If instead entrepreneurs sort toward the low-τ location, then the low-τ location exhibits*

higher pollution if and only if

$$\nu(n_l - n_h) > (1-\nu)(\tau_h - \tau_l),$$

or equivalently if only if $\nu\Pi > (1-\nu)(\tau_h - \tau_l)$ *and* $\eta > \widehat{\eta}(\nu)$*, where* $\widehat{\eta}(\nu)$ *is a decreasing function of* ν *included in the Appendix.*

Taken together, these results imply three regimes. First, if $\eta < \eta^*$, firms sort toward the high-τ location, which is therefore also more polluted. Second, if $\eta^* < \eta < \widehat{\eta}(\nu)$, firms sort toward the low-τ location, which remains less polluted. Third, if $\eta > \max\{\eta^*, \widehat{\eta}(\nu)\}$, firms sort toward the low-τ location and that location also becomes the more polluted one because strong firm concentration endogenously generates enough traffic as to lead to more pollution.

Explaining the Empirical Results. The model therefore admits two mechanisms through which firms may sort into polluted locations.

The first mechanism is the one that appears most empirically relevant in our setting. When η is small, traffic is the main source of demand. Entrepreneurs then choose to locate in high-traffic areas because these locations offer greater customer visibility and stronger demand. Because traffic also generates pollution, the same locations are more polluted.

A second mechanism is also possible in principle, but it appears less relevant in this context. When firm concentration itself becomes an important source of demand, even locations with relatively low exogenous traffic may attract many firms. For this mechanism to generate a strong link between profitability and pollution exposure, however, firms must not only value proximity to other firms, but also be an important source of traffic—and therefore pollution—themselves. When both conditions hold, traffic and pollution become increasingly shaped by firms' own location choices rather than by exogenous traffic alone.

Finally, the model also provides a natural explanation for the coexistence of large profit pollution premia with relatively modest wage pollution premia. Using the expressions above, we can write the profit and wage pollution premia of being located in a polluted location j relative to a less polluted location k as

$$\underbrace{\pi_j(n_j) - \pi_k(n_k)}_{\text{Profit Pollution Premium}} = (1-\beta)\underbrace{\left[(D_j(n_j) - D_k(n_k)) - \kappa_w\left(p_j(n_j) - p_k(n_k)\right)\right]}_{\text{Surplus Gap}} \tag{6}$$

$$\underbrace{w_j(n_j) - w_k(n_k)}_{\text{Wage Pollution Premium}} = \underbrace{\kappa_w\left(p_j(n_j) - p_k(n_k)\right)}_{\text{Compensating Differential}} + \frac{\beta}{1-\beta}\underbrace{\left(\pi_j(n_j) - \pi_k(n_k)\right)}_{\text{Profit Pollution Premium}}, \tag{7}$$

These expressions show that large profit pollution premia may coexist with modest wage premia when workers' perceived pollution costs and bargaining power are limited. In that case, firms capture most of the surplus generated by locating in high-demand areas while workers

receive only limited compensation for higher pollution exposure.

Overall, the framework shows that the empirical patterns are consistent with a simple spatial equilibrium. The model can jointly rationalize the sorting of firms into more polluted locations, the positive relationship between profitability and pollution exposure, and the comparatively modest wage premia. The main takeaway is that the evidence is consistent with an equilibrium allocation in which agents behave optimally given the spatial distribution of demand and pollution.

6.3 Accounting for Magnitudes

The model implies that, in the observed equilibrium, the monetary benefits from the current spatial distribution of firms must compensate the perceived costs of pollution exposure for both entrepreneurs and workers. For entrepreneurs this follows directly from revealed preference: conditional on the set of available locations, the observed sorting pattern implies that entrepreneurs prefer to locate in those places despite their higher pollution. For workers, instead, this follows from the equilibrium structure of the labor market: in locations with higher pollution exposure, wages must adjust sufficiently to compensate workers for the disamenity.

This naturally raises the empirical question of whether the higher profits and wages associated with locating on busy roads are indeed large enough to offset the health costs of higher pollution exposure.

Motivated by this logic, we use our empirical estimates to perform a simple accounting exercise aimed at quantifying the magnitude of this trade-off. In particular, we measure the monetary value of the observed spatial allocation of firms for entrepreneurs and workers relative to two alternative allocations within each sub-county: one in which firms are randomly assigned across locations, and another in which firms actively avoid the most polluted locations. We then compare the implied income losses from moving away from the observed allocation to the associated gains from lower pollution exposure.

This exercise should be interpreted as an accounting exercise rather than as a structural counterfactual. It holds fixed the local relationship between traffic, pollution, profits, and wages, and therefore isolates the consequences of changing the *weighting* of locations induced by the spatial distribution of firms. It does not allow for general-equilibrium adjustments in customer demand, congestion, or pollution that would arise if many firms were relocated simultaneously. For this reason, the exercise is informative about the magnitude of the trade-off embedded in the observed allocation, but not about the full effects of relocation policies.

Measuring the Benefits and Costs of the Current Firm Distribution. We focus on average values for workers and active entrepreneurs, defined as population-weighted averages of wages, profits, and pollution exposure across locations. In practice, this corresponds to

comparing average predicted outcomes under the observed distribution of firms across grid cells to those implied by alternative hypothetical allocations within the same sub-county. Consistent with the logic of the model, locations with more firms receive greater weight in the aggregate calculations.

To implement this exercise, we proceed in three steps. First, using our estimated elasticities, we predict pollution, profits, and wages at the grid-cell level as functions of road traffic. More specifically, we use the empirical relationships between road size and pollution, profits, and wages estimated in the previous sections to assign each grid cell in our sample a predicted level of $PM_{2.5}$ exposure, profits, and wages.[69] Second, for each sub-county, we aggregate these predicted outcomes under different allocations of firms across grid cells: the observed allocation, a random allocation across cells with roads, and an alternative allocation that shifts firms toward cleaner cells. Third, we translate the implied changes in $PM_{2.5}$ exposure into welfare-relevant health costs expressed in monetary units.[70]

Our first benchmark compares the observed allocation to one in which firms actively avoid pollution by relocating toward the cleaner part of the within-sub-county distribution of available sites. Our second benchmark compares the observed allocation to a random allocation of firms across grid cells within each sub-county.

The results of this exercise are reported in Table 6. Relative to an allocation in which firms actively avoid pollution, the observed spatial distribution of firms increases average profits for entrepreneurs by 578.7 dollars per year and wages for workers by 29.1 dollars, while raising pollution exposure by 4.6 $\mu g/m^3$ of $PM_{2.5}$, or 1.8 lost months of life expectancy which we value at 324.6 dollars using a value of a life-year saved equal to three times Uganda's GDP per capita. Relative to a random allocation, the observed allocation yields profit gains of 207.7 dollars, at the cost an additional 1.6 $\mu g/m^3$ $PM_{2.5}$, which we value at 113.9 dollars.

To make the income and health effects comparable, we convert the annual profit and wage gains into present discounted values using a 3% discount rate over a 40-year horizon. Under this benchmark, relative to pollution avoidance, the observed allocation raises the present discounted value of profits by about 13,376 dollars per entrepreneur, compared to a health cost of 325 dollars. For workers, the corresponding present discounted value of the wage gain is about 673 dollars, compared to a health cost of 325 dollars. Relative to a random allocation, the observed allocation raises the present discounted value of profits by about 4,800 dollars, compared to a health cost of 114 dollars. These comparisons imply that entrepreneurs strongly prefer the current allocation, consistent with the sorting patterns documented in the data. For workers,

[69] As in the empirical analysis, road size is normalized within sub-county, so the exercise exploits within-sub-county spatial variation. More implementation details are provided in Appendix A.5

[70] Specifically, we map differences in $PM_{2.5}$ into losses in life expectancy using the estimated marginal effect from Ebenstein et al. (2017) and then assign a monetary value to these health changes using conservative policy-relevant benchmarks based on standard cost-effectiveness calculations. The precise implementation is described in Appendix A.5.

the trade-off is substantially flatter: the monetary benefits of the observed allocation remain positive, but they are much smaller than for entrepreneurs because wage pollution premia are modest even though the pollution consequences are similar in magnitude. As a result, the observed allocation appears considerably less attractive for workers than for entrepreneurs.

Heterogeneous Benefits. The average numbers in Table 6 mask substantial heterogeneity across sub-counties. The consequences of the observed sorting pattern depend on the local joint distribution of roads, pollution, and firms.

This heterogeneity is evident in Table 6, where we report the median, p20, and p80. We find substantial dispersion around the mean values. This heterogeneity is important because it suggests that even if the average entrepreneur prefers the current allocation, the strength of that preference may vary widely across local contexts.

Robustness to Alternative Valuations of Health Gains. The quantitative conclusions of the accounting exercise necessarily depend on how health gains from lower pollution are valued. To assess the robustness of the results, we therefore complement the baseline calculations with a simple indifference-value exercise.

Specifically, we ask: what is the minimum value of a statistical life that an entrepreneur or worker would need to assign to the health gains from lower pollution in order to be willing to move from the observed location to a random location within the same sub-county?

Figure 7 reports the resulting indifference curves separately for entrepreneurs and workers under two alternative assumptions about discounting. In the first, life-expectancy gains are left undiscounted, while income losses are discounted as a standard annuity. In the second, both income losses and future survival gains are discounted, so that health benefits occurring later in life receive less weight. The implied indifference value of life is much higher for entrepreneurs than for workers, reflecting the fact that entrepreneurs give up substantially more income when moving away from the observed allocation. By construction, if plausible external benchmarks for the value of life lie below the indifference curve, individuals prefer the current allocation; if they lie above it, they would prefer relocation.

The figure shows that it is difficult to overturn the revealed preference of entrepreneurs under empirically plausible parameterizations. For workers, by contrast, the comparison is more sensitive to the assumed valuation of health and to discounting.

6.4 Discussion and Policy Implications

The accounting exercise above quantifies the trade-off implied by the current spatial distribution of firms. These findings have direct implications for policies aimed at relocating firms away from congested urban areas—an intervention frequently discussed in developing country contexts

(Gechter and Kala, 2025). In particular, they suggest that such policies are likely to encounter substantial resistance from entrepreneurs, since relocating away from busy roads may involve large profit losses.

Importantly, the accounting exercise holds fixed the spatial distribution of demand, traffic, and pollution. It therefore captures the consequences of relocating a marginal firm or worker given the current environment, but not the aggregate effects of relocating many firms simultaneously. If a large number of firms were relocated, traffic patterns and demand conditions would likely adjust, potentially altering both profitability and pollution exposure across locations.

Our model provides a useful lens through which to interpret these general equilibrium considerations. In particular, the parameters ν and η govern the extent to which pollution and profitability themselves depend on the spatial distribution of firms. The parameter ν captures the extent to which firms generate traffic and therefore pollution. If ν is close to zero, most traffic is exogenous to firm location, and relocating firms would have limited effects on pollution itself.

Our empirical evidence suggests that ν is likely to be small: most traffic appears to be driven by broader urban mobility patterns rather than by the presence of individual firms. Under this interpretation, the environmental benefits from relocating firms away from busy roads are likely to be similar to those captured in the accounting exercise above.

The parameter η, instead, governs the strength of agglomeration forces. When η is small, firm productivity primarily depends on traffic and customer visibility, making locations near busy roads particularly valuable. Our empirical results are consistent with this interpretation: the profitability of a location appears to be closely tied to traffic and customer visibility, suggesting that relocating firms away from busy roads would likely reduce their access to customers and therefore reduce profitability.[71]

More broadly, the framework highlights how the relationship between profitability and pollution exposure may evolve over the development process as the organization of production changes (Engbom et al., 2025). In many low-income settings, production and retail activities are tightly integrated, and firms rely heavily on physical proximity to customers. As economies develop, firms often adopt alternative marketing channels, improve logistics networks, and increasingly separate production from retail locations. These changes may weaken the link between profitability and pollution exposure.

Finally, the model also suggests a possible source of path dependence in the spatial organization of economic activity, especially if the underlying parameters evolve over the course of development. To fix ideas, consider an economy like our current empirical setting, in which

[71] This reasoning applies when relocation affects only a subset of firms. If all firms in a given market were relocated simultaneously, aggregate demand would likely adjust over time as customers adapt their consumption and travel patterns. In that case, the long-run demand for the relocated firms may recover, even though the short-run losses from reduced customer visibility could still be substantial.

firms sort into highly polluted locations because traffic is largely exogenous and high-traffic roads bring more customers. In that case, polluted locations are attractive primarily because they are associated with greater exogenous demand.

Now suppose that, as the economy develops, the relative importance of agglomeration forces rises, so that η becomes larger over time—for example because customer demand depends less on raw traffic and more on proximity to other firms. In that case, firms may remain concentrated in the same locations not because those places continue to have greater exogenous demand, but because past concentration itself generates a self-reinforcing productivity advantage. A high-congestion, high-pollution spatial allocation may then persist even if it is no longer efficient from a broader social perspective. In such an environment, a one-time policy intervention that coordinates firm relocation could help cities transition toward a cleaner spatial equilibrium.

7 Conclusion

In Ugandan cities, the need to locate near customers creates strong incentives for small manufacturing firms to cluster on the most congested and polluted roads. The costs of this mechanism are large: the observed firm sorting raises pollution exposure by an amount we estimate to cost 1.8 months of life expectancy, relative to an alternative in which firms avoid pollution. Since this mechanism operates through the spatial organization of production within the city, it is invisible to approaches focusing on city-level averages, leading such approaches to underestimate the costs of urban air pollution in developing-country cities.

Our findings point to a fundamental tension in the development process: the same forces that make cities productive engines of growth—the concentration of firms, customers, and road traffic—also make them places where workers are systematically exposed to harmful air quality. First-best policies that directly reduce pollution emissions, such as congestion pricing (Kreindler, 2024), enforcement of vehicle emissions standards (Jacobsen et al., 2023), and investment in public transportation (Gendron-Carrier et al., 2022; Kreindler et al., 2023), are therefore especially valuable in this context, as they would reduce the health costs of urban production without disrupting the customer-access benefits that drive firm location. Second-best firm relocation policies face a harder trade-off: the environmental gains from moving firms away from major roads would be substantial, but the productivity losses would be real, as firm profitability is closely tied to customer visibility. More broadly, our results suggest that as developing-country cities grow and the organization of production evolves—with firms increasingly able to separate production from retail, access customers digitally, and invest in logistics—the bundling of pollution and customer access that drives our results may weaken, reducing one of the key welfare costs of urban production. Understanding how policy can accelerate this transition remains an important avenue for future research.

References

Ahlfeldt, Gabriel M., Stephen J. Redding, Daniel M. Sturm, and Nikolaus Wolf. 2015. "The Economics of Density: Evidence From the Berlin Wall." *Econometrica* 83:2127–2189. URL https://ideas.repec.org/a/wly/emetrp/v83y2015ip2127-2189.html.

Akbar, Prottoy, Victor Couture, Gilles Duranton, and Adam Storeygard. 2023a. "Mobility and Congestion in Urban India." *American Economic Review* 113 (4):1083–1111.

Akbar, Prottoy A, Victor Couture, Gilles Duranton, and Adam Storeygard. 2023b. "The fast, the slow, and the congested: Urban transportation in rich and poor countries." *NBER Working Paper w31642* .

Alaran, Aishat Jumoke, Natasha O'Sullivan, Lambed Tatah, Richard Sserunjogi, and Gabriel Okello. 2024. "Air pollution ($PM_{2.5}$) and its meteorology predictors in Kampala and Jinja cities, in Uganda." 4 (10):1145–1156. URL https://xlink.rsc.org/?DOI=D4EA00074A.

Anderson, Stephen J., Rajesh Chandy, and Bilal Zia. 2018. "Pathways to Profits: The Impact of Marketing vs. Finance Skills on Business Performance." *Management Science* 64 (12):5559–5583. URL https://ideas.repec.org/a/inm/ormnsc/v64y2018i12p5559-5583.html.

Aragon, Fernando M., Juan Jose Miranda, and Paulina Oliva. 2017. "Particulate matter and labor supply: The role of caregiving and non-linearities." *Journal of Environmental Economics and Management* 86 (C):295–309. URL https://ideas.repec.org/a/eee/jeeman/v86y2017icp295-309.html.

Atuyambe, Lynn M., Samuel Etajak, Felix Walyawula, Simon Kasasa, Agnes Nyabigambo, William Bazeyo, Heather Wipfli, Jonathan M. Samet, and Kiros T. Berhane. 2024. "Air quality and attributable mortality among city dwellers in Kampala, Uganda: results from 4 years of continuous PM2.5 concentration monitoring using BAM 1022 reference instrument." *Journal of Exposure Science & Environmental Epidemiology* URL https://doi.org/10.1038/s41370-024-00684-9.

Balboni, Clare, Johannes Boehm, and Mazhar Waseem. 2024. "Firm adaptation and production networks: Structural evidence from extreme weather events in Pakistan." *PEDL Working Paper* .

Balboni, Clare, Gharad Bryan, Melanie Morten, Caylee O'Connor, and Bilal Siddiqi. 2025. "Impacts of infrastructure: People versus place." Tech. rep., working paper.

Banzhaf, H. Spencer and Randall P. Walsh. 2008. "Do People Vote with Their Feet? An Empirical Test of Tiebout." *American Economic Review* 98 (3):843–863. URL http://www.aeaweb.org/articles?id=10.1257/aer.98.3.843.

Barwick, Panle Jia, Dave Donaldson, Shanjun Li, Yatang Lin, and Deyu Rao. 2024. "Transportation Networks, Short-term Mobility, and Pollution Exposure: Evidence from High-Speed Rail in China." *NBER Working Paper w30462* .

Bassi, Vittorio, Jung Hyuk Lee, Alessandra Peter, Tommaso Porzio, Ritwika Sen, and Esau Tugume. 2024. "Self-Employment Within the Firm." *NBER Working Paper w31740* URL https://EconPapers.repec.org/RePEc:nbr:nberwo:31740.

Bassi, Vittorio, Raffaela Muoio, Tommaso Porzio, Ritwika Sen, and Esau Tugume. 2022. "Achieving Scale Collectively." *Econometrica* 90 (6):2937–2978. URL https://onlinelibrary.wiley.com/doi/abs/10.3982/ECTA18773.

Bird, Julia and Anthony J. Venables. 2020. "Land tenure and land-use in a developing city: A quantitative spatial model applied to Kampala, Uganda." *Journal of Urban Economics* 119 (C). URL https://ideas.repec.org/a/eee/juecon/v119y2020ics0094119020300395.html.

Bryan, Gharad, Edward Glaeser, and Nick Tsivanidis. 2020. "Cities in the developing world." *Annual Review of Economics* 12 (1):273–297.

Carozzi, Felipe and Sefi Roth. 2023. "Dirty density: Air quality and the density of American cities." *Journal of Environmental Economics and Management* 118:102767. URL https://www.sciencedirect.com/science/article/pii/S0095069622001206.

Chay, Kenneth Y. and Michael Greenstone. 2005. "Does Air Quality Matter? Evidence from the Housing Market." *Journal of Political Economy* 113 (2):376–424. URL https://www.journals.uchicago.edu/doi/10.1086/427462.

Chen, Shuai, Paulina Oliva, and Peng Zhang. 2022. "The effect of air pollution on migration: evidence from China." *Journal of Development Economics* 156:102833.

Combes, Pierre-Philippe and Laurent Gobillon. 2015a. "Chapter 5 - The Empirics of Agglomeration Economies." In *Handbook of Regional and Urban Economics*, vol. 5, edited by Gilles Duranton, J. Vernon Henderson, and William C. Strange. Elsevier, 247–348. URL https://www.sciencedirect.com/science/article/pii/B9780444595171000052.

———. 2015b. "The Empirics of Agglomeration Economies." In *Handbook of Regional and Urban Economics*, vol. 5. Elsevier, 247–348. URL https://linkinghub.elsevier.com/retrieve/pii/B9780444595171000052.

Conley, T. G. 1999. "GMM estimation with cross sectional dependence." *Journal of Econometrics* 92 (1):1–45. URL https://www.sciencedirect.com/science/article/pii/S0304407698000840.

Currie, Janet, Lucas Davis, Michael Greenstone, and Reed Walker. 2015. "Environmental Health Risks and Housing Values: Evidence from 1,600 Toxic Plant Openings and Closings." *The American Economic Review* 105 (2):678–709. URL http://www.jstor.org.proxy.uchicago.edu/stable/43495396. Publisher: American Economic Association.

Davis, Lucas W and Matthew E Kahn. 2010. "International trade in used vehicles: The environmental consequences of NAFTA." *American Economic Journal: Economic Policy* 2 (4):58–82.

de Mel, Suresh, David McKenzie, and Christopher Woodruff. 2019. "Labor Drops: Experimental Evidence on the Return to Additional Labor in Microenterprises." *American Economic Journal: Applied Economics* 11 (1):202–35. URL https://www.aeaweb.org/articles?id=10.1257/app.20170497.

Deffebach, Peter, David Lagakos, Yuhei Miyauchi, and Eiji Yamada. 2025. "The spatial distribution of income in cities: New global evidence and theory." Tech. rep., National Bureau of Economic Research.

Deschenes, Olivier, Michael Greenstone, and Joseph S. Shapiro. 2017. "Defensive Investments and the Demand for Air Quality: Evidence from the NOx Budget Program." *American Economic Review* 107 (10):2958–2989. URL http://www.aeaweb.org/articles?id=10.1257/aer.20131002.

Diamond, Peter A. 1982. "Aggregate Demand Management in Search Equilibrium." *Journal of Political Economy* 90 (5):881–894. URL http://www.jstor.org/stable/1837124.

Duranton, Gilles. 2015. "Growing through cities in developing countries." *The World Bank Research Observer* 30 (1):39–73.

Duranton, Gilles and Diego Puga. 2004. "Chapter 48 - Micro-Foundations of Urban Agglomeration Economies." In *Cities and Geography*, *Handbook of Regional and Urban Economics*, vol. 4, edited by J. Vernon Henderson and Jacques-Francois Thisse. Elsevier, 2063–2117. URL https://www.sciencedirect.com/science/article/pii/S1574008004800051.

Ebenstein, Avraham, Maoyong Fan, Michael Greenstone, Guojun He, and Maigeng Zhou. 2017. "New evidence on the impact of sustained exposure to air pollution on life expectancy from China's Huai River Policy." *Proceedings of the National Academy of Sciences* 114 (39):10384–10389. URL https://www.pnas.org/doi/abs/10.1073/pnas.1616784114.

Ellison, Glenn, Edward L Glaeser, and William R Kerr. 2010. "What Causes Industry Agglomeration?

Evidence from Coagglomeration Patterns." *American Economic Review* 100 (3):1195–1213. URL https://pubs.aeaweb.org/doi/10.1257/aer.100.3.1195.

Engbom, Niklas, Hannes Malmberg, Tommaso Porzio, Federico Rossi, and Todd Schoellman. 2025. "Economic development according to chandler." Tech. rep., National Bureau of Economic Research.

Gechter, Michael and Namrata Kala. 2025. "Firm Presence, Pollution, and Agglomeration: Evidence from a Randomized Environmental Place-Based Policy." NBER Working Papers 33707, National Bureau of Economic Research, Inc. URL https://ideas.repec.org/p/nbr/nberwo/33707.html.

Gendron-Carrier, Nicolas, Marco Gonzalez-Navarro, Stefano Polloni, and Matthew A Turner. 2022. "Subways and urban air pollution." *American economic journal: Applied economics* 14 (1):164–196.

Glaeser, Edward L and Wentao Xiong. 2017. "Urban productivity in the developing world." *Oxford Review of Economic Policy* 33 (3):373–404.

Gollin, Douglas, Martina Kirchberger, and David Lagakos. 2021. "Do urban wage premia reflect lower amenities? Evidence from Africa." *Journal of Urban Economics* 121:103301.

Greenstone, Michael. 2002. "The Impacts of Environmental Regulations on Industrial Activity: Evidence from the 1970 and 1977 Clean Air Act Amendments and the Census of Manufactures." *Journal of Political Economy* 110 (6):1175–1219. URL https://www.journals.uchicago.edu/doi/10.1086/342808.

Greenstone, Michael and B. Kelsey Jack. 2015. "Envirodevonomics: A Research Agenda for an Emerging Field." *Journal of Economic Literature* 53 (1):5–42. URL https://pubs.aeaweb.org/doi/10.1257/jel.53.1.5.

Greenstone, Michael, Kenneth Lee, and Harshil Sahai. 2021. "Indoor Air Quality, Information, and Socioeconomic Status: Evidence from Delhi." *AEA Papers and Proceedings* 111:420–424. URL https://www.aeaweb.org/articles?id=10.1257/pandp.20211006.

Hanna, Rema and Paulina Oliva. 2015. "The effect of pollution on labor supply: Evidence from a natural experiment in Mexico City." *Journal of Public Economics* 122 (C):68–79. URL https://econpapers.repec.org/article/eeepubeco/v_3a122_3ay_3a2015_3ai_3ac_3ap_3a68-79.htm.

Harari, Mariaflavia. 2020. "Cities in Bad Shape: Urban Geometry in India." *American Economic Review* 110 (8):2377–2421. URL https://pubs.aeaweb.org/doi/10.1257/aer.20171673.

———. 2024. "Residential patterns and local public goods in urban Brazil." *Wharton School, Unpublished manuscript* .

Heblich, Stephan, Alex Trew, and Yanos Zylberberg. 2021. "East-Side Story: Historical Pollution and Persistent Neighborhood Sorting." *Journal of Political Economy* 129 (5):1508–1552. URL https://www.journals.uchicago.edu/doi/10.1086/713101.

Heise, Sebastian and Tommaso Porzio. 2022. "Labor Misallocation Across Firms and Regions." Tech. rep., National Bureau of Economic Research.

Hjort, Jonas, Vinayak Iyer, and Golvine de Rochambeau. 2020. "Informational Barriers to Market Access: Experimental Evidence from Liberian Firms." *NBER Working Paper w27662* URL https://ideas.repec.org/p/nbr/nberwo/27662.html.

Hoffmann, Bridget and Juan Pablo Rud. 2024. "The Unequal Effects of Pollution on Labor Supply." *Econometrica* 92 (4):1063–1096. URL https://onlinelibrary.wiley.com/doi/abs/10.3982/ECTA20484.

Hsiang, Solomon M. 2010. "Temperatures and cyclones strongly associated with economic production in the Caribbean and Central America." *Proceedings of the National Academy of Sciences* 107 (35):15367–15372. URL https://www.pnas.org/content/107/35/15367.

Iino, Haru, Masayuki Hashiguchi, and Satoko Hori. 2022. "Estimating the range of incremental cost-

effectiveness thresholds for healthcare based on willingness to pay and GDP per capita: A systematic review." *PloS one* 17 (4).

Ito, Koichiro and Shuang Zhang. 2020. "Willingness to Pay for Clean Air: Evidence from Air Purifier Markets in China." *Journal of Political Economy* 128 (5):1627–1672. URL https://www.journals.uchicago.edu/doi/abs/10.1086/705554.

Jacobsen, Mark R, James M Sallee, Joseph S Shapiro, and Arthur A Van Benthem. 2023. "Regulating untaxable externalities: Are vehicle air pollution standards effective and efficient?" *The Quarterly Journal of Economics* 138 (3):1907–1976.

Jensen, Robert and Nolan H. Miller. 2018. "Market Integration, Demand, and the Growth of Firms: Evidence from a Natural Experiment in India." *American Economic Review* 108 (12):3583–3625. URL https://www.aeaweb.org/articles?id=10.1257/aer.20161965.

Kahn, Matthew E. and Randall Walsh. 2015. "Cities and the Environment." In *Handbook of Regional and Urban Economics*, vol. 5. Elsevier, 405–465. URL https://linkinghub.elsevier.com/retrieve/pii/B9780444595171000076.

Karner, Alex A, Douglas S Eisinger, and Deb A Niemeier. 2010. "Near-roadway air quality: synthesizing the findings from real-world data." *Environmental science & technology* 44 (14):5334–5344.

KCCA, (Kampala Capital City Authority). 2014. "Strategic Plan 2014/15-2018/19, Laying the Boundation for Kampala City Transformation." Tech. rep. URL https://www.kcca.go.ug/uploads/KCCA_STRATEGI_PLAN_2015-2016.pdf.

Kelejian, Harry H. and Ingmar R. Prucha. 2007. "HAC estimation in a spatial framework." *Journal of Econometrics* 140 (1):131–154. Analysis of spatially dependent data.

Khanna, Gaurav, Wenquan Liang, Ahmed Mushfiq Mobarak, and Ran Song. 2025. "The Productivity Consequences of Pollution-Induced Migration in China." *American Economic Journal: Applied Economics* 17 (2):184–224. URL https://www.aeaweb.org/articles?id=10.1257/app.20220655.

Kirenga, Bruce J, Qingyu Meng, Frederik van Gemert, Hellen Aanyu-Tukamuhebwa, Niels Chavannes, Achilles Katamba, Gerald Obai, Thys van der Molen, Stephan Schwander, and Vahid Mohsenin. 2015. "The State of Ambient Air Quality in Two Ugandan Cities: A Pilot Cross-Sectional Spatial Assessment." *International journal of environmental research and public health* 12 (7):8075–8091. URL https://pubmed.ncbi.nlm.nih.gov/26184273.

Kreindler, Gabriel. 2024. "Peak-Hour Road Congestion Pricing: Experimental Evidence and Equilibrium Implications." *Econometrica* 92 (4):1233–1268. URL https://onlinelibrary.wiley.com/doi/abs/10.3982/ECTA18422.

Kreindler, Gabriel, Arya Gaduh, Tilman Graff, Rema Hanna, and Benjamin A Olken. 2023. "Optimal Public Transportation Networks: Evidence from the World's Largest Bus Rapid Transit System in Jakarta." Tech. rep., National Bureau of Economic Research.

Lagakos, David. 2016. "Explaining Cross-Country Productivity Differences in Retail Trade." *journal of political economy* 124 (2):42.

Levinson, Arik. 1996. "Environmental regulations and manufacturers' location choices: Evidence from the Census of Manufactures." *Journal of Public Economics* 62 (1):5–29. URL https://www.sciencedirect.com/science/article/pii/0047272796015721.

Marshall, Albert. 1920. *Principles of Economics*. London: MacMillan.

McKenzie, David and Christopher Woodruff. 2017. "Business Practices in Small Firms in Developing Countries." *Management Science* 63 (9):2967–2981. URL https://ideas.repec.org/a/inm/ormnsc/v63y2017i9p2967-2981.html.

Michaels, Guy, Dzhamilya Nigmatulina, Ferdinand Rauch, Tanner Regan, Neeraj Baruah, and Amanda Dahlstrand. 2021. "Planning ahead for better neighborhoods: Long-run evidence from

tanzania." *Journal of Political Economy* 129 (7):2112–2156.

Mortensen, Dale. 1982. "The Matching Process as a Noncooperative Bargaining Game." In *The Economics of Information and Uncertainty*. National Bureau of Economic Research, 233–258. URL https://EconPapers.repec.org/RePEc:nbr:nberch:4437.

Okure, Deo, Engineer Bainomugisha, Nancy Lozano-Gracia, and Maria Edisa Soppelsa. 2022. "Characterization of Ambient Air Quality in Selected Urban Areas in Uganda Using Low-Cost Sensing and Measurement Technologies." *Environ Sci Technol* 15;56(6):3324–3339.

Oster, Emily. 2019. "Unobservable Selection and Coefficient Stability: Theory and Evidence." *Journal of Business & Economic Statistics* 37 (2):187–204.

Pelnik, Carolyn. 2025. "Moving to Profitability? Alleviating Constraints on Microentrepreneur Location." *Working Paper* .

Pissarides, Christopher A. 1985. "Short-Run Equilibrium Dynamics of Unemployment, Vacancies, and Real Wages." *The American Economic Review* 75 (4):676–690.

Sorin, Jeanne. 2025. "Public Roads on Private Lands: Land Costs and Optimal Road Improvements in Urban Uganda." .

Startz, Meredith. 2025. "The Value of Face-to-Face: Search and Contracting Problems in Nigerian Trade." *Econometrica* URL https://drive.google.com/file/d/1CBBGmqq-VmYNTsdOUbEF9hQlYBuFVml-/view. Conditionally accepted.

Sullivan, Daniel M and Alan Krupnick. 2018. "Using Satellite Data to Fill the Gaps in the US Air Pollution Monitoring Network." *Working Paper* :33.

Sun, Cong, Matthew E. Kahn, and Siqi Zheng. 2017. "Self-protection investment exacerbates air pollution exposure inequality in urban China." *Ecological Economics* 131 (C):468–474.

UBOS. 2011. "Census of Business Establishments, 2010/11." Tech. rep.

UBOS. 2021. "Uganda National Household Survey 2019/2020." Survey report, Uganda Bureau of Statistics (UBOS), Kampala, Uganda. URL https://www.ubos.org.

van Donkelaar, Aaron, Melanie S. Hammer, Liam Bindle, Michael Brauer, Jeffery R. Brook, Michael J. Garay, N. Christina Hsu, Olga V. Kalashnikova, Ralph A. Kahn, Colin Lee, Robert C. Levy, Alexei Lyapustin, Andrew M. Sayer, and Randall V. Martin. 2021. "Monthly Global Estimates of Fine Particulate Matter and Their Uncertainty." *Environmental Science & Technology* 55 (22):15287–15300. URL https://doi.org/10.1021/acs.est.1c05309.

Vitali, Anna. 2025. "Consumer Search and Firm Location: Evidence from the Garment Sector in Uganda." *Working Paper* .

Wang, Xueyuan, Chunting Zhang, and Zhijian Zhang. 2019. "Pollution haven or porter? The impact of environmental regulation on location choices of pollution-intensive firms in China." *Journal of Environmental Management* 248:109248.

WHO. 2021. *WHO Global Air Quality Guidelines: Particulate Matter ($PM_{2.5}$ and PM_{10}), Ozone, Nitrogen Dioxide, Sulfur Dioxide and Carbon Monoxide.* Geneva: World Health Organization. URL https://iris.who.int/server/api/core/bitstreams/551b515e-2a32-4e1a-a58c-cdaecd395b19/content.

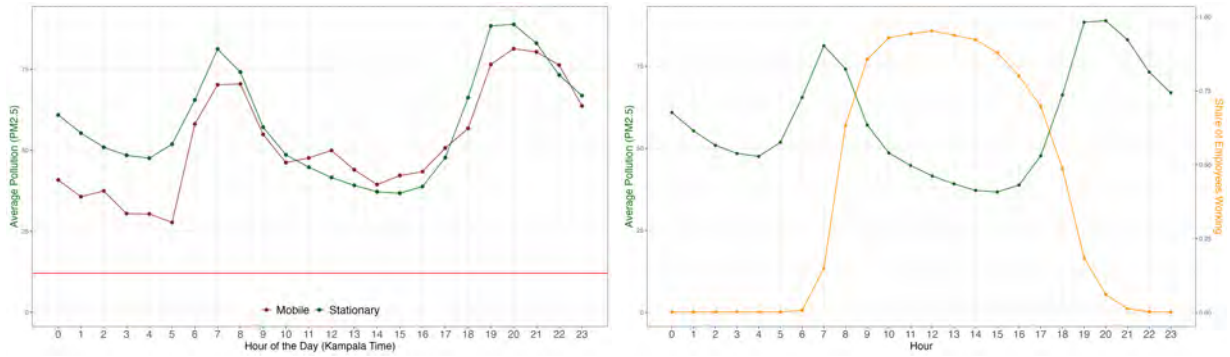
WHO, (World Health Organization). 2016. "Ambient Air Pollution: A Global Assessment of Exposure and Burden of Disease." Tech. rep. URL https://apps.who.int/iris/bitstream/handle/10665/250141/9789241511353-eng.pdf.

Wijnen, Wim, Said Dahdah, and Nino Pkhikidze. 2025. "The Value of a Statistical Life in the Context of Road Safety: A New Value Transfer Approach." *Traffic Injury Prevention* Published online April 22, 2025.

Figure 1: Cyclicality of Pollution and Production Within the Day

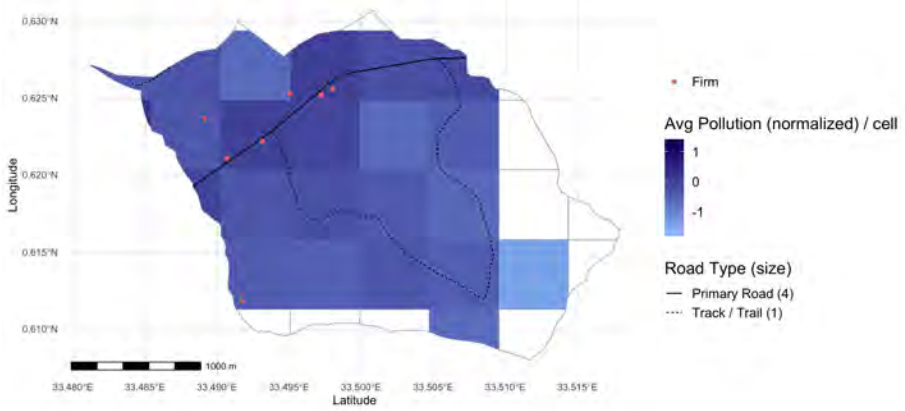
(a) Cyclicality of Pollution

(b) Cyclicality of Production



Notes: The left panel shows pollution cyclicality during the day, as measured by our stationary and mobile monitors. The red line corresponds to the 2021 EPA guideline for average annual $PM_{2.5}$ exposure. The right panel overlays pollution as measured by our stationary monitors with the share of employees who report working by hour of the day. In our survey, both managers and employees are asked at what time they started and finished work at the firm during the last day worked.

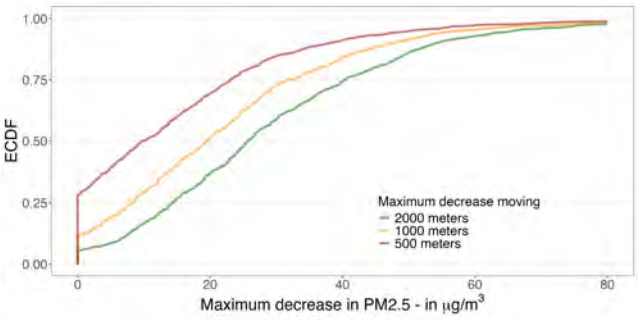
Figure 2: Average Residual Pollution, Firm Location and Road Size in a Sampled Sub-county



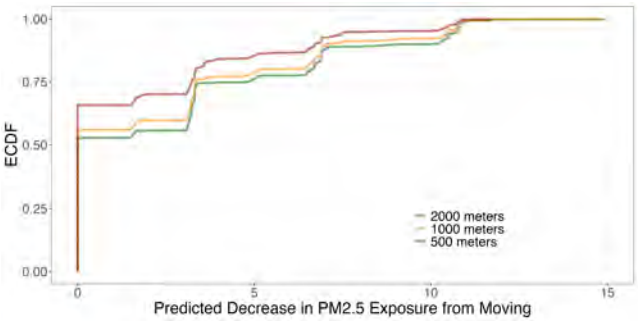
Notes: Location of firms in our survey, roads and average pollution residual per grid cell for the sampled parish in Nakalama sub-county (Iganga District). Road sizes are defined in Section 3.4 and the computation of pollution residuals is described in Section 4.1. Grid cell dimensions are 500m x 500m.

Figure 3: Local Spatial Variation in Air Pollution

(a) Decay in $PM_{2.5}$

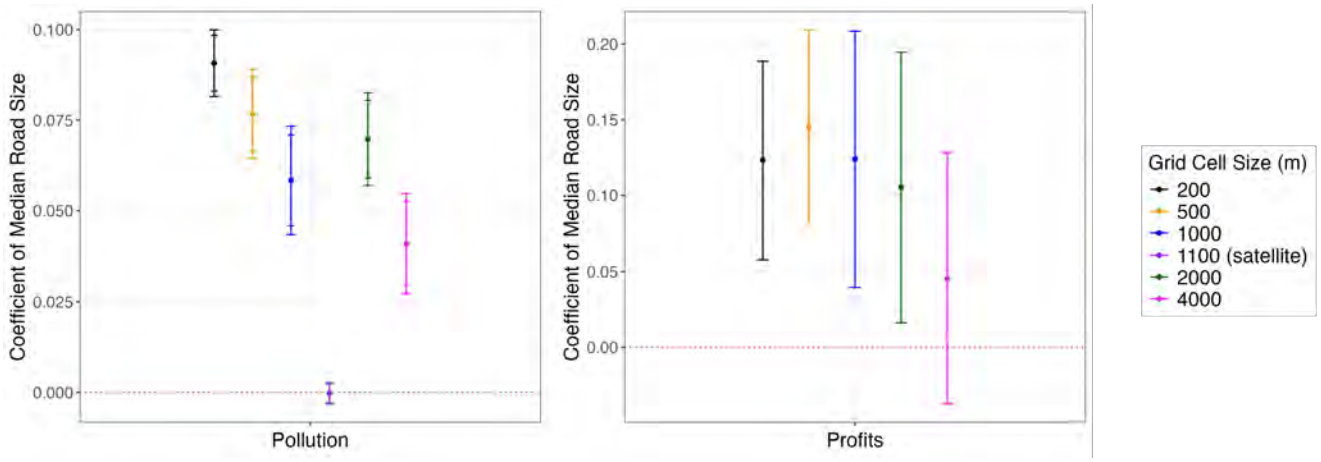


(b) Predicted Decay in $PM_{2.5}$



Notes: Panels (a) and (b) show the distribution of the maximum decrease in $PM_{2.5}$ levels that could be achieved by moving at most 500, 1000, and 2000 meters across the 500×500m grid cells in our data. Panel (a) uses pollution measured by our mobile monitors (netted out of temporal variation) and panel (b) uses pollution as predicted by our estimate of the elasticity of pollution to road size, restricting to grid cells with at least one road. In panel (b) the move is restricted to grid cells in the same sub-county as the elasticity is estimated with sub-county fixed effects. In panel (b), the predicted pollution in grid cells with 0 gain from moving 500 meters is 5.6 $\mu g/m^3$ lower than in grid cells with strictly positive predicted gain from moving.

Figure 4: Pollution-Road Size and Profits-Road Size Correlations with Different Grid-Cell Sizes

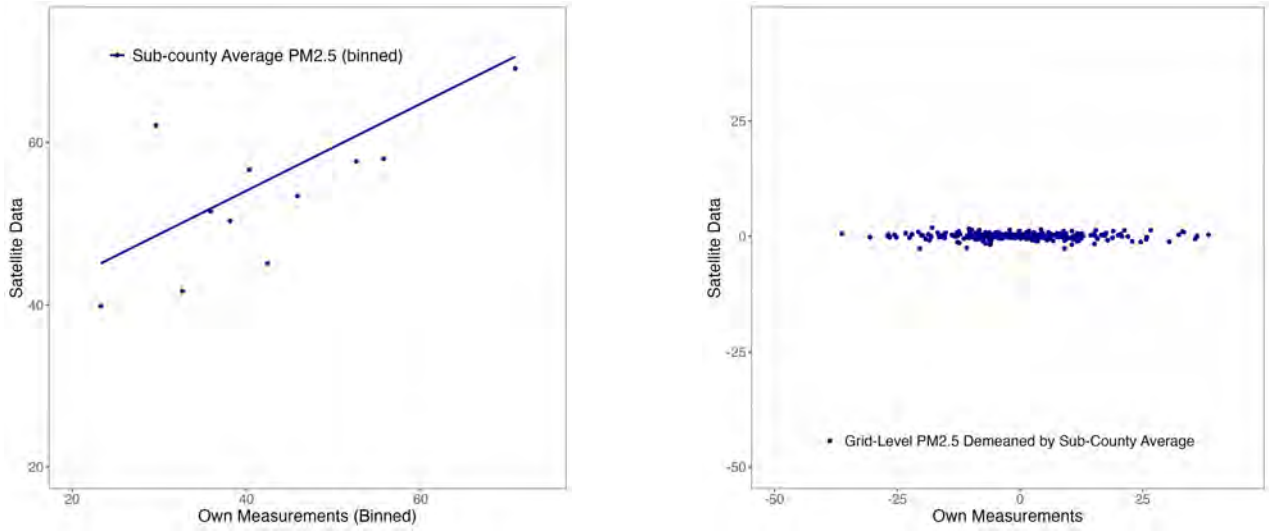


Notes: The left Panel displays the estimates and both the 95th and 90th confidence intervals of α_1 from equation 3 when varying the size of the grid cells. The right Panel displays the estimates and both the 95th and 90th confidence intervals of β_1 from equation 4 when varying the size of the grid cells. Standard errors are bootstrapped for the pollution regression (left panel) as described in Footnote 38 (400 draws). Standard errors are clustered at the grid cell level for the profit regression (right panel). In the left Panel, we additionally display the estimated coefficient when using Satellite pollution data from van Donkelaar et al. (2021), available at a definition of approximately 1100m x 1100m.

Figure 5: Correlation between Satellite Data and Our Own Pollution Measurements

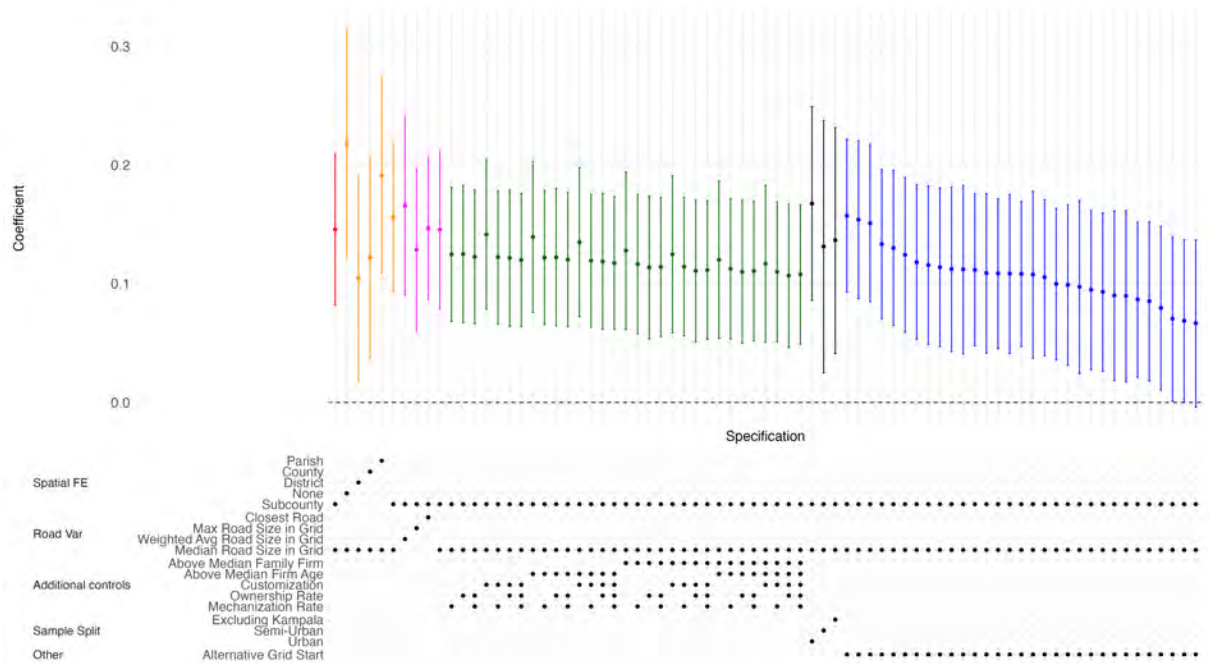
(a) Sub-county level correlation

(b) Grid-cell level correlation (within-sub-county)



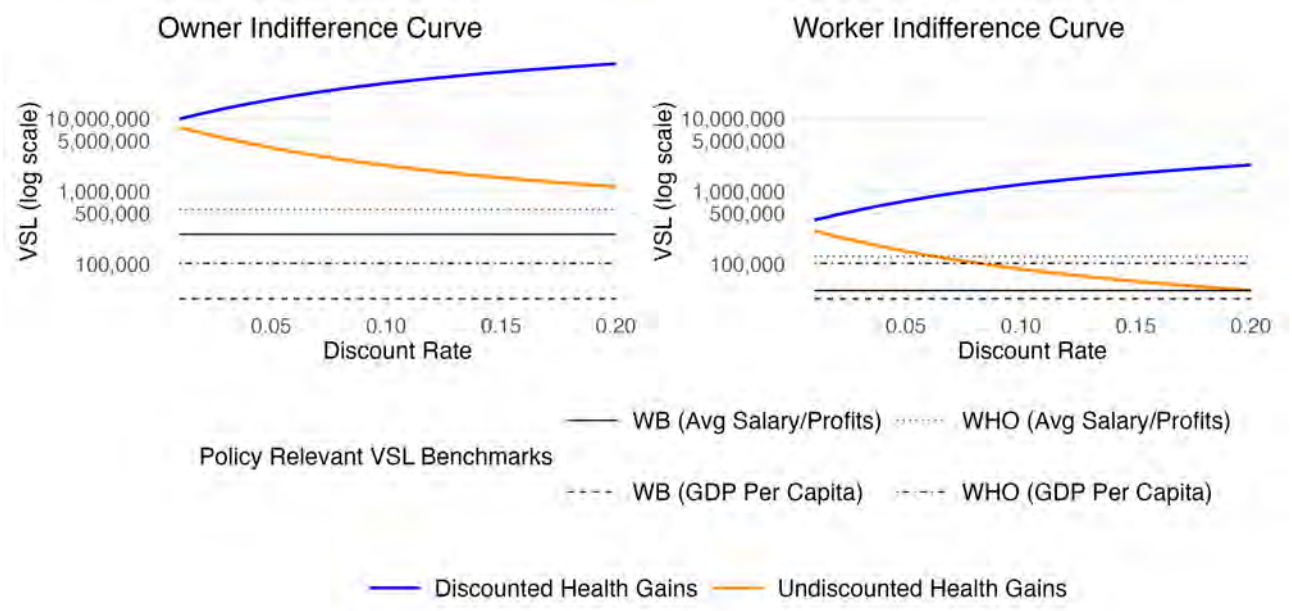
Notes: Panel (a) shows the correlation between satellite-based pollution measures and our own measurements at the sub-county level. Panel (b) shows the same correlation at the grid-cell level, exploiting within-sub-county variation only. Pollution measurements are $PM_{2.5}$ concentration in $\mu g/m^3$.

Figure 6: Profit Premium from Locating Near Large Roads— Robustness



Notes: OLS regression coefficients for the regression of log profits on road size. The main specification (red) corresponds to column 1 of Table 4. Other specifications include alternative spatial fixed-effects (orange), alternative definitions of road size (pink), controls for other aspects of production that may be affected by road size (green), splitting the sample between urban and semi-urban sub-counties or excluding Kampala (black) and alternative starting point for drawing the grid cells (blue). Above median family firm is a dummy equal to 1 if the share of a firm employees' hired through family or friends is greater than the median. Above median firm age is a dummy equal to 1 if the firm's age is greater than the median. Customization is the share of a firm sales made to order. Mechanization rate is the number of machines used by the firm in the making of their main product, relative to a sector standard. Ownership rate is the share of these machines owned by the firm. In all specifications, the covering grid is by default anchored so that its bottom-left corner aligns with the bottom-left corner of the smallest rectangle covering the sampled parishes, which may mechanically affect the aggregation of firms, pollution, and road measures at the grid cell level. The blue estimates assess robustness to this choice, using 30 random starting points as well as a specification anchoring the top-right corner instead. Standard errors are clustered at the grid cell level and the 95th CI are displayed.

Figure 7: Indifference Curves of Firm Owners and Workers for Relocation



Notes: These figures display the pair of Value of Statistical Life (VSL) and discount rate that would make the average firm owner (left panel) and worker (right panel) indifferent between the average firm's observed location and a random location within their sub-county . We report the results under two alternative assumptions about discounting life gains. In orange, life expectancy gains are left undiscounted, while income losses are discounted. In blue, both income losses and future survival gains are discounted, so that health benefits occurring later in life receive less weight. We report benchmarks VSL using the WHO cost-effectiveness benchmark per year of life saved, multiplied by Uganda's life expectancy, as well as the VSL formula used in World Bank's evaluations (Wijnen, Dahdah, and Pkhikidze, 2025). For discount rate and VSL pairs below the colored lines, the average firm's owner and worker would prefer their observed location (high profits, high pollution) to a random location in their sub-county, as the value of the health gains from moving is too low compared to the decline in earning flows.

Table 1: Correlation Between Road Size and Pollution

	(1) Avg log(Pollution) Resid.	(2) Avg log(Pollution) Resid.	(3) log(Pollution) Resid.	(4) log(Pollution) Resid.
Median Road Size/Cell	0.0767	0.0701		
	(0.0063)	(0.006)		
Closest Road Size			0.0982	0.0599
			(0.0158)	(0.0336)
N	972	972	52685	52685
R2	.3511	.1631	.158	.0352
Sub-county FE	Yes		Yes	
Level of Observation	Grid Cell	Grid Cell	Poll. measure	Poll. measure
SE clustering	Bootstrap	Bootstrap	Grid Cell	Grid Cell

Notes: OLS regression coefficients, standard errors in parentheses. In columns 1 and 2, pollution measurements are aggregated at the grid cell level and we report bootstrapped standard errors following the procedure described in Footnote 38 (400 iterations). In columns 3 and 4 we report standard errors clustered at the grid cell level. We control for log distance to the main city in the region in all specifications. In regressions at the grid cell level, we control for a dummy for whether the grid cell contains any road , a dummy for whether the grid cell is incomplete (i.e., 500m x 500m), its area, as well as a dummy for whether the grid cell falls in our main surveyed area. The top and bottom one percent of pollution residuals are trimmed. Regressions at the pollution measure level have the same geographical coverage as regressions at the grid cell level and include a dummy for whether observations fall in our main surveyed area. Road size goes from 1 (Trail/Track) to 5 (Highway). The procedure to construct pollution residuals is detailed in Section 4.1.

Table 2: Correlation Between Pollution, Road Size, and Firm Density

	(1) Any Firm	(2) Any Firm	(3) log(Firm Density)	(4) log(Firm Density)	(5) log(Firm Density)	(6) log(Firm Density)	(7) log(Firm Density)
Median Road Size/Cell	0.0398		0.133		0.122		
	(0.0173)		(0.0446)		(0.0451)		
Avg log(Pollution) Resid.		0.202		0.269		0.243	
		(0.0239)		(0.0718)		(0.0732)	
Avg Man. Score					0.00908	0.00786	
					(0.0664)	(0.0679)	
log(Pollution) Resid.							0.191
							(0.0500)
N	972	972	420	420	420	420	57009
R2	.2983	.3048	.4426	.4365	.485	.4795	.4334
Sub-county FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Level of Observation	Grid Cell	Grid Cell	Grid Cell	Grid Cell	Grid Cell	Grid Cell	Poll. Measure
SE clustering	SHAC	Bootstrap	SHAC	Bootstrap	SHAC	Bootstrap	Grid Cell

Notes: OLS regression coefficients, standard errors displayed in parentheses. In columns 2, 4 and 6, pollution measurements are aggregated at the grid cell level and we report bootstrapped standard errors following the procedure described in Footnote 38 (400 iterations). In columns 1, 3 and 5 we report SHAC Bartlett standard errors (spatial weighting kernel decaying linearly in distance) and the distance cutoff for spatial correlation is 5km. Man. Score is a standardized index of managerial ability constructed using our survey (see Appendix A.1 for details). We control for log distance to the main city in the region. In regressions at the grid cell level we also control for a dummy for whether the grid cell contains any road, a dummy for whether the grid cell is incomplete (i.e., 500m x 500m), its area, as well as a dummy for whether it is in our main surveyed area. In columns 5 and 6, we also control for missing managerial score (dummy). The top and bottom one percent of pollution residuals are trimmed. In column 7, the regression is at the pollution measurement level, has the same geographical coverage as regressions at the grid cell level, and log(Firm Density) is defined as log of the sum of inverse squared distances between each pollution measurement and all firms. Road size goes from 1 (Trail/Track) to 5 (Highway). The procedure to construct pollution residuals is detailed in section 4.1.

Table 3: Correlation Between Firm Density and Road Size in the Ugandan Firm Census

	(1) Log (Manuf firm density)	(2) Log (Manuf firm density)	(3) Log (Manuf firm density) > 10 emp.	(4) Log (Agr firm density)	(5) Log (Retail firm density)	(6) Log (Low skill Serv firm density)	(7) Log (High skill Serv firm density)
Median Road Size	0.127	0.125	0.0513	-0.0671	0.216	0.143	0.0635
	(0.0428)	(0.0240)	(0.0300)	(0.0356)	(0.0213)	(0.0247)	(0.0303)
N	410	4942	382	1776	13994	6971	2602
R2	0.378	0.514	0.645	0.486	0.416	0.505	0.632
Fixed Effects	Subcounty	Subcounty	Subcounty	Subcounty	Subcounty	Subcounty	Subcounty
Level of Observation	Grid Cell	Grid Cell	Grid Cell	Grid Cell	Grid Cell	Grid Cell	Grid Cell
SE clustering	SHAC	Subcounty	Subcounty	Subcounty	Subcounty	Subcounty	Subcounty
Sample	Our Survey (Furn. + Weld.)	UBOS	UBOS	UBOS	UBOS	UBOS	UBOS

Notes: OLS regression coefficients, standard errors displayed in parentheses. SHAC standard errors are Bartlett (spatial weighting kernel decaying linearly in distance) and the distance cutoff for spatial correlation is 5km. Census data comes from the 2010 UBOS census of establishments. In the UBOS census, grain millers are considered as agricultural firms instead of manufacturing, therefore in column 1 we restrict our sample to carpentry and welding firms only to increase comparability with column 2 where we repeat the results for manufacturing firms in the UBOS census. In column 3, we compute the log firm density for manufacturing firms with at least 10 employees. In columns 4, 5, 6 and 7, we repeat the results for agricultural firms, retail firms, low-skill service firms and high-skill service firms in the UBOS census, respectively. Road size goes from 1 (Trail/Track) to 5 (Highway).

Table 4: Returns from Locating Near Large Roads

	(1) log(Profit)	(2) log(Profit)	(3) log(Salary)	(4) Nb Customers	(5) Log(Price)	(6) Output Quality	(7) Log(Input Price)	(8) Input Access	(9) log(Rent)
Med. Road Size/Cell	0.155	0.145	0.0250	0.250	0.0409	-0.0476	0.0156	-0.0106	0.106
	(0.0314)	(0.0325)	(0.0152)	(0.0975)	(0.0177)	(0.0650)	(0.0230)	(0.0231)	(0.0288)
Man. Score		0.237	0.0842	0.413	0.0361	0.210	0.0797	0.0668	0.0747
		(0.0310)	(0.0192)	(0.106)	(0.0164)	(0.0863)	(0.0310)	(0.0335)	(0.0296)
log(Size Premises)									0.0499
									(0.0213)
N	967	967	2272	792	730	273	5747	6669	655
R2	0.506	0.537	0.392	0.374	0.953	0.318	0.445	0.148	0.476
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sub-county FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Level of Observation	Firm	Firm	Employee	Firm	Firm	Firm	Firm x Input	Firm x Input	Firm
SE clustering	Grid Cell	Grid Cell	Grid Cell	Grid Cell	Grid Cell	Grid Cell	Grid Cell	Grid Cell	Grid Cell
Employee Controls			Yes						
Input FE							Yes	Yes	

Notes: OLS regression coefficients, standard errors clustered at the grid cell level and displayed in parentheses. Man. Score is a standardized index of managerial ability constructed using our survey (see Appendix A.1 for details). We control for log distance to the main city in the region and a dummy for whether the grid cell contains any road. We also control for a dummy for whether the grid cell is incomplete (i.e., 500m x 500m), its area, as well as a dummy for whether it is in our main surveyed area. All specifications include sector and sub-county fixed effects. Employee controls include education, age, age squared, any vocational training (dummy), cognitive ability (measured through a Raven matrices test), employee tenure. We control for missing managerial score (dummy) and missing employee controls (dummies). The top and bottom one percent of all monetary dependent variables are trimmed. Road size goes from 1 (Trail/Track) to 5 (Highway). For regressions at the Firm x Input level, we include input fixed effects, as well as controls for the quantity of input purchased and the input unit. Input Accessibility is a standardized index (mean 0, sd 1) of seven variables reflecting input accessibility. Analogous regressions for each individual variable can be found in Appendix Table B9. In column 6, we compute output quality as the standardized sum of various component z-scores, as detailed in Bassi et al. (2022)'s supplemental appendix, we restrict the sample to firms making the core product (e.g, doors in carpentry) and we control for the type of product the quality measurement was done for (e.g., 2-panel or 4-panel doors in carpentry).

Table 5: Descriptives on Access to Demand and Location Choice

	Share (%)
Panel A: Access to demand and customers	
(a) Marketing strategies	
Owner spends money on marketing	6.6
Owner talks directly to customers	59.6
Firms with products on display	69
When on display: explicitly to attract customers	64.9
(b) Sales characteristics	
Orders by phone	17.2
Orders from walk-in consumers	79.5
Sales to final customers	92.8
Shipping to final customers	16
Panel B: Main perceived advantage of locating near a major road	
Visibility and new customers	75.6
Easier for existing customers to reach the firm	12
Easier for suppliers to reach the firm	5.6
Easier to interact with other firms	5.6
Other	0.6
No advantage	0.7
Panel C: Main perceived drawback of locating near a major road	
Higher rents	40.5
Lower revenues because of competition from other firms	15.6
Harder to reach the firm because of heavy traffic	11.5
No drawback	10.9
Higher air pollution	8.3
More damages on products and accidents	5.1
More thefts of products	4.8
More noise	4.3
Panel D: Reasons for location choice	
Closeness to customers / market	52.5
Affordable rent / land price	40
Closeness to a good transportation network	32.4
Low exposure to air pollution	9.6
Low exposure to water pollution	2.2
Low exposure to solid waste pollution	1.5

Notes: The questions reported in Panels B and C, as well as the two questions about products on display in Panel A come from the follow-up phone survey, which was answered by 695 out of the 1,027 firms at baseline. Data from Panels A and D come from the baseline survey. The questions in Panel D were only asked to firms that had relocated (or considered to relocate) their premises in the previous year (138 firms). For Panel D, firms were asked to indicate their top 3 out of a list of 18 potential reasons for their location choice. Panel D then reports the share of firms indicating each reason in their top 3. To keep the table short, we do not report all 18 reasons: the three top rows of Panel D report the most common reasons; the three bottom rows report the environmental-related reasons.

Table 6: Quantifying the Trade-Off Between Pollution and Profitability

	Pollution Avoidance (1000m)	Random Allocation
A. Profit Change (USD/year, per firm)		
Mean	-578.7	-207.7
NPV (3%)	-13,376	-4,800
[p20; p50; p80]	[-1,318.9; -413.4; 0.0]	[-418.4; -139.3; -64.2]
B. Wage Change (USD/year, per worker)		
Mean	-29.1	-11.4
NPV (3%)	-673	-264
[p20; p50; p80]	[-64.2; -21.3; 0.0]	[-29.8; -7.4; -3.4]
C. Pollution Change at the Workplace (μg/m^3 PM$_{2.5}$)		
Mean	-4.6	-1.6
[p20; p50; p80]	[-10.3; -3.3; -0.0]	[-3.0; -1.2; -0.6]
D. Life Expectancy Change (months)		
Mean	1.8	0.6
[p20; p50; p80]	[0.0; 1.3; 4.0]	[0.2; 0.5; 1.2]
E. Value of Life Expectancy Change (USD)		
Mean	324.6	113.9
[p20; p50; p80]	[0.0; 235.8; 726.2]	[40.1; 81.7; 211.3]

Notes: This table displays the change in profit, wage and pollution for the average, median, 20th percentile and 80th percentile firm in our sample comparing the observed distribution of firm locations to firms' locations if they were to actively avoid pollution by moving to the grid cell with the lowest pollution within at most 1,000 meters from their current location in the same sub-county (column 1) and to a random distribution of firms within a sub-county (column 2). We predict profits, salary and pollution in each grid cell using the estimated elasticities of profits, salary and pollution on a grid-cell's median road size. To convert the change in pollution into a change in life expectancy, we use the estimated marginal effect from Ebenstein et al. (2017), weighting by the time spent at the firm by the average manager (9.2h a day, 6.09 days per week). More details are available in Appendix A.5.

Online Appendix

The Online Appendix is divided in three sections.

First, Appendix A reports additional details and results. In particular, Section A.1 details the construction of the managerial ability index; Section A.2 discusses the robustness of the estimated profitability returns from locating on large roads to sorting on productivity; Section A.3 gives details of our results on adaptation; Section A.4 shows that worker sorting across firms plays a limited role in explaining the adaptation results; Section A.5 presents additional details on our counterfactual exercises; and Section A.6 shows results on perceptions about pollution and demand for information about pollution. Second, in Appendix B we present the proofs of Lemmas in the Model. Third, in Appendix C we report additional appendix figures and tables cited in the main text.

A Additional Details and Results

A.1 Managerial Ability Index

We develop a composite index of managerial ability largely in line with the methodology used in McKenzie and Woodruff (2017) and de Mel, McKenzie, and Woodruff (2019). The index comprises of several component scores including scores for marketing, stock, recording, financial and forecasting abilities of firm owners/managers.[72] We use a standardized index of the sum of these component parts, where the total sum ranges from a minimum of -1 to a maximum of +27.

- The *marketing* score ranges from a minimum score of 0 to a maximum score of +7 (with 0 indicative of the lowest possible attainment in this category). The score is calculated by adding one point for each of the following activities that the business may have implemented in the *three* months preceding the date of the survey (unless explicitly stated otherwise):

    1. The firm owner/manager visited at least one competing firm to see what prices they were charging.
    2. The firm owner/manager visited at least one competing firm to find out what products they had available for sale.
    3. The firm owner/manager spoke with existing customers to ascertain if there were other products they would like the firm to sell or produce,

[72] Our approach differs from de Mel, McKenzie, and Woodruff (2019) in some areas, particularly with regard to calculations of the recording score, the financial score and the forecasting score.

4. The firm owner/manager asked any of their former customers why they stopped buying from the business.
5. The firm owner/manager asked any of the company's suppliers which products were selling well in the sector.
6. The firm owner/manager attracted new customers by providing special offers.
7. The firm spent any money in marketing/advertising its products in the past *six* months.

- The *stock* score ranges from a minimum of -1 to a maximum of +2. One point is subtracted (-1) if the owner/manager reports that the firm ran out of goods, inputs, or materials at least once a month (specifically, that this occurred weakly more than three times in the three months preceding the survey). One point is added (+1) if the owner/manager ever tried to negotiate a lower price with a supplier of material inputs in the past three months. A point is also added (+1) if the owner/manager asked at least one alternate domestic or foreign supplier (whom the firm was not sourcing from at the time of the interview) for a price quotation any time over the past year.

- The *recording* score ranges from a minimum score of 0 to a maximum score of +7. The score is calculated by adding one point for each of the following business practices reported at the time of the survey:

1. The firm owner/manager kept written track of the performance of the business, in terms of its output, revenues and profits.
2. The firm owner/manager maintained written records of every input purchased and every product sold by the business.
3. The owner/manager reported they were able to infer how much cash on hand the firm has at any point in time using the written records.
4. The owner/manager regularly utilized the firm's written records to monitor if the sales of a particular product were increasing or decreasing from one month to the next.
5. The owner/manager typically worked out the costs of each main product sold by the firm.
6. The owner/manager maintained a written budget with records of how much was owed each month for rent, electricity, equipment maintenance, transport, advertising, and other indirect costs.

7. The owner/manager kept written records that would allow one to gauge how much money was left each month after paying off business expenses, which could be used as documentation to apply for a loan.

- The *financial* score ranges from 0 to +6, and is calculated as follows:

  1. Add up to three points depending on how frequently the owner or manager reports having reviewed the firm's financial performance. That is, add 0 if the respondent reports "never" and +1, +2 or +3 if he/she answers "once a year", "two or three times per year" or "monthly or more often", respectively.
  2. As above, add up to three points depending on how frequently the owner/manager compares the firm's performance to a sales target (if any).

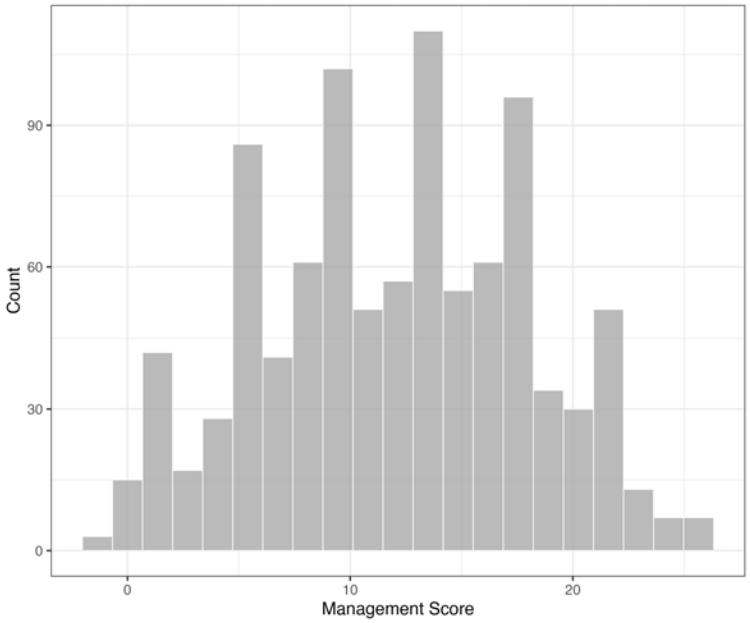
- The *forecasting* score ranges from a minimum score of 0 to a maximum of +5. The score is calculated by adding one point for each of the following activities reported by the firm owner/manager at the time of the survey:

  1. The firm had set a target for sales over the forthcoming year.
  2. The firm had a budget of the likely costs it would incur over the next year.
  3. The firm maintained an annual profit and loss statement.
  4. The firm kept an annual statement of its cash flow.
  5. The firm had an annual balance sheet.

Appendix Figure A1 shows the distribution of our raw managerial ability index for all firms in our survey. There is considerable overlap of the managerial ability index distribution across sectors.[73] In our analysis we standardize the managerial ability index across all firms in our sample.

[73]The average ([Q25, Q75]) raw managerial ability score index is 11.6 ([8, 16]) for carpentry, 11.9 ([8, 16]) for metal fabrication and 12.6 ([7, 18]) for grain milling.

Figure A1: Managerial Ability Index Distribution



Notes: This figure shows the distribution of our managerial ability index for all firms in our survey (not standardized).

A.2 Returns from Locating on Large Roads: Robustness to Sorting on Productivity

One important identification assumption to causally establish the relationship between road size and profitability is the absence of sorting on major roads based on underlying firm productivity. In this section, we provide three pieces of evidence that reassure us that sorting on (observable or unobservable) productivity is not likely to bias the results in Table 4.

In Appendix Table A1 we investigate the correlation between road size and several firm owner and worker characteristics that are plausible proxies for productivity. In column 1 we focus on the managerial ability of the firm owner. The coefficient on median road size shows that an increase in one unit in the size of the median road in the grid cell is associated with an increase of 0.0558 standard deviations in our index of managerial ability. This effect is rather small, and is not significant at conventional statistical levels. In columns 2-8, we show that there is also no correlation between road size and owner's age, education and gender, as well as employees' age, education, gender and vocational training: all coefficients are small in magnitude and far from statistical significance.

The lack of significant sorting on the wide range of observable proxies for productivity studied in Table A1 indicates that any substantial sorting on unobservable proxies for productivity is also unlikely, to the extent that observable and unobservable proxies for productivity are correlated. Nevertheless, to assess the importance of any remaining selection on unobservables, we

follow Oster (2019) and calculate lower bounds on the coefficient on the median road size in the cell in specification 4, by making assumptions on the relative importance of selection on observables and unobservables. Specifically, Oster (2019) shows that movements in the coefficients of interest and in the R-squared when additional controls are included are informative of selection on unobservables, once assumptions on the relative importance of selection on observables and unobservables are made.

To use this method, we need to make assumptions on: (i) the degrees of proportionality between selection on observables and unobservables (δ), and (ii) the maximum R-squared (R_{max}) from a regression that in addition to controlling for all the variables already included in our equation 4, was also controlling for other unobservable determinants of profitability correlated with median road size. We follow the author's recommendation and set $\delta = 1$ (so that selection on observables and unobservables are equally important), and $R_{max} = 1.3 \times \tilde{R}$ where $\tilde{R}$ is the R-squared from a regression of profits on median road size like equation 4, but where sub-county and sector fixed effects are netted out before running the regression.[74] We also show robustness to using the more conservative assumption of $R_{max} = 2 \times \tilde{R}$ and even $R_{max} = 3 \times \tilde{R}$, which assumes that if we were able to fully control for all unobservable determinants of profits correlated with median road size in the cell, the R-squared from such hypothetical regression would be twice and even three times as large, respectively. We recover a lower bound on the correlation between road size and profits that accounts for selection on unobservables under these assumptions.

The results are displayed in Table A2. In columns 1 and 2 we report the lower bound on the coefficient on the median road size in the cell under the assumption of $R_{max} = 1.3 \times \tilde{R}$. In column 1 we include the exact same controls as in Table 4. In column 2, we additionally control for firm owner's age, gender and education. The lower bound on the estimated elasticity between profits and road size in columns 1 and 2 ranges between 0.144-0.154, which remains very close to the magnitude of the elasticity in the main specification of Table 4, which is 0.145. This is consistent with the lack of significant selection on managerial ability and other observable proxies for owner and worker productivity shown in Table A1, and with the fact that the coefficient on median road size in column 1 of Table 4 changes very little once we control for our index of managerial ability in column 2 of Table 4: since selection on observables is limited, the Oster procedure then implies that any selection on unobservables is also likely limited. Columns 3 and 4 of Table A2 show that our main elasticity of interest remains above 0.13 even under the more extreme assumptions of $R_{max} = 2 \times \tilde{R}$ and even $R_{max} = 3 \times \tilde{R}$, which further reassures us that any selection on unobservables is not first order.

Finally, in Table A3, we estimate a version of equation 4 where we add an interaction

[74] Since our analysis is always conditional on sub-county and sector fixed effects, we first net out sub-county and sector fixed effects from both the dependent and independent variables to make sure that these are not taken into account in the computation of $\tilde{R}$.

between managerial ability and median road size in the cell, thus allowing the returns from locating near a major road to be heterogeneous by managerial ability. We focus on profits and profits per worker, which are our key outcomes summarizing the economic benefits of locating near larger roads. We find no evidence that the returns from locating near major roads are larger for higher ability managers. These results are again consistent with the lack of sorting near major roads based on managerial ability, and therefore reinforce our confidence that the positive relationship between major roads and profits estimated in Table 4 does not suffer from significant selection bias.

Table A1: Sorting on Large Roads Based on Productivity

	(1) Man. Score	(2) Man. Age	(3) Man. Educ.	(4) Man. is Male	(5) Emp. Age	(6) Emp. Educ	(7) Vocational Training	(8) Emp. is Male
Median Road Size/Cell	0.0558	0.332	0.108	-0.00175	0.156	-0.101	-0.00658	-0.00103
	(0.0378)	(0.395)	(0.147)	(0.00657)	(0.208)	(0.0819)	(0.00707)	(0.00284)
N	950	978	972	1007	2615	2633	2627	2657
R2	0.185	0.197	0.163	0.151	0.165	0.145	0.110	0.0584
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sub-county FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Level of Observation	Firm	Firm	Firm	Firm	Employee	Employee	Employee	Employee
SE clustering	Grid Cell	Grid Cell	Grid Cell	Grid Cell	Grid Cell	Grid Cell	Grid Cell	Grid Cell
Employee Controls					No	No	No	No

Notes: OLS regression coefficients, standard errors clustered at the grid cell level and displayed in parentheses. Man. Score is a standardized index of managerial ability constructed using our survey (see Appendix A.1 for details). We control for log distance to the main city in the region and a dummy for whether the grid cell contains any road. We also control for a dummy for whether the grid cell is incomplete (i.e., 500m x 500m), its area, as well as a dummy for whether it is in our main surveyed area. All specifications include sector and sub-county fixed effects. Road size goes from 1 (Trail/Track) to 5 (Highway). Dependent variables in columns 1 to 4 (5 to 8) are related to manager (employees) characteristics. Education is measured in years.

Table A2: Returns from Locating on Large (and Polluted) Roads - Oster (2019) Lower Bound

Dep. Var:	Log(Profit)			
	(1)	(2)	(3)	(4)
		Oster Lower Bound		
Median Road Size/Cell	0.144	0.154	0.141	0.136
N	967	967	967	967
R2 baseline (within subcounty & sector)	0.0938	0.1083	0.0938	0.0938
R2 max	1.3 * baseline	1.3 * baseline	2 * baseline	3 * baseline
Additional Controls	No	Yes	No	No
Level of Observation	Firm	Firm	Firm	Firm

Notes: The additional independent variables included in columns 1, 3 and 4 include: dummy for whether the grid cell contains any road; dummy for whether the grid cell is incomplete (i.e., 500m x 500m); area of the grid cell; dummy for whether the grid cell falls in our main surveyed area; standardized index of managerial ability (see Appendix A.1 for details); log distance to main city in the region; dummies for missing values in any of the covariates. In column 2 we further control for firm owner's age, gender and education (and corresponding dummies for missing values). To compute the Oster lower bound (Oster 2019) for the elasticity of profits to road size, we first net out both the dependent variable and all independent variables from sub-county and sector fixed effects. The R-squared displayed corresponds to the residual variation of the dependent variable explained by the independent variables. We set $\delta = 1.0$ and R-max as shown in the table. The Oster method compares the size of the coefficient on median road size in the cell and the R-squared when the additional independent variables are added to the regression. In the initial (uncontrolled) regression that serves as starting point in the Oster procedure, we still control for a dummy for whether the grid cell contains any road and for a dummy for whether the grid cell falls in our main surveyed area (in addition to controlling for the size of the median road in the cell).

Table A3: Returns from Locating on Large (and Polluted) Roads - Heterogeneity

	(1) Log(Profit)	(2) Log(Profit / Worker)
Median Road Size/Cell	0.146	0.0803
	(0.0325)	(0.0328)
Man. Score	0.209	0.103
	(0.0631)	(0.0572)
Man. Score × Road	0.0119	0.0120
	(0.0224)	(0.0205)
N	967	967
R2	0.537	0.483
Sector FE	Yes	Yes
Sub-county FE	Yes	Yes
Level of Observation	Firm	Firm
SE clustering	Grid Cell	Grid Cell

Notes: OLS regression coefficients, standard errors clustered at the grid cell level and displayed in parentheses. Man. Score is a standardized index of managerial ability constructed using our survey (see Appendix A.1 for details). We control for log distance to the main city in the region and a dummy for whether the grid cell contains any road. We also control for a dummy for whether the grid cell is incomplete (i.e., 500m x 500m), its area, as well as a dummy for whether it is in our main surveyed area. All specifications include sector and sub-county fixed effects. We control for missing managerial score (dummy). The top and bottom one percent of all monetary dependent variables are trimmed. Road size goes from 1 (Trail/Track) to 5 (Highway). Man. Score × Road corresponds to the interaction between managerial ability and median road size in the grid cell.

A.3 Adaptation Results: Details

We use our survey data to study the adaptation that takes place, and whether this differs for owners with high or low managerial ability. We estimate firm- and worker-level regressions analogous to equation 4 but with various measures of adaptation from our survey as outcomes.[75]

The dependent variable in column 1 of Table A4 is a dummy equal to one if firm owners report providing any pollution protective equipment to their workers, such as air filters or masks. The mean of this variable shows that only 5% of owners engage in such investments. The estimates show that a one standard deviation increase in managerial ability is associated with an increase of 1.9pp in the probability of providing such equipment, corresponding to an increase of 40% over the mean. We also asked workers whether they do anything to protect themselves from air pollution on days when air quality at the firm premises is bad, such as wearing a scarf or a mask.[76] Consistent with the results in column 1, column 2 shows that employees working for higher ability owners take more protective measures themselves.

In columns 3 to 5 we focus on organizational strategies to limit exposure. Workers were asked if avoiding pollution on the commuting route was an important reason why they could arrive late at work and/or may leave work early (column 3), and if owners allow them flexibility in working hours to avoid being exposed to such pollution (column 4). The means of these variables are again low: only around 6-13% of workers are allowed such flexibility. The coefficients on our measure of managerial ability are positive and significant in both cases. For instance, column 4 shows that a one standard deviation increase in managerial ability leads to an increase in the probability that workers are granted flexibility in commuting by 5.3pp, or 40% relative to the mean. In columns 2-5, we include a host of employee controls to disentangle whether this effect is driven by higher ability managers actually treating their workers differently rather than differential worker sorting across owners.[77] Our coefficient of interest is remarkably stable when employee-level controls are excluded (not shown), which confirms that the results are more consistent with higher ability owners treating their workers differently. In Appendix A.4,

[75] As shown in Table 2 and discussed more in detail in Appendix A.2, we note again that managerial ability does *not* predict location choices, which justifies looking at the role of managerial ability for adaptation conditional on location choice.

[76] Appendix Figure A2 reports the breakdown of workers' answers. Almost half of the workers report taking some protective measures. Dominant strategies are wearing a scarf/tissue, which are unlikely to be very effective. Wearing a mask is also relatively common among those who protect themselves. Notably, very few workers report staying inside the firm premises when air quality is bad, which is consistent with work being predominantly outdoor. Figure A2 also shows that the availability of larger (and more expensive) technologies such as air conditioners is extremely limited. As the firms in our sample operate at small scale and mostly outdoor, this might prevent them from overcoming the fixed costs of purchasing these types of lumpy equipment. In the context of households, Sun, Kahn, and Zheng (2017) show that richer individuals in China are more likely to invest in lumpy pollution-abating technologies such as air filters.

[77] Employee controls include the employee's education, age, age squared, cognitive ability (measured through a Raven matrices test), tenure (in years), vocational training (dummy). When explicitly noted, we also control for the employee's log salary.

we perform additional checks to show that the role of worker-firm sorting in explaining our adaptation results is limited. Finally, in column 5 we create a dummy equal to one if the worker reported that their firm owner is careful in avoiding exposing them to pollution. Our index of managerial ability is again a significant predictor in this regression.[78]

Taken together, these results show that while investments by owners in protecting workers are overall low, higher ability owners are better able to protect their workers from pollution exposure. This is not just the consequence of higher ability owners having more financial resources to purchase protective equipment; rather, it also reflects the adoption of different organizational strategies to avoid pollution exposure.

Finally, we note that our measures of road size are always positive throughout Table A4, although they are largely insignificant. These results on lack of significant spatial heterogeneity in adaptation are consistent with the evidence from Panel D of Table 5 that pollution levels are not a relevant factor in the firm location choice, and confirm that the reason why wages are on average only marginally higher near larger roads is not that workers receive more (or better) protection from air pollution.

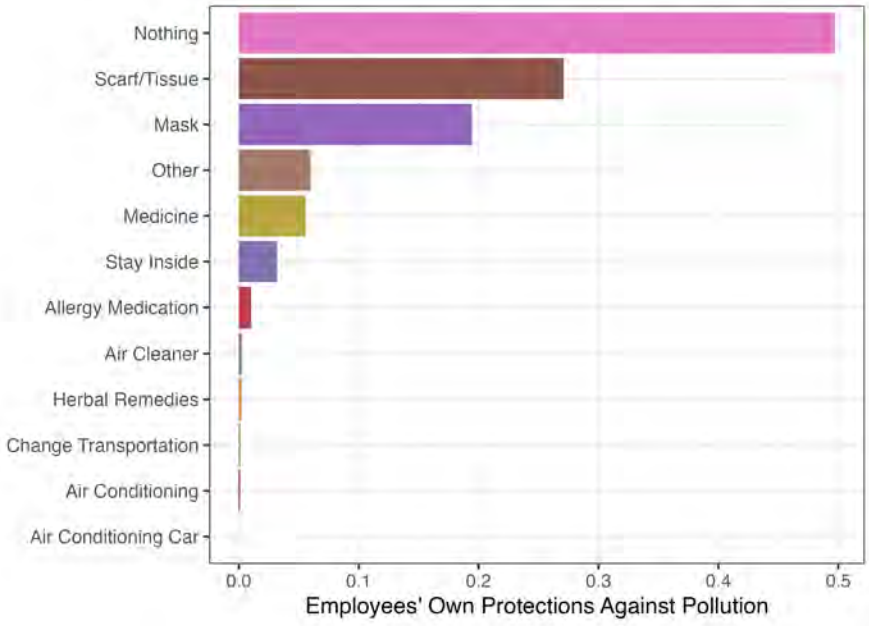
[78]It is worth noting that columns 2-5 of table A4 are obtained from a survey of workers, and do not use, apart from the independent variable (i.e., managerial ability), any information provided by firm owners. Therefore, our results cannot be contaminated by any reporting bias correlated with managerial ability.

Table A4: Correlation Between Firm Owner's Ability and Protective Investments

	(1) Poll Equipment	(2) Own Protect	(3) Late Commute	(4) Flex Commute	(5) Managers Careful
Median Road Size/Cell	0.00206	0.0125	0.0135	0.0142	0.0146
	(0.00600)	(0.0145)	(0.00748)	(0.0134)	(0.0119)
Man. Score	0.0194	0.0450	0.0260	0.0529	0.0633
	(0.00686)	(0.0182)	(0.00883)	(0.0146)	(0.0153)
N	1000	2045	2020	2002	1959
R2	0.105	0.205	0.0972	0.186	0.142
Sector FE	Yes	Yes	Yes	Yes	Yes
Sub-county FE	Yes	Yes	Yes	Yes	Yes
Level of Observation	Firm	Employee	Employee	Employee	Employee
SE clustering	Grid Cell	Grid Cell	Grid Cell	Grid Cell	Grid Cell
Employee Controls		Yes	Yes	Yes	Yes
Mean(dependent var)	.047	.523	.056	.132	.21
Answer scale	Dummy	Dummy	Dummy	Dummy	Dummy

Notes: OLS regression coefficients, standard errors clustered at the grid cell level and displayed in parentheses. Man. Score is a standardized index of managerial ability constructed using our survey (see Appendix A.1 for details). We control for log distance to the main city in the region and a dummy for whether the grid cell contains any road. We also control for a dummy for whether the grid cell is incomplete (i.e., 500m x 500m), its area, as well as a dummy for whether it is in our main surveyed area. Employee controls include education, age, age squared, vocational training (dummy), cognitive ability and employee tenure. We control for missing managerial score (dummy) and missing employee controls (dummies). All specifications include sector and sub-county fixed effects. Road size goes from 1 (Trail/Track) to 5 (Highway). The dummy dependent variables are defined as follows: Poll Equipment is equal to 1 if any anti-pollution technology or equipment that can be used by individual workers (e.g., masks) is provided by the firm; Own Protect is equal to 1 if the employee reports doing anything to protect herself against air pollution; Late Commute is equal to 1 if the employee reports that avoiding pollution on the commuting route is an important reason why she may arrive (leave) late (early) at work; Flex Commute is equal to 1 if the employee reports that her manager allows her to come in or leave early or late to avoid pollution on the commuting route; Managers Careful is equal to 1 if the employee thinks that her employer / manager is careful with trying to avoid exposing her to pollution.

Figure A2: Workers' Own Protective Measures Against Pollution



Notes: In the baseline survey, workers were asked whether they do anything to protect themselves from air pollution on days when air quality at the firm premises is bad. If the answer was positive, they were invited to give up to three examples. The histogram plots the share of workers in our sample listing a given protective measure as part of their strategy. About half of the workers take protective measures against pollution, and the dominant strategies are to use a scarf, tissue or mask. Less than 4% of workers address air pollution by staying inside the firm's premises.

A.4 Limited Role of Worker Sorting in Explaining the Results

We conduct further checks to shed more light on the potential role of sorting between owners and workers in driving our results. First, we look for direct evidence of sorting. We do so in Appendix Table A5, columns 3-8. In columns 3 and 4, the dependent variable is a measure of employee awareness of pollution that we argue is plausibly pre-determined with respect to their current employer. That is, each worker was asked whether low exposure to pollution was an important consideration in deciding where to live.[79] We construct a dummy equal to one for those who answered positively to this question, and use this as dependent variable. The results in columns 3-4 show no evidence of sorting between higher ability managers and workers based on this (pre-determined) measure of pollution awareness. Columns 5-8 instead show that there is sorting by age and education.[80]

The lack of sorting on our pre-determined measure of employee pollution awareness limits concerns that the specifications in Table A4 with employee controls might capture sorting. Nevertheless, in Appendix Table A6 we verify that the results in Table A4 are robust to controlling for our pre-determined measure of employee pollution awareness (even columns), as well as to controlling for our standardized index of employee awareness that combines the outcome variables in Table A7. This further reassures us that the results on owners' adaptation are not primarily driven by sorting.[81]

Finally, columns 3 and 4 of Table A5 also show that there is no sorting of employees near larger roads based on our pre-determined measure of pollution awareness. This helps the interpretation of the results in Table 4, by ruling out that compensation for pollution exposure is low because polluted areas attract workers who are less aware of pollution as a problem.

[79] 18% of workers report that pollution was an important consideration in their location decision.

[80] Appendix Table A7 shows that employee age and education do predict awareness as pollution as a problem.

[81] As discussed in section A.3, the inclusion of worker-level controls in the regressions in Table A4 barely affects the coefficient on the managerial ability index. This is again consistent with the sorting of workers to managers not being a driver of the results on adaptation.

Table A5: Correlation Between Firm Owner Ability and Employees' Awareness of Pollution

	(1) Poll Awareness At The Firm	(2) Poll Awareness At The Firm	(3) Poll Awareness At Home	(4) Poll Awareness At Home	(5) Age Employee	(6) Years Schooling Employee	(7) Age Employee	(8) Years Schooling Employee
Median Road Size/Cell	0.0440	0.0469	0.00615	0.00560	0.160	-0.121	0.0845	-0.103
	(0.0326)	(0.0319)	(0.0114)	(0.0115)	(0.205)	(0.0825)	(0.199)	(0.0834)
Man. Score	0.288	0.272	0.00588	0.00979	0.121	0.207		
	(0.0332)	(0.0324)	(0.0165)	(0.0151)	(0.229)	(0.0791)		
Age Manager							0.0873	
							(0.0195)	
Years School. Man.								0.0656
								(0.0218)
N	2045	2045	2045	2045	2615	2633	2615	2633
R2	0.166	0.181	0.113	0.122	0.166	0.151	0.175	0.150
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sub-county FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Level of Observation	Employee	Employee	Employee	Employee	Employee	Employee	Employee	Employee
SE clustering	Grid Cell	Grid Cell	Grid Cell	Grid Cell	Grid Cell	Grid Cell	Grid Cell	Grid Cell
Employee Controls	No	Yes	No	Yes	No	No	No	No
Mean(dependent var)	-.019	-.019	.175	.175	27.59	9.13	27.59	9.13

Notes: OLS regression coefficients, standard errors clustered at the grid cell level and displayed in parentheses. Man. Score is a standardized index of managerial ability constructed using our survey (see Appendix A.1 for details). We control for log distance to the main city in the region and a dummy for whether the grid cell contains any road. We also control for a dummy for whether the grid cell is incomplete (i.e., 500m x 500m), its area, as well as a dummy for whether it is in our main surveyed area. Employee controls include education, age, age squared, vocational training (dummy), cognitive ability and employee tenure. All specifications include sector and sub-county fixed effects. We control for missing managerial score (dummy) and missing employee controls (dummies). Road size goes from 1 (Trail/Track) to 5 (Highway). The dummy dependent variables are defined as follows: Poll Awareness - At the Firm is a normalized average of four questions asked to employees: how concerned she is about the effects of air pollution on the health of the planet; to what extent she is concerned about the effects of air pollution on his own health; to what extent she agrees that the government should do more to promote and encourage a better air quality even if her taxes had to go up slightly; and whether her ideal job features low levels of air pollution (mean 0, sd 1). Poll Awareness - At Home is a dummy variable equal to one if the employee reports that air pollution, solid water pollution or water pollution have affected her home location choice.

Table A6: Correlation Between Firm Owner Ability, Employees' Awareness of Pollution, and Protective Investments

	(1) Own Protect	(2) Own Protect	(3) Late Commute	(4) Late Commute	(5) Flex Commute	(6) Flex Commute	(7) Managers Careful	(8) Managers Careful
Median Road Size/Cell	0.0111	0.0131	0.0117	0.0130	0.0113	0.0138	0.0118	0.0130
	(0.0141)	(0.0141)	(0.00736)	(0.00751)	(0.0133)	(0.0135)	(0.0121)	(0.0120)
Man. Score	0.0302	0.0447	0.0148	0.0235	0.0360	0.0492	0.0498	0.0582
	(0.0189)	(0.0182)	(0.00867)	(0.00864)	(0.0139)	(0.0141)	(0.0156)	(0.0153)
Log Salary	-0.0198	-0.0107	0.0329	0.0362	0.0582	0.0624	0.0634	0.0667
	(0.0300)	(0.0301)	(0.0108)	(0.0111)	(0.0221)	(0.0222)	(0.0241)	(0.0239)
Poll Awareness - At The Firm	0.0599		0.0321		0.0481		0.0314	
	(0.0158)		(0.00650)		(0.00968)		(0.0130)	
Poll Awareness - At Home		0.127		0.00505		-0.0332		0.0164
		(0.0366)		(0.0162)		(0.0242)		(0.0325)
N	2045	2045	2020	2020	2002	2002	1959	1959
R2	0.220	0.216	0.120	0.104	0.212	0.197	0.153	0.148
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sub-county FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Level of Observation	Employee	Employee	Employee	Employee	Employee	Employee	Employee	Employee
SE clustering	Grid Cell	Grid Cell	Grid Cell	Grid Cell	Grid Cell	Grid Cell	Grid Cell	Grid Cell
Employee Controls	No	No	No	No	No	No	No	No
Mean(dependent var)	.523	.523	.056	.056	.132	.132	.21	.21
Answer scale	Dummy	Dummy	Dummy	Dummy	Dummy	Dummy	Dummy	Dummy

Notes: OLS regression coefficients. Standard errors are clustered at the grid cell level and displayed in parentheses. Man. Score is a standardized index of managerial ability constructed using our survey (see Appendix A.1 for details). We control for log distance to the main city in the region and a dummy for whether the grid cell contains any road. We also control for a dummy for whether the grid cell is incomplete (i.e., 500m x 500m), its area, as well as a dummy for whether it is in our main surveyed area. Employee controls include education, age, age square, vocational training (dummy), cognitive ability, employee tenure and log wage. We control for missing managerial score (dummy) and missing employee controls (dummies). All specifications include sector and sub-county fixed effects. Road size goes from 1 (Trail/Track) to 5 (Highway). The dummy dependent variables are defined as follows: Own Protect is equal to 1 if the employee reports doing anything to protect herself against air pollution; Late Commute is equal to 1 if the employee reports that avoiding pollution on the commuting route is an important reason why they may arrive (leave) late (early) at work; Flex Commute is equal to 1 if the employee report that their manager allows her to come in or leave early or late to avoid pollution on commuting route; Managers Careful is equal to 1 if the employee thinks that her employers / managers are careful with trying to avoid exposing her to pollution. Poll Awareness - At the Firm is a normalized average of how concerned managers report being of the impact of pollution on productivity, of the impact of pollution on health, and of the impact of pollution on the planet (mean 0, sd 1). Poll Awareness - At Home is a dummy variable equal to one if the employee reports that air pollution, solid water pollution or water pollution have affected her home location choice.

Table A7: Correlation Between Employees' Characteristics and Perceptions of Pollution as a Problem

	(1) Concerned Poll Health	(2) Ideal Job Low Poll	(3) Concerned Poll Planet	(4) Gov Address Poll
main				
Years Schooling	0.0169	0.000982	0.0358	0.00491
	(0.00959)	(0.00375)	(0.00980)	(0.0101)
Age	0.0122	-0.0132	0.0124	-0.0120
	(0.0157)	(0.00588)	(0.0170)	(0.0210)
Age^2	-0.0000509	0.000213	-0.0000601	0.000173
	(0.000220)	(0.0000804)	(0.000242)	(0.000308)
Vocational Training (Dummy)	0.210	-0.0132	0.163	0.0165
	(0.0844)	(0.0349)	(0.0951)	(0.100)
N	2052	2045	2053	2053
R2		0.115		
Sector FE	Yes	Yes	Yes	Yes
Sub-county FE	Yes	Yes	Yes	Yes
Level of Observation	Employee	Employee	Employee	Employee
SE clustering	Grid Cell	Grid Cell	Grid Cell	Grid Cell
Mean(dependent var)	3.735	.298	3.964	4.045
Answer scale	0-5	Dummy	1-5	1-5
Model	O. Probit	OLS	O. Probit	O. Probit

Notes: Standard errors are clustered at the grid cell level and displayed in parentheses. We control for log distance to the main city in the region. The dependent variables are defined as follows: the employee is asked how concerned she is about the effects of air pollution on her health (column 1) and on the health of the planet (column 3); whether her ideal job features low levels of air pollution (column 2) and to what extent she agrees that the government should do more to promote and encourage a better air quality even if her taxes have to go up slightly (column 4). For non-dummy variables, an ordered probit model is used, while we use OLS when the dependent variable is a dummy. All specifications include sector and sub-county fixed effects.

A.5 Counterfactual Exercise

In Table 6, we conduct a series of back of the envelope analyses where we predict pollution and profits from road traffic in each grid cell using the estimated elasticity of pollution to road size from Table 1, column 1, and the elasticity of profits and wage to road size from Table 4, respectively. Here we give more details on the calculations.

Predicting Grid-Level Profits

In Table 4, column 2, we estimate a version of the following regression for firm i in grid cell c, where $Y \in \{profit, salary\}$, controlling for sub-county fixed effects (γ_s) and firm characteristics ($X_{i,c}$) (ignoring the error term for simplicity):

$$\log Y_{i,c} = a + b \times MedianRoad_c + \eta \times X_{i,c} + \gamma_s.$$

Because the specification includes sub-county fixed effects, the coefficient b is identified from within-sub-county variation in road size. Equivalently, the regression can be written in deviations from sub-county means, denoted by an overbar and superscript s:

$$\log Y_{i,c} - \overline{\log Y}^{\,s} = b \times \left(MedianRoad_c - \overline{MedianRoad}^{\,s} \right) + \eta \times \left(X_{i,c} - \overline{X}^{\,s} \right).$$

We consider a firm with average characteristics within each sub-county, so that

$$X_{i,c} - \overline{X}^{\,s} = 0.$$

Letting Y_c denote the predicted outcome for a firm with average characteristics in grid cell c, this gives:

$$\log Y_c - \overline{\log Y}^{\,s} = b \times \left(MedianRoad_c - \overline{MedianRoad}^{\,s} \right).$$

Using the estimated coefficient $\hat{b}$, the exact percentage difference in predicted outcomes relative to the sub-county average is therefore:

$$\frac{\hat{Y}_c - \overline{Y}^{\,s}}{\overline{Y}^{\,s}} = \exp\Big(\hat{b} \times \left(MedianRoad_c - \overline{MedianRoad}^{\,s} \right) \Big) - 1.$$

We use this expression to compute the predicted percentage difference in profits (or wages) for each grid cell relative to the sub-county average road size. To express these predicted differences in levels, we multiply the percentage difference by the sample average outcome:

$$\widehat{\Delta Y_c} = \Big[\exp\Big(\hat{b} \times \left(MedianRoad_c - \overline{MedianRoad}^{\,s} \right) \Big) - 1 \Big] \times \overline{Y},$$

where $\overline{Y}$ is the sample average of profits when predicting firm profits, and the sample average of wages when predicting worker salaries.

Because the coefficient $\hat{b}$ is estimated in a specification with sub-county fixed effects, this prediction exercise should be interpreted as using within-sub-county variation in road size to recover relative differences in predicted profits and wages across grid cells, rather than as separately identifying sub-county-specific outcome levels.

Predicting Grid-Level Pollution

In Table 1, we estimate the following regression at the grid-cell level c, where res_c is the average pollution residual in grid cell c and γ_s denotes sub-county fixed effects:

$$res_c = a + b \times MedianRoad_c + \gamma_s.$$

Because the specification includes sub-county fixed effects, the coefficient b is identified only from within-sub-county variation in road size. Equivalently, the regression can be written in deviations from sub-county means, denoted by an overbar and superscript s:

$$res_c - \overline{res}^s = b \times \left(MedianRoad_c - \overline{MedianRoad}^s \right).$$

Using the estimated coefficient $\hat{b}$, we can therefore recover the predicted pollution residual in a grid cell relative to its sub-county average as:

$$\widehat{res_c - \overline{res}^s} = \hat{b} \times \underbrace{\left(MedianRoad_c - \overline{MedianRoad}^s \right)}_{\text{data}}.$$

This implies that the fixed-effects regression identifies only relative pollution differences within sub-counties; it does not separately identify sub-county-level pollution anchors. Accordingly, our prediction exercise should be interpreted as using within-sub-county variation in road size to rank locations by predicted pollution, rather than as recovering absolute pollution differences across sub-counties.

To express these predicted residuals in levels, we normalize them around the sample average road size and write:

$$\widehat{res}_c = \hat{b} \times \left(MedianRoad_c - \overline{MedianRoad} \right),$$

where $\overline{MedianRoad}$ is the sample average road size across grid cells. This normalization is a convenient way to express the predicted residuals in common units and does not imply that the regression separately identifies between-sub-county pollution differences.

To convert predicted residuals into pollution levels, we use the relationship

$$res_{m,t} = \log poll_{m,t} - FE'_t,$$

where FE'_t denotes the hour and day fixed effects estimated using the stationary monitors. Evaluated at the average fixed effects, the predicted pollution level in grid cell c is:

$$\widehat{poll}_c = \exp\left(\widehat{res}_c + \log(\overline{poll})\right),$$

where $\overline{poll}$ is the average pollution level across all grid cells in the sample.

Computing Counterfactuals

After predicting pollution, profits and salary for each grid cell in our sample, we contrast these average predicted outcomes in three scenarios.[82] First, we compute average predicted exposure, profits and salary given the observed distribution of firms in our sample. We assume zero costs of the extra commuting in the calculations.[83] For each sub-county s, we compute the average predicted outcome $\overline{\hat{Y}}^s_{actual}, Y \in \{poll, profits, salary\}$, given the total number of firms in sub-county s, N_s, and the number of firms in each grid cell c, $n_{c,s}$:

$$\overline{\hat{Y}}^s_{actual} = \frac{1}{N_s}\sum_{c=1}^{C_s}(n_{c,s} \times \hat{Y_{c,s}}),$$

where C_s is the number of grid cells in sub-county s and $\hat{Y_{c,s}}$ is the predicted outcome in grid cell c in sub-county s, following the procedure described above. $\overline{\hat{Y}}^s_{actual}$ is effectively a weighted average across grid cells, where the weights are the number of firms in each grid cells.

We compare $\overline{\hat{Y}}^s_{actual}$ to the average predicted outcome if all firms were to actively avoid polluted and busy roads (with minimal change in commuting costs) and move to the least polluted grid cell within at most 1,000 meters from their observed location, within their sub-county: $\overline{\hat{Y}_{min1000}}^s$. The difference between the two, $\Delta\overline{\hat{Y}}^s_{min1000-actual} = \overline{\hat{Y}}^s_{min1000} - \overline{\hat{Y}}^s_{actual}$ corresponds to the change in exposure resulting from firms relocating to a location avoiding pollution within a sub-county from their observed location. We average across sub-counties by maintaining the

[82] We do not include in this exercise the 18% of firms interviewed in the survey that fall slightly outside the boundaries of the sampled sub-counties — often by just a few meters — because we did not conduct a full firm listing in those sub-counties. As a result, we cannot construct a representative within-sub-county distribution of firms for the counterfactuals.

[83] As moves are restricted to within the same sub-county, changes in commuting costs should be small.

number of firms in each sub-county:

$$\Delta\overline{\hat{Y}}_{min1000-actual} = \frac{1}{N}\sum_{s=1}^{S}[N_s \times \Delta\overline{\hat{Y}}^{s}_{min1000-actual}],$$

where S is the number of sub-counties in the data and N is the total number of firms in the data.

We also implement an analogous exercise comparing firms' predicted outcomes from their actual location, $\overline{\hat{Y}}^{s}_{actual}$, to the average predicted grid cell level outcome in sub-county s

$$\overline{\hat{Y}}^{s}_{random} = \frac{1}{C_s}\sum_{c=1}^{C_s}\hat{Y_{c,s}}.$$

$\overline{\hat{Y}}^{s}_{random}$ corresponds to the average predicted outcome if firms were randomly located because it is a simple average that weighs equally all grid cells in a sub-county. The difference between the two, $\Delta\overline{\hat{Y}}^{s}_{random-actual} = \overline{\hat{Y}}^{s}_{random} - \overline{\hat{Y}}^{s}_{actual}$ corresponds to the change in exposure resulting from firms relocating randomly within a sub-county from their observed location. We average across sub-counties by maintaining the number of firms in each sub-county as above.

Valuing Pollution Exposure

We use a linear relationship between $PM_{2.5}$ concentration and loss of life expectancy (LLE, in months) (Ebenstein et al. 2017) to go from pollution levels to LLE, weighting this relationship by the share of time spent at the firm:

$$\hat{LLE_c} = \frac{poll_c - \hat{\overline{poll_c}}^{s}}{10} \times 0.98 \times 12 \times \frac{h_{\text{firm}}}{24} \times \frac{\text{d}_{\text{firm}}}{7}$$

For simplicity, we assume that both owners and workers spend the same number of hours and days at the firm on average h_{firm} and d_{firm}, or 9.2 hours per day and 6.09 days per week, the amount reported by firm owners (Table B1).[84]

To monetize the change in pollution exposure from moving between grid-cells, we value the change in life expectancy using a conservative policy-relevant benchmark based on standard cost-effectiveness calculations. More specifically, we use the WHO guidelines (Iino, Hashiguchi, and Hori, 2022), which indicates that a policy investment should cost no more than 3 times GDP per capita for one year of life saved. Given that per capita GDP in Uganda is 720 USD at the time of the study, this is equivalent to valuing each year of life gained at 2,160 USD. In Figure 7, we investigate the sensitivity of the results to alternative benchmarks, for example

[84]This is a conservative estimate for workers, who report spending 9.9 hours per day and 6.05 days per week at the firm on average, or 8% more than owners overall (Table B1).

using an analogous approach but for workers' and firm owners' annual earnings rather than Uganda's GDP per capita (852 USD and 2,923 USD, respectively), or using a World Bank-derived formula (Wijnen, Dahdah, and Pkhikidze, 2025) to compute the value of statistical life (VSL).

Comparing Lifetime Changes in Earnings and Pollution Exposure Impacts

To compare the net present value of change in earning flow to a change in life expectancy, we must also make assumptions on discount rates. We assume that earning losses (gains) from a move happen between ages 18 and 58 (40 years) and life expectancy gains (losses) are distributed from age 18 to age 100, such that baseline life expectancy is 63 years (Uganda's life expectancy).

In Figure 7, we solve for the pair of VSL and discount rate s.t. firm owners (left panel) and workers (right panel) would be indifferent between their observed location and moving to a random location within the same sub-county. We report the results under two alternative assumptions about discounting life gains. In the first, life-expectancy gains are left undiscounted, while income losses are discounted as a standard annuity. In the second, both income losses and future survival gains are discounted, so that health benefits occurring later in life receive less weight.

A.6 Awareness of Pollution

In this section, we use our survey data and a simple information experiment to study awareness of pollution in our sample. We present three key results. First, firm owners are broadly aware of the spatial distribution of pollution. Second, both firm owners and employees are concerned about the effects of pollution on health, particularly employees. Third, firm owners demand more precise information about pollution levels when it becomes available, suggesting that information on pollution is imperfect and firm owners value this information. Together, these results confirm that although information is incomplete, location choices in this context are made with at least some broad awareness of the spatial distribution of pollution and its health consequences.

A.6.1 Awareness of Spatial Distribution of Pollution and Health Consequences

We use our survey to study awareness of the spatial distribution of pollution and reported concerns about the health consequences of pollution exposure.

Firm owners perceive the correlation between pollution, road traffic, and profitability. In the follow-up survey, we elicited firm owners' beliefs about pollution levels, road traffic, and profitability near their firm. Specifically, we asked firm owners whether they think that air pollution in the area where their firm is located is "low", "average" or "high" compared to other locations in their sub-county. We then repeated the same question for perceived road traffic and customer demand (i.e., profitability). Analogously, within each sub-county, we categorize grid cells into low (1^{st} tercile), average (2^{nd} tercile) or high (3^{rd} tercile) actual pollution, based on the measurements from our mobile pollution monitors (net of time variation, as described in Section 4.1). We use these variables to study the correlation between perceived and actual local pollution as well as the correlation between perceived pollution, traffic, and profitability. The results are in Table A8.

First, we establish that firm owners correctly perceive that pollution is higher near major roads by regressing perceived relative pollution near their firm on median road size in the grid cell where the firm is located (column 1). In line with this, we find a positive correlation between perceived and actual pollution levels: firm owners are more likely to answer that their location is relatively polluted if it is actually polluted (column 2). The low significance of the coefficient on actual relative pollution may be explained by the small sample of firms for which pollution data is available.[85] In columns 3 and 4 we study whether firm owners perceive the bundling of pollution and profitability through road traffic by regressing perceived relative pollution on

[85] As explained in Section 3.2, information on pollution is available in 32 of our 52 sampled sub-counties, while road size is available in all sub-counties, thus explaining why the sample drops substantially from column 1 to column 2.

perceived relative profitability (column 3) and perceived relative traffic (column 4) near their firm. The residual correlations are, respectively, 0.336 (SE 0.0465) for perceived pollution and profitability, and 0.471 (SE 0.0434) for perceived pollution and road traffic, thus implying that firm owners are well aware that more polluted areas are more profitable and that pollution and traffic are correlated.

These results confirm that firm owners overall are aware of the spatial distribution of pollution and its correlation with traffic and profitability. Yet, our survey suggests that firm owners tend to underestimate the overall levels of pollution: the dependent variable in Table A8 has a has a mean of 1.7 (on the 3-point scale), thus implying that the average firm owner believes that pollution near their firm is below average—while in reality it is above average (mean of 2.1 on the 3-point scale), given the sorting of firm owners to polluted areas documented in Section 5.

Concerns about health consequences of pollution among owners and employees. In columns 5 and 6 of Table A8, we study firm owners' and employees' perceptions of the health consequences of pollution. Both firm owners and employees were asked how concerned they are with the effects of pollution on their own health (using a 0-5 scale). This question was asked in the baseline survey to employees and in the follow-up survey to firm owners. In column 5 we pool the sample of firm owners and workers and regress their perception of the health cost of pollution on median road size in the cell, the index of managerial ability of the firm owner, and a dummy for whether the respondent is a firm owner vs an employee. The results show that: (i) concerns about the health costs of pollution are relatively high among both firm owners and workers, with an average reported concern of 3.6 out of 5 (as shown by the mean of the dependent variable in columns 5-6); (ii) firm owners are significantly less concerned than employees, by about 0.4 points on the 6-point scale, although with the obvious caveat that perceptions for owners and employees were measured at different times; (iii) working near larger roads is not a predictor of perceptions about the health costs of pollution; (iv) managers and workers in firms with higher ability managers are more concerned about the effects of pollution on health. Finally, column 6 confirms that the gap in perceptions between firm owners and employees remains of similar magnitude within a given firm.

These results are important in two ways. First, they show that both firm owners and workers are at least somewhat concerned about the health costs of pollution exposure. Second, they confirm again that the reason why the wage premia for working in polluted areas are low is not that workers in those areas are less aware of the health consequences of pollution or that, more generally, workers are less aware than firm owners of the costs of pollution exposure—if anything, we find that employees are more concerned than firm owners.

Finally, we notice that managerial ability does not predict awareness of pollution levels

(columns 1-4) but does predict concerns about the health costs of pollution exposure (columns 5-6). This suggests that the higher levels of adaptation by higher ability owners documented in Table A4 are the result of higher awareness of pollution as a problem, rather than of higher awareness of pollution levels *per se*.

A.6.2 Demand for Additional Information on Pollution

We have shown that firm owners are broadly aware of the spatial distribution of pollution but tend to underestimate pollution levels. In this section, we report the results of an experiment that shows that firm owners have significant demand for additional information about local pollution, thus confirming that information on pollution is incomplete and that firm owners value this information.

A simple experiment on demand for information about pollution. The core idea of the experiment is to test how the provision of some initial information about local pollution impacts the willingness to pay (WTP) for more information about the spatial distribution of air quality within the city. We implement the experiment with firm owners.[86]

The experiment was implemented as follows. First, we asked all firm owners to estimate the relative levels of pollution and customer demand (i.e., profitability) near the premises of their firm (*low, average, high*), compared to other locations in their sub-county. Second, we randomly divided all firms with available information on actual pollution in their grid cell into a treatment group that received information on the actual relative pollution levels near their firm (i.e., in their grid cell) compared to the rest of their sub-county, and a control group that did not receive any information. Similarly, we divided all firms with available information on actual profitability into a treatment group that received additional information on local relative profitability, and a control group.[87] Thus, there are two separate information experiments, each with its own treatment and control groups. The two treatments are independent.[88] Third, we

[86] As entrepreneurs in this setting are more educated, older and more skilled than employees (Bassi et al., 2024), focusing on entrepreneurs likely provides an upper bound for the awareness of pollution of their employees. Consistent with this, in Appendix Table A7 we show that among our sample of employees, more educated and more skilled individuals (as proxied by whether they attended vocational training) are more aware of pollution as a problem. We choose firm owners rather than workers for two reasons. First, to implement our design, it is important to benchmark the estimated WTP for information about pollution with the WTP for other relevant information. Focusing on firm owners allows us to use the spatial distribution of profits, which we have shown vary substantially within the city. Workers' wages, instead, vary little within the city. Second, asking workers about their WTP for information on wages might not have led to truthful answers, due to concerns about the firm owner overhearing their answers.

[87] To calculate the actual relative pollution and profitability of each grid cell we use baseline data. To calculate pollution exposure, we use actual pollution data. To calculate access to customers / profitability, by sector, we use the elasticity of revenues to road size and predict a grid cell's revenues, net of firm owners' ability and sub-county fixed effects. We average actual pollution and (predicted) revenues at the grid cell level. We then divide grid cells into low (1^{st} tercile), average (2^{nd} tercile) or high (3^{rd} tercile) within the sub-county.

[88] Firms with available information on both relative pollution and profitability can be part of both experiments.

asked all firm owners (in both treatment and control groups) whether they would be willing to give back part of their compensation for the study (UGX 5,000, or about $1.5) to acquire: (i) a map of relative pollution and (ii) a map of relative profitability in their sub-county (that we compiled with the baseline data). We first offered them the opportunity to buy either map for a *high* price of UGX 3,000, so that they would have to choose at most one between the two. Then, for the maps not chosen at the high price, we again offered them for a *medium* price (UGX 2,000). If at least one map was still not purchased at this price, we made one last offer at a *low* price (UGX 1,000).[89]

The elicitation of willingness to pay for the maps was incentive compatible because when firm owners were offered the map at UGX 3,000, they did not know that if they declined, we would offer the map at a lower price.[90] Also, the incentives did not differ between the pollution and profitability information experiments, and our key test, as explained in more detail in the next paragraph, is in comparing behavior across the two experiments. The stakes were also relevant given the amounts ($1.5 is about 15% of daily profits). We create two sets of outcomes: a dummy if the owner was willing to pay the high price for the pollution/profitability map, and a variable taking values 0 to 3, depending on whether the owner was willing to pay the high (3), medium (2), low price (1), or no price at all (0). We regress these outcomes on the treatment indicators, controlling for the stratification variables (sub-county and sector fixed effects). Treatment effects are estimated separately on the two experimental samples (pollution and profitability). Standard errors are robust since the randomization is at the firm level.

Results from the experiment. The results are in Table A9. Column 1 shows that providing information on local pollution increases the probability that the firm owner was willing to pay the high price for the air pollution map by 9pp, a result significant at the 5% level. This is a large effect, as only about 11% of firm owners in the control group were willing to pay the high price for this map. Column 2 shows that the treatment effect remains positive (although at the margin of significance) when the dependent variable is the 0-3 scale of willingness to pay. In column 3, we look at the (non-experimental) correlates of willingness to pay for the pollution

The randomization was stratified by sector and sub-county. As described in Section 3.2, pollution data is available in 32 of our 52 sub-counties, which explains why some firms are excluded from the pollution information experiment. We excluded firms in grain milling from the profitability information experiment because given the low number of grain millers (see Table B1) we did not feel confident in the precision of our estimates of (predicted) local profitability for grain milling. Appendix Table B12 shows the sample sizes and balance checks for the two experiments.

[89]The maps were delivered digitally to firm owners: we created a website with all the relevant maps and gave an access key to firm owners who purchased the maps.

[90]Once they see that the price is reduced to UGX 2,000, firm owners that declined at UGX 3,000 might naturally realize that if they do not accept at UGX 2,000, we will reduce the price even further, so that the elicitation at the medium and low price is possibly not incentive compatible anymore. We show that our results are robust to only using responses to the offer of the map at the high price (i.e., at the price where we are confident that the elicitation is incentive compatible).

maps in the full sample, finding that higher ability owners demand more information, while there is no correlation between being located on larger roads and demand for information.[91] Importantly, as shown in columns 4-6, we do *not* find treatment effects on demand for the profitability map, nor a significant correlation between managerial ability and demand for this map, which is consistent with larger information frictions on relative pollution levels than profitability (which serves as our benchmark).

These results confirm that information on pollution is limited in this context, and that firm owners value more information when it becomes available.

[91]This is consistent with high-ability managers being more aware of pollution as a problem but not of relative pollution levels, something that in Appendix A.6 we show holds for our non-experimental data. Comparing column 2 with column 3, we notice that the treatment leads to an increase in willingness to pay comparable to a 2σ increase in managerial ability. That is, the treatment effect is roughly equivalent to turning low ability managers into high ability ones, in terms of their demand for information.

Table A8: Perceptions of Pollution, Profitability, Road Traffic, and the Health Consequence of Pollution

	(1) Perceived Rel Poll	(2) Perceived Rel Poll	(3) Perceived Rel Poll	(4) Perceived Rel Poll	(5) Concerned Poll Health	(6) Concerned Poll Health
Median Road Size/Cell	0.0589	0.0378	0.0523	0.0315	-0.0157	
	(0.0346)	(0.0501)	(0.0322)	(0.0301)	(0.0330)	
Man. Score	-0.00630	-0.0351	-0.0283	-0.0175	0.183	
	(0.0334)	(0.0511)	(0.0299)	(0.0320)	(0.0402)	
Actual Rel Poll		0.0762				
		(0.0559)				
Perceived Rel Prof			0.336			
			(0.0465)			
Perceived Rel Traffic				0.471		
				(0.0434)		
Owner (dummy)					-0.432	-0.373
					(0.102)	(0.131)
N	677	336	677	660	2714	2714
R2	0.192	0.157	0.285	0.372	0.135	0.554
Sector FE	Yes	Yes	Yes	Yes	Yes	No
Sub-county FE	Yes	Yes	Yes	Yes	Yes	No
Firm FE	No	No	No	No	No	Yes
Level of Observation	Firm	Firm	Firm	Firm	Individual	Individual
SE clustering	Grid Cell	Grid Cell	Grid Cell	Grid Cell	Grid Cell	Grid Cell
Mean Dep Var	1.689	1.689	1.689	1.689	3.639	3.639
Scale	[1;3]	[1;3]	[1;3]	[1;3]	[0;5]	[0;5]

Notes: OLS regression coefficients, standard errors clustered at the grid cell level and displayed in parentheses. Man. Score is a standardized index of managerial ability constructed using our survey (see Appendix A.1 for details). We control for log distance to the main city in the region and a dummy for whether the grid cell contains any road. We also control for a dummy for whether the grid cell is incomplete (i.e., 500m x 500m), its area, as well as a dummy for whether it is in our main surveyed area. We control for missing managerial score (dummy). Road size goes from 1 (Trail/Track) to 5 (Highway). The dependent variable is obtained from the follow up phone survey, where owners are asked whether they think air pollution at the premises of the firm is low (1), average (2) or high (3) compared to other locations in their sub-county. Owners are asked analogous questions for relative profitability (Perceived Rel Prof) and relative traffic (Perceived Rel Traffic). Actual Rel Poll is a grid cell's average relative pollution (tercile) calculated from our pollution data, within the grid cell's sub-county. In columns 5 and 6, observations are at the individual level (owners and workers). Both firm owners and employees were asked how concerned they are with the effects of pollution on their own health (using a 0-5 scale). This question was asked in the baseline survey to employees and in the follow-up survey to firm owners.

Table A9: Results of Information Experiment

	(1) WTP poll = max	(2) WTP poll	(3) WTP poll	(4) WTP profit = max	(5) WTP profit	(6) WTP profit
Treatment Pollution	0.0869	0.185				
	(0.0382)	(0.134)				
Man. Score			0.0892			0.0159
			(0.0510)			(0.0577)
Median Road Size/Cell			0.00769			-0.0223
			(0.0495)			(0.0531)
Treatment Profitability				-0.0109	-0.0299	
				(0.0496)	(0.130)	
N	339	339	695	430	430	695
R2	0.0657			0.0977		
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Sub-county FE	Yes	Yes	Yes	Yes	Yes	Yes
Scale	Dummy	0-3	0-3	Dummy	0-3	0-3
Standard Errors	Robust	Robust	Robust	Robust	Robust	Robust
Model	OLS	O. Probit	O. Probit	OLS	O. Probit	O. Probit

Notes: OLS and probit regression coefficients, robust standard errors displayed in parentheses. Man. Score is a standardized index of managerial ability constructed using our survey (see Appendix A.1 for details). All specifications include sector and sub-county fixed effects (the stratification variables). Columns 1 and 4 report OLS coefficients. Columns 2-3 and 5-6 report ordered probit regression coefficients. In columns 1-2 and 5-6, we restrict observations to the firms that were included in the pollution and profitability experiments, respectively. Treatment Pollution is a dummy equal to one if the firm was randomized into the treatment group for the pollution information experiment. Treatment Profit is a dummy equal to one if the firm was randomized in the treatment group for the profitability information experiment. WTP poll = max, and WTP profit = max are dummies equal to 1 if the firm was willing to pay UGX 3,000 for pollution or profitability maps, respectively. WTP poll is a variable taking values 0-3, depending on whether the firm owner was willing to pay UGX 0, 1,000, 2,000 or 3,000 for the pollution map. WTP profit is defined similarly, but for the profitability map.

B Proofs of Lemmas in the Model

B.1 Proof of Lemma 1

Using

$$t_j = (1-\nu)\tau_j + \nu n_j \qquad \text{and} \qquad p_j = \psi t_j,$$

revenue productivity can be written as

$$D_j = (1-\eta)t_j + \eta n_j = (1-\eta)\big((1-\nu)\tau_j + \nu n_j\big) + \eta n_j.$$

If an entrepreneur locates in j, her ex-ante expected utility is

$$v_j = \theta\pi_j - \kappa_\pi p_j.$$

Using

$$\pi_j = (1-\beta)(D_j - \kappa_w p_j),$$

this becomes

$$v_j = \theta(1-\beta)D_j - \big(\theta(1-\beta)\kappa_w + \kappa_\pi\big)p_j.$$

Substituting for D_j and p_j yields

$$v_j = \theta(1-\beta)\Big[(1-\eta)\big((1-\nu)\tau_j + \nu n_j\big) + \eta n_j\Big] - \psi\big(\theta(1-\beta)\kappa_w + \kappa_\pi\big)\big((1-\nu)\tau_j + \nu n_j\big).$$

Collecting terms in τ_j and n_j gives

$$v_j = A_\tau \tau_j + A_n n_j,$$

where

$$A_\tau = (1-\nu)\Big[\theta(1-\beta)(1-\eta) - \psi\big(\theta(1-\beta)\kappa_w + \kappa_\pi\big)\Big]$$

and

$$A_n = \theta(1-\beta)\big[\eta + \nu(1-\eta)\big] - \psi\nu\big(\theta(1-\beta)\kappa_w + \kappa_\pi\big).$$

This proves the result.

B.2 Proof of Lemma 2

Let

$$x \equiv n_h - n_l, \qquad \Delta\tau \equiv \tau_h - \tau_l > 0.$$

Since $n_h + n_l = \Pi$, we have

$$n_h = \frac{\Pi + x}{2}, \qquad n_l = \frac{\Pi - x}{2}.$$

Using the logit formula and Lemma 1, the equilibrium condition can be written as

$$x = \Pi \tanh\left(\frac{A_\tau \Delta\tau + A_n x}{2\sigma}\right).$$

Define

$$T(x) \equiv \Pi \tanh\left(\frac{A_\tau \Delta\tau + A_n x}{2\sigma}\right)$$

and

$$F(x) \equiv x - T(x).$$

Then

$$T'(x) = \frac{\Pi {A_n}^2}{2\sigma}\left(\frac{A_\tau \Delta\tau + A_n x}{2\sigma}\right),$$

so

$$F'(x) = 1 - \frac{\Pi {A_n}^2}{2\sigma}\left(\frac{A_\tau \Delta\tau + A_n x}{2\sigma}\right).$$

If

$$\frac{\Pi A_n}{2\sigma} < 1,$$

then, because $0 <^2 (\cdot) \leq 1$,

$$F'(x) \geq 1 - \frac{\Pi A_n}{2\sigma} > 0 \qquad \text{for all } x.$$

Hence F is strictly increasing.

Moreover,

$$F(-\Pi) = -\Pi - \Pi \tanh\left(\frac{A_\tau \Delta\tau - A_n \Pi}{2\sigma}\right) < 0,$$

because $\tanh(z) > -1$ for every finite z, and similarly

$$F(\Pi) = \Pi - \Pi \tanh\left(\frac{A_\tau \Delta\tau + A_n \Pi}{2\sigma}\right) > 0,$$

because $\tanh(z) < 1$ for every finite z.

Therefore, by the intermediate value theorem, F has a root in $[-\Pi, \Pi]$, and because F is strictly increasing, that root is unique. This proves that the spatial equilibrium is unique.

B.3 Proof of Lemma 3

Let

$$x \equiv n_h - n_l, \qquad \Delta\tau \equiv \tau_h - \tau_l > 0,$$

and define

$$F(x) \equiv x - \Pi \tanh\left(\frac{A_\tau \Delta\tau + A_n x}{2\sigma}\right).$$

Under the condition in Lemma 2, F is strictly increasing, so the equilibrium is the unique root of F.

Now evaluate F at zero:

$$F(0) = -\Pi \tanh\left(\frac{A_\tau \Delta\tau}{2\sigma}\right).$$

Since $\tanh(\cdot)$ is strictly increasing and odd, the sign of $F(0)$ is the opposite of the sign of $A_\tau \Delta\tau$. Because F is strictly increasing, the sign of the unique root x^* is therefore the same as the sign of $A_\tau \Delta\tau$:

$$x^* > 0 \iff A_\tau \Delta\tau > 0.$$

Since $\Delta\tau > 0$ and $(1-\nu) > 0$, this is equivalent to $A_\tau > 0$, namely

$$\theta(1-\beta)(1-\eta) - \psi\big(\theta(1-\beta)\kappa_w + \kappa_\pi\big) > 0.$$

Dividing by $\theta(1-\beta) > 0$ gives

$$1 - \eta - \psi\kappa_w - \frac{\psi\kappa_\pi}{\theta(1-\beta)} > 0,$$

or equivalently

$$\eta < 1 - \psi\kappa_w - \frac{\psi\kappa_\pi}{\theta(1-\beta)} \equiv \eta^*.$$

Thus firms sort toward the high-τ location if and only if $\eta < \eta^*$.

B.4 Proof of Lemma 4

Pollution satisfies

$$p_j = \psi\big((1-\nu)\tau_j + \nu n_j\big),$$

so

$$p_h - p_l = \psi\Big((1-\nu)(\tau_h - \tau_l) + \nu(n_h - n_l)\Big) = \psi\big((1-\nu)\Delta\tau + \nu x\big).$$

If firms sort toward the high-τ location, then $x > 0$, so both terms on the right-hand side are positive and therefore $p_h > p_l$.

Now suppose firms sort toward the low-τ location, so $x < 0$. Then the low-τ location is

more polluted if and only if

$$p_l > p_h \iff -\psi\big((1-\nu)\Delta\tau + \nu x\big) > 0 \iff x < -\frac{1-\nu}{\nu}\Delta\tau.$$

Equivalently, since $x = n_h - n_l$,

$$\nu(n_l - n_h) > (1-\nu)(\tau_h - \tau_l).$$

Define the threshold

$$\bar{x} \equiv -\frac{1-\nu}{\nu}\Delta\tau.$$

If

$$\nu\Pi \leq (1-\nu)\Delta\tau,$$

then $\bar{x} \leq -\Pi$, which is impossible since $x \in [-\Pi, \Pi]$. Hence in this case the low-τ location can never be both more populated and more polluted.

Consider instead the case

$$\nu\Pi > (1-\nu)\Delta\tau,$$

so that $\bar{x} \in (-\Pi, 0)$. Under uniqueness, F is strictly increasing, so the unique equilibrium satisfies $x^* < \bar{x}$ if and only if $F(\bar{x}) > 0$.

Using the definition of F,

$$F(\bar{x}) = \bar{x} - \Pi \tanh\left(\frac{A_\tau \Delta\tau + A_n \bar{x}}{2\sigma}\right).$$

A direct substitution of A_τ, A_n, and $\bar{x} = -(1-\nu)\Delta\tau/\nu$ gives

$$A_\tau \Delta\tau + A_n \bar{x} = -\frac{\theta(1-\beta)\eta(1-\nu)}{\nu}\Delta\tau.$$

Therefore

$$F(\bar{x}) = -\frac{1-\nu}{\nu}\Delta\tau + \Pi \tanh\left(\frac{\theta(1-\beta)\eta(1-\nu)}{2\sigma\nu}\Delta\tau\right).$$

Hence $x^* < \bar{x}$ if and only if

$$\Pi \tanh\left(\frac{\theta(1-\beta)\eta(1-\nu)}{2\sigma\nu}\Delta\tau\right) > \frac{1-\nu}{\nu}\Delta\tau.$$

Since the left-hand side is strictly increasing in η, this inequality holds if and only if

$$\eta > \widehat{\eta}(\nu),$$

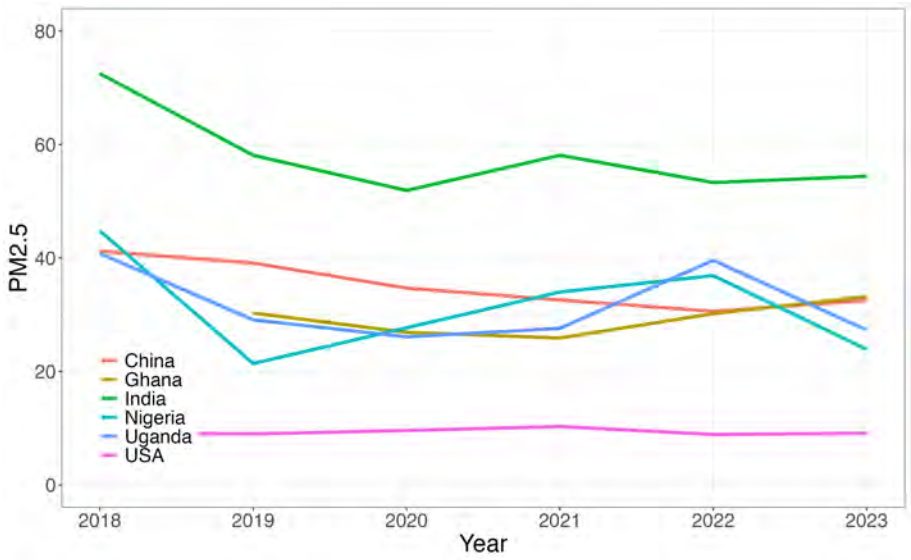
where, for notational simplicity,

$$\widehat{\eta}(\nu) \equiv \frac{2\sigma\nu}{\theta(1-\beta)(1-\nu)\Delta\tau} \operatorname{arctanh}\left(\frac{(1-\nu)\Delta\tau}{\nu\Pi}\right).$$

Replacing $\Delta\tau$ by $\tau_h - \tau_l$ yields the stated expression.

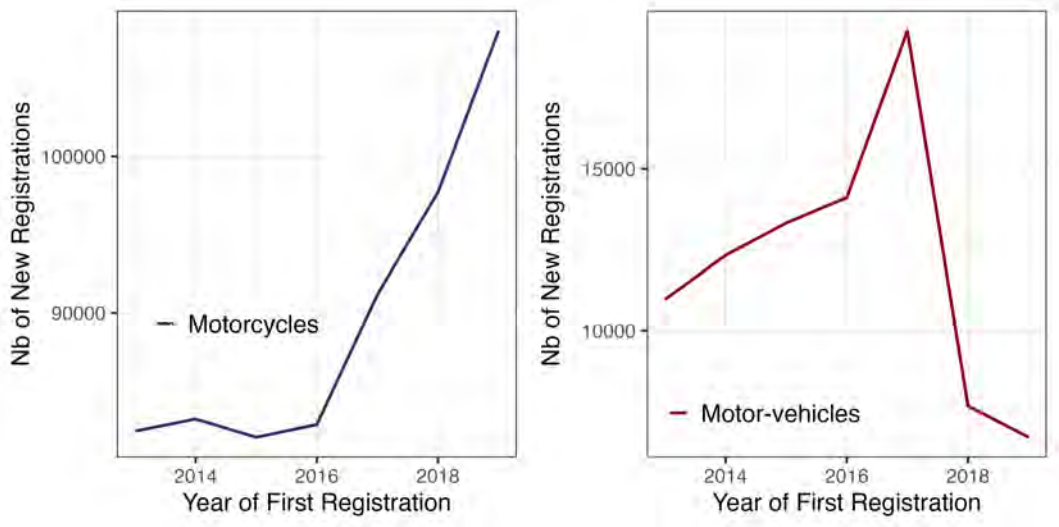
C Additional Appendix Tables and Figures

Figure B1: Average Annual Pollution Over Time in Selected Countries



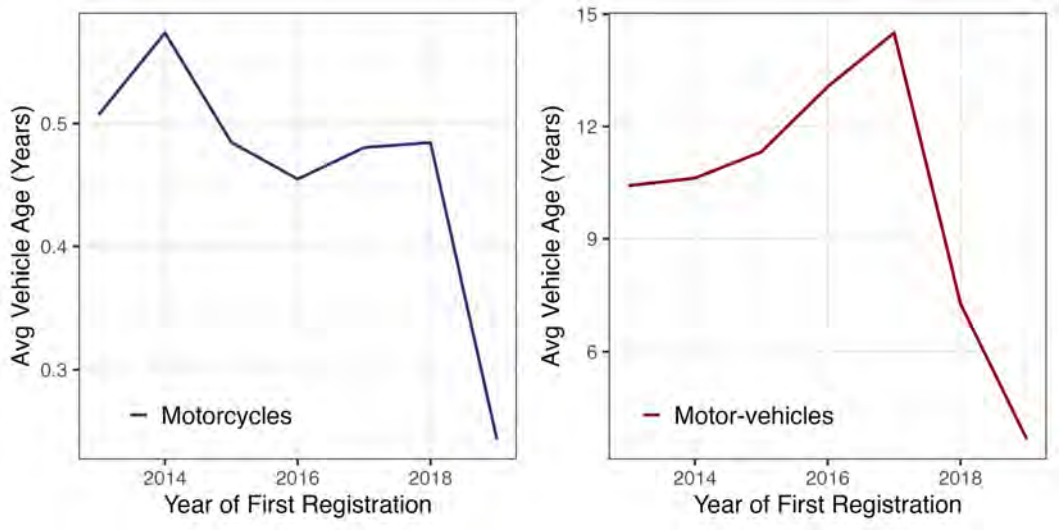
Notes: Average $PM_{2.5}$ concentration (microgram per cubic meter) in selected countries over time since 2018. Source: IQAIR

Figure B2: Vehicle Registrations Over Time in Uganda



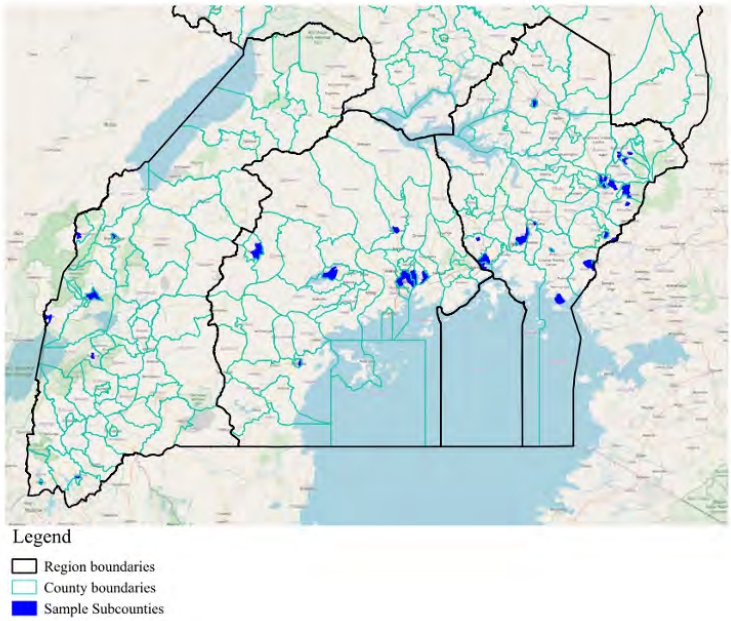
Notes: Annual number of first registrations for motorcycles (left panel) and motor-vehicles (right panel) from 2013 to 2019. The number of new motorcycle registrations has been sharply increasing since 2016. The number of newly registered motor-vehicles peaked in 2017. Source: Uganda Revenue Authority (URA).

Figure B3: Average Vehicle Age at Registration Over Time



Notes: Average vehicle age at first registration in the country for motorcycles (left panel) and motor vehicles (right panel). The 2018 ban on imports of motor vehicles older than 15 years significantly decreased the average age of newly registered vehicles. Source: Uganda Revenue Authority (URA).

Figure B4: Geographical Scope of the Survey



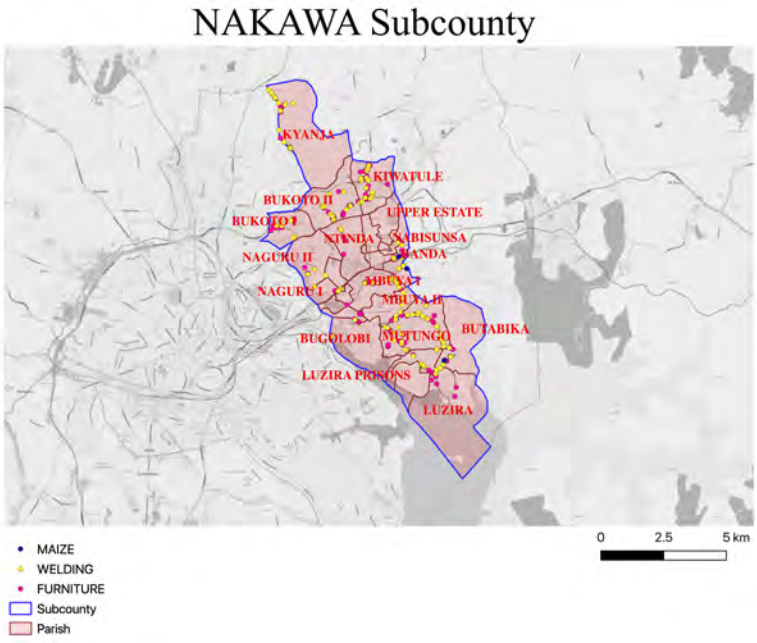
Notes: The figure shows in dark blue the sub-counties in our sample. The figure highlights that our sample region is scattered across three of the four regions of the country (Central, Eastern and Western).

Figure B5: Stationary and Mobile Monitors



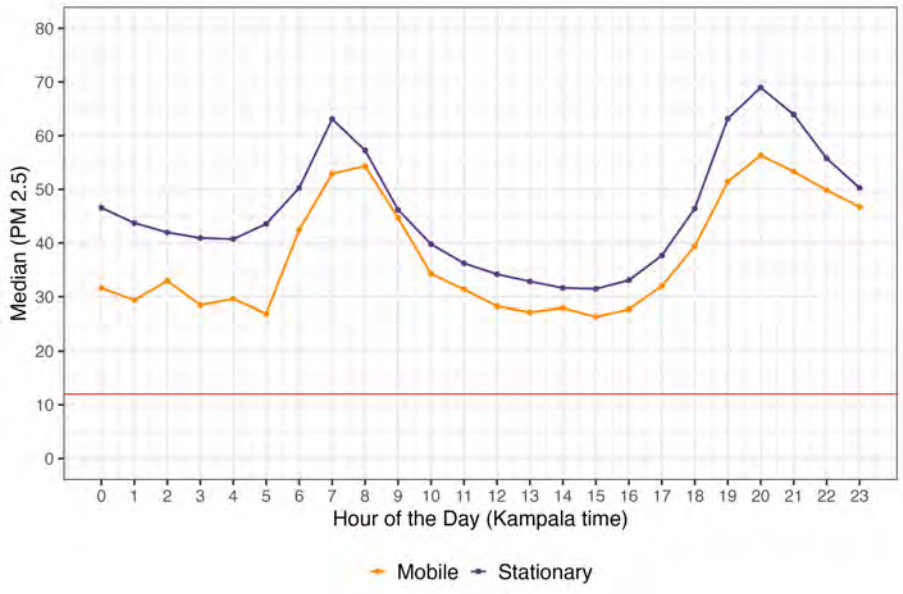
Notes: Photos of AirQo stationary (left panel) and mobile (right panel) pollution monitors.

Figure B6: Example of Listing Exercise in One Sampled Sub-county



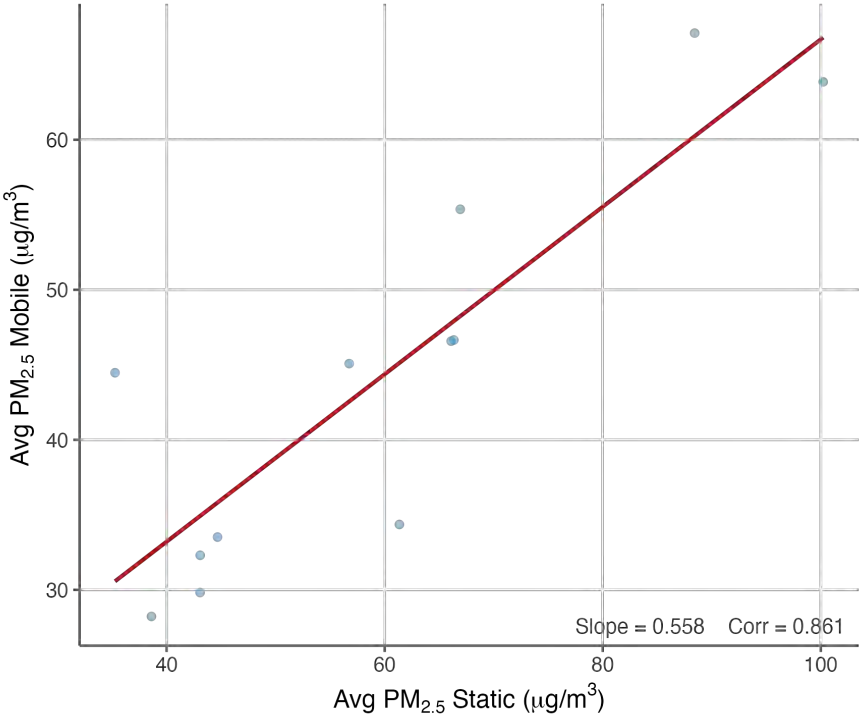
Notes: The figure shows the location of the firms identified in our initial listing in one sampled sub-county.

Figure B7: Hourly Fluctuation in Pollution Within the Day (Medians)



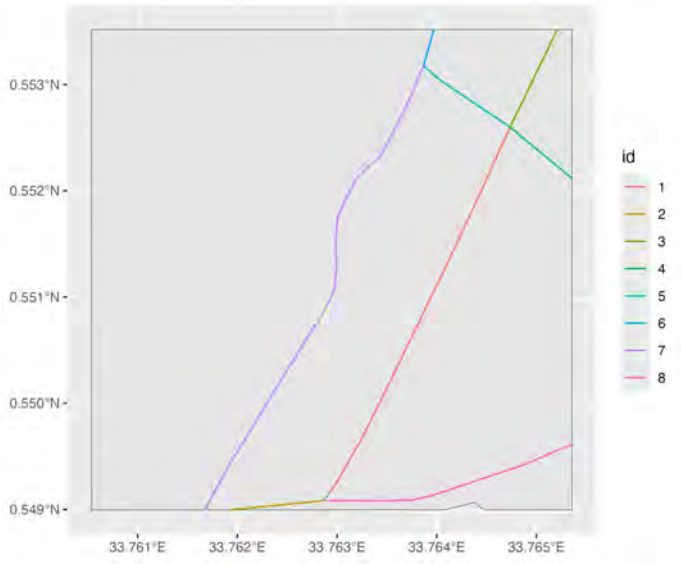
Notes: Medians of $PM_{2.5}$ measurements from our stationary and mobile monitors are plotted for each hour in Kampala time. The red line corresponds to the 2021 EPA guideline for average annual $PM_{2.5}$ values.

Figure B8: Correlation Between Average Measurements from Stationary and Mobile Monitors at the Sub-county Level



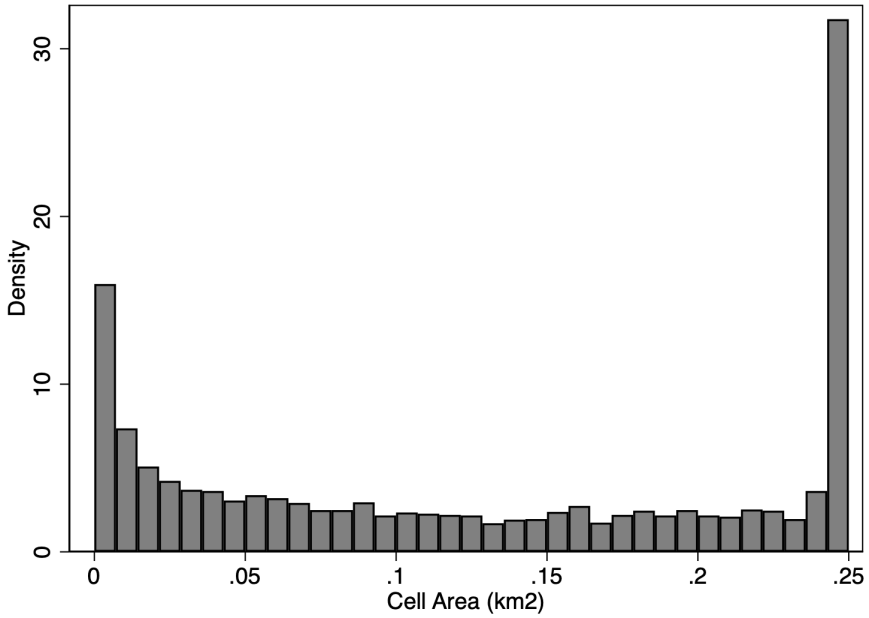
Notes: Data is from the full sample of $PM_{2.5}$ measurements from the stationary and mobile monitors. We create sub-county level averages of pollution measurements from both types of monitors and plot them against each other. The figure shows that the two are positively correlated.

Figure B9: Illustration of Road Definition



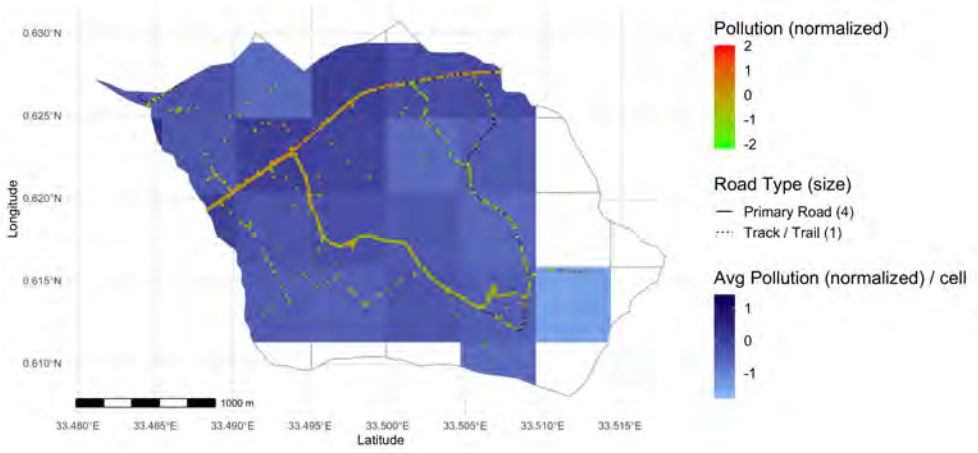
Notes: Each color represents a different road as defined in our dataset by a road segment not intersected by any other road. This grid cell, part of Bugiri Eastern Division, contains eight different roads. The median average grid cell in our sample contains 6 roads (average 11).

Figure B10: Histogram of Grid Cell Areas



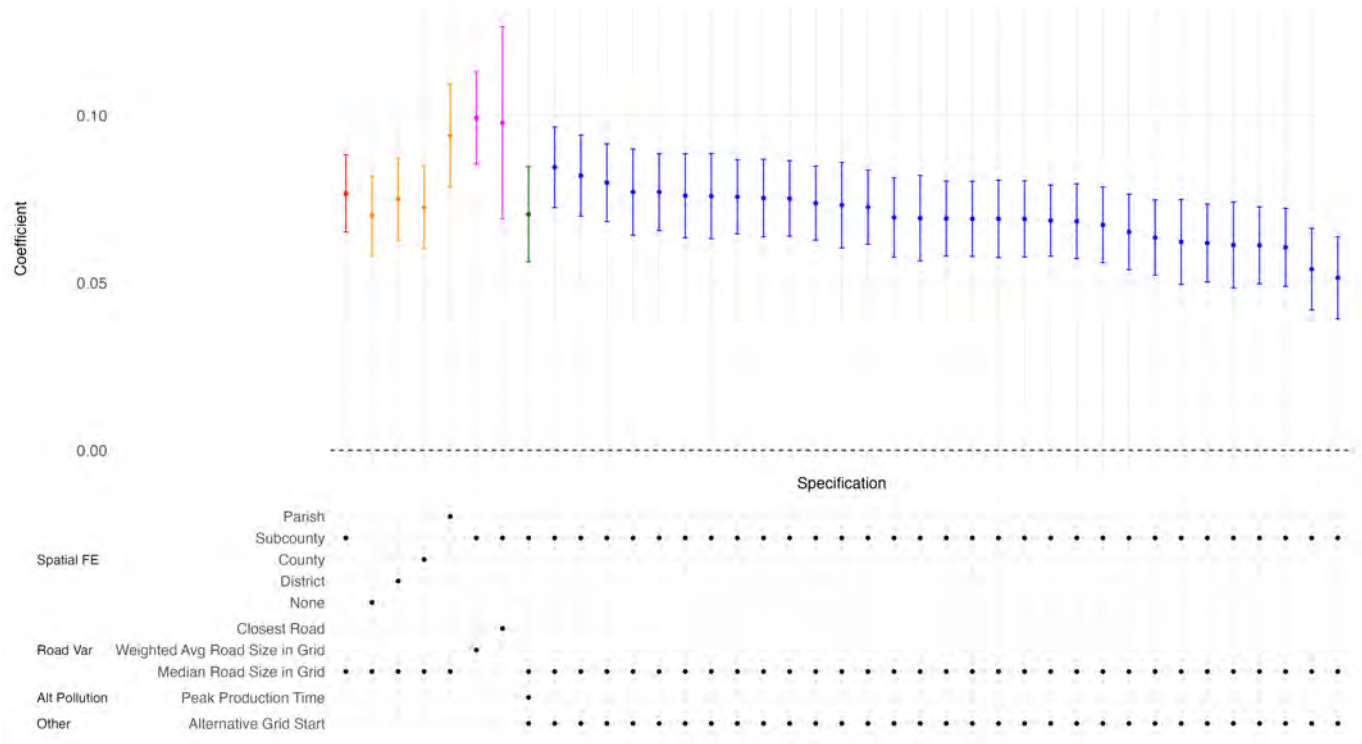
Notes: Distribution of grid cell area in km2 in our data. Our sample contains 3,936 grid cells in total.

Figure B11: Residual Pollution and Road Size in a Sampled Sub-county



Notes: Location of roads, location of pollution measurements from mobile monitors and average pollution residual per grid cell for the sampled parish in Nakalama sub-county (Iganga District). Road sizes are defined in Section 3.4 and the computation of pollution residuals is described in Section 4.1. Grid cell dimensions are 500m x 500m.

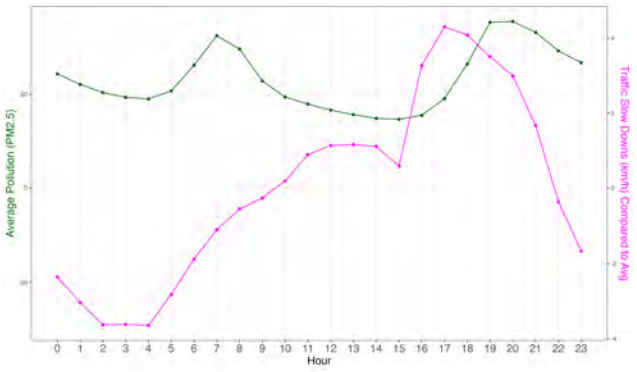
Figure B12: Robustness: Estimated Elasticity of Pollution Residual on Road Size



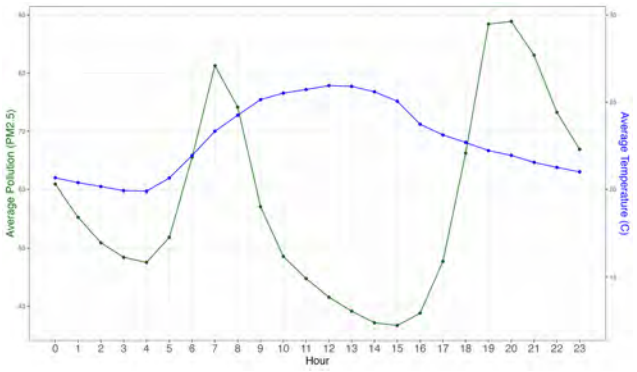
Notes: This figure displays estimated elasticities of average pollution residual in a grid cell on road size in the grid cell, as per Equation (3) for alternative specifications: alternative spatial fixed-effects (orange), alternative definition of local road size (pink), pollution restricted to measurements during peak production times (i.e. 10am-3pm) (green), and alternative starting points used to divide sub-counties into grid cells (blue). In all specifications, the covering grid is by default anchored so that its bottom-left corner aligns with the bottom-left corner of the smallest rectangle covering the sampled parishes, which may mechanically affect the aggregation of firms, pollution, and road measures at the grid cell level. The blue estimates assess robustness to this choice, using 30 random starting points as well as a specification anchoring the top-right corner instead. The main specification is displayed in red. Standard errors are bootstrapped 400 times following the procedure described in Footnote 38. In the specification where road is defined as the closest road to the pollution measurement, pollution measurements are not aggregated at the grid cell and we display SHAC standard errors.

Figure B13: Cyclicality of Pollution, Traffic Speed, and Temperature

(a) Cyclicality of Pollution and Traffic Slow Downs



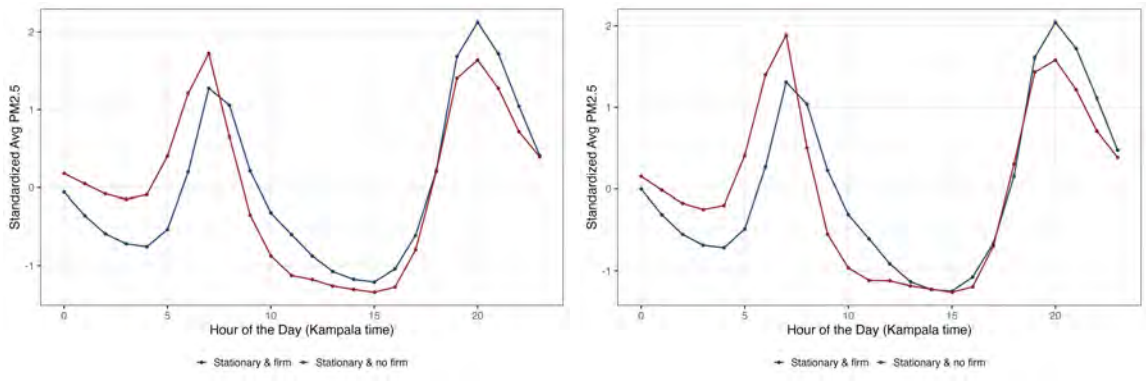
(b) Cyclicality of Pollution and Temperature



Notes: Air pollution is measured from our stationary monitors and averaged at the hourly level. In the left panel, traffic data is from GoogleMaps multiple API queries between March 2023 and August 2024 between all pairs of Kampala Parishes (more details in (Sorin, 2025)), restricted to trips with average speed below 50km/h. Traffic slow downs are computed as the hourly average traffic speed compared to the sample average of 22.4km/h. In the right panel, temperature data comes from NOAA's Global Hourly Integrated Surface Database (ISD) for the Station at Entebbe International Airport (the only station in Uganda with hourly data available) in 2019. Temperature is averaged by hour.

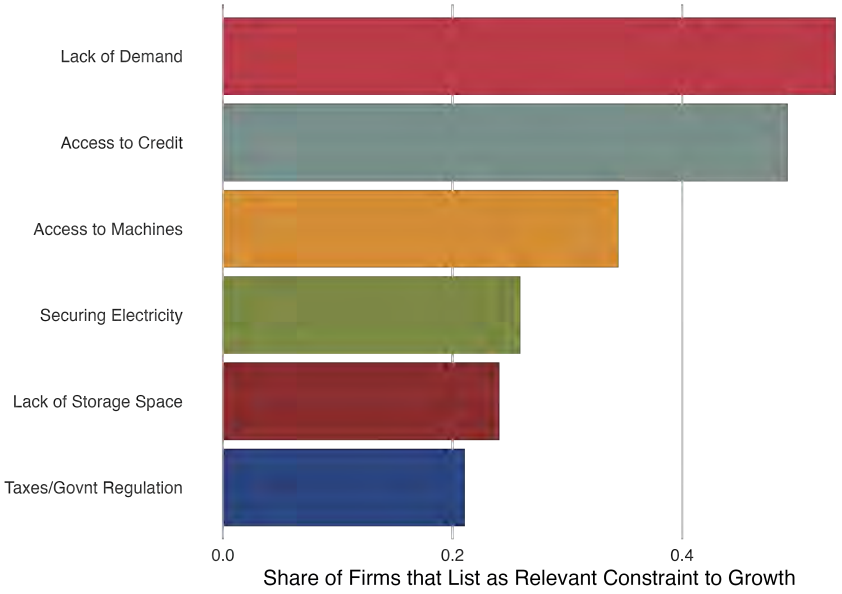
Figure B14: Cyclicality of Pollution Does Not Depend on Firm Density

(a) Full Sample (b) Restricting to Cells with at Least One Road



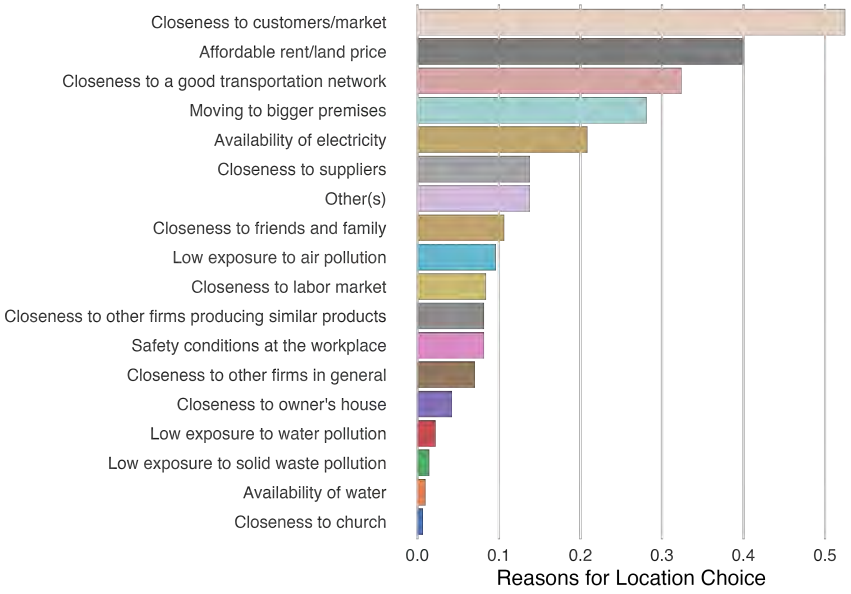
Notes: Avg ($PM_{2.5}$) is the standardized mean $PM_{2.5}$ measurement from stationary monitors by grid cell and hour. Grid cells with (without) firm correspond to grid cells containing at least one (no) firm from our initial listing. Normalizing $PM_{2.5}$ concentrations allows us to focus on pollution cyclicality. In the right panel, the sample is restricted to grid cells containing at least one road.

Figure B15: Lack of Demand is the Main Reported Constraint to Firm Growth



Notes: In the baseline survey, firm owners were asked about the main perceived constraint when thinking about increasing the profitability of their business. Managers could choose among a list of 14 possible constraints, indicating up to three constraints. For each potential constraint, we report the share of firms that listed it among the top three most important ones. We only report in the graph the six most common constraints.

Figure B16: Reasons for Location Choice



Notes: In the baseline survey, firms that had relocated (or considered to relocate) their premises in the previous year (138 firms) were asked which factors affected their decision of where to set up the firm. They were invited to give up to three factors. The histogram plots the share of firms in our sample listing the reason as one of the factors affecting their location choice.

Table B1: Firm Descriptives

All Sectors	Mean	Sd
Number of firms	1027	
Carpentry (%)	49.3	
Metal fabrication (%)	37	
Grain milling (%)	13.7	
Panel A: Firm characteristics		
Number of employees	4.9	3.1
Monthly revenues (USD)	1481	1645.4
Monthly profits (USD)	243.6	262
Firm age (years)	10.1	9
Panel B: Owner characteristics		
Owner is male (%)	96.1	
Owner age (years)	39.6	10.9
Owner years of education	10	3.6
Owner hours usually worked per day for the firm	9.2	3
Panel C: Employee characteristics		
Employee is male (%)	98.2	
Employee age (years)	28.5	9.3
Employee years of education	9.2	2.6
Employee hours usually worked per day for the firm	9.9	1.6
Employee monthly wage (USD)	70.9	67
Panel D: Production location characteristics		
Firm produces only outside	39.7	
Firm produces mostly outside	24.4	
Firm produces sometimes outside	20.1	
Firm produces only inside	15.7	

Notes: Descriptive statistics across firms in our firm survey. Firm, owner and employee characteristics are reported in Panels A, B and C, respectively. Statistics for the average firm are shown. Monetary amounts, originally in UGX, are converted to USD using the exchange rate 1 USD = 3,800 UGX. The data was obtained during our baseline survey.

Table B2: Correlation Between Road Size and Pollution - Outside Kampala

	Avg log(Pollution) Resid.			log(Profits)		
	(1)	(2)	(3)	(4)	(5)	(6)
Primary Road (dummy)	0.174	0.191	0.201	0.371	0.419	0.303
	(0.0223)	(0.027)	(0.0368)	(0.110)	(0.123)	(0.202)
N	489	436	252	599	535	244
R2	0.0770	0.0812	0.0739	0.586	0.602	0.699
Sample	Outside Kampala	< 4500 pop/km2	< 2000 pop/km2	Outside Kampala	< 4500 pop/km2	< 2000 pop/km2
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Sub-county FE	Yes	Yes	Yes	Yes	Yes	Yes
Level of Observation	Grid cell	Grid cell	Grid cell	Firm	Firm	Firm
SE clustering	Bootstrap	Bootstrap	Bootstrap	Grid-cell	Grid-cell	Grid-cell

Notes: OLS regression coefficients, standard errors in parentheses. In columns 1-3, pollution measurements are aggregated at the grid cell level and we report bootstrapped standard errors (400 iterations) following the procedure described in Footnote 38. The top and bottom one percent of pollution residuals are trimmed. In columns 4-6, standard errors are clustered at the grid cell level and displayed in parentheses and specifications include sector fixed effects. The top one percent of the monetary dependent variables are trimmed. In all specifications, we control for log distance to the main city in the region, a dummy for whether the grid cell contains any road, a dummy for whether the grid cell is incomplete (i.e., 500m x 500m), its area, as well as a dummy for whether the grid cell falls in our main surveyed area. All specifications include sub-county fixed-effects. The road variable is a dummy equal to 1 if the grid cell includes a primary road or motorway. In columns 1 and 4, the sample is restricted to grid cells outside of Kampala. In columns 2 and 5, the sample is restricted to parishes with population density lower or equal than 4,500 inhabitants/km2 (median in our sample). In columns 3 and 6, the sample is restricted to parishes with population density lower or equal than 2,000 inhabitants/km2 (25th percentile in our sample). The procedure to construct pollution residuals is detailed in Section 4.1.

Table B3: Correlation Between Pollution and Road Size is Robust to Controlling for Polluting Industries

	(1)	(2)	(3)	(4)	(5)
	Avg log(Poll) Resid.	Avg log(Poll) Resid.	Avg log(Poll) Resid.	Avg log(Poll) Resid.	Avg log(Poll) Resid.
Median Road Size/Cell	0.0767	0.0763	0.0778	0.0737	0.0768
	(0.0063)	(0.0064)	(0.0063)	(0.0064)	(0.0063)
Count TRI		0.000476			
		(0.000507)			
Count TRI > 10 employees			-0.00900		
			(0.00748)		
Log density TRI				0.0168	
				(0.00745)	
Log density TRI > 10 employees					-0.000493
					(0.0107)
N	972	972	972	972	972
R2	.3511	.3513	.3516	.3548	.3511
Level of Observation	Grid Cell	Grid Cell	Grid Cell	Grid Cell	Grid Cell
SE clustering	Bootstrap	Bootstrap	Bootstrap	Bootstrap	Bootstrap

Notes: OLS regression coefficients, standard errors in parentheses. Pollution measurements are aggregated at the grid cell level and we report bootstrapped standard errors for Median Road Size following the procedure described in Footnote 38 (400 iterations). We control for log distance to the main city in the region, a dummy for whether the grid cell contains any road, a dummy for whether the grid cell is incomplete (i.e., 500m x 500m), its area, as well as a dummy for whether the grid cell falls in our main surveyed area. The top and bottom one percent of pollution residuals are trimmed. Road size goes from 1 (Trail/Track) to 5 (Highway). The procedure to construct pollution residuals is detailed in Section 4.1. Toxics Release Inventory (TRI) firms are identified by first mapping Uganda's industry classification (ISIC rev 4) to the NAISC classification, and then recovering the NAISC industries flagged by the U.S. EPA's Toxics Release Inventory (TRI) as polluting industries.

Table B4: Attrition Table - Follow-up Phone Survey

	(1)	(2)	(3)
	follow_up	follow_up	follow_up
Man. Score	-0.0392	-0.0299	-0.00950
	(0.0251)	(0.0212)	(0.0173)
Median Road Size/Cell	0.00462	0.0281	0.00675
	(0.0244)	(0.0207)	(0.0172)
Treatment Pollution	-0.00249		
	(0.0448)		
Treatment Profitability		-0.0355	
		(0.0395)	
N	499	615	1027
R2	0.0899	0.102	0.102
Sector FE	Yes	Yes	Yes
Sub-county FE	Yes	Yes	Yes
Standard Errors	Robust	Robust	Robust
Model	OLS	OLS	OLS
Sample	Pollution Treatment	Profitability Treatment	All
Mean Dep Var	.	.	.677

Notes: Robust standard errors are in parenthesis. For the follow-up survey, we attempted to reach the 1,014 firms with valid phone number at baseline, out of our initial 1,027 firms. The dependent variable is a dummy equal to one if the firm was successfully surveyed at follow-up, and zero otherwise. 499 out of these 1,014 firms were randomized into treatment or control groups for the pollution experiment. We excluded firms in sub-counties with strictly less than three grid cells with pollution measures. 615 out of these 1,014 firms were randomized into treatment or control groups for the profitability experiment. We excluded firms in the maize sector because the limited number of such firms prevented us from computing a robust measure of each firm's profitability. We also excluded firms with missing information on revenues at baseline or outliers (top and bottom 1%), and firms in sub-counties with less than three grid cells with sector-specific profitability. See Section A.6 for more details on the sample and randomization for the experiment. We control for missing managerial score (dummy) and for whether the grid cell contains any road (dummy). All specifications include sector and sub-county fixed effects.

Table B5: Kilometers by Road Size

Road Type	Corresponding Size	Length (km)	Share	Length (km) U	Share U
Motorway	5	8	0.003	55	0
Primary Road	4	670	0.243	1280	0.011
Secondary Road	3	503	0.183	3056	0.025
Tertiary Road	2	534	0.194	11824	0.098
Track / Trail	1	1039	0.377	104996	0.866
Total		2754	1	121211	1

Notes: This table presents summary statistics about the number of kilometers per road type and the corresponding share of total kilometers, both for the country as a whole and for our sampled area (grid). Our sample contains 2,754km of roads, or about 2 percent of Ugandan roads, and roads are larger in our sample than in the rest of the country: 24 percent of the roads in our sample are primary roads and only 38 percent are classified as track/trail, while the corresponding figures for the country as a whole are 1 and 87 percent, respectively. Reflecting our sampling strategy, this shows that our sample is more urban, and therefore denser, than the average Ugandan geographic area. Kilometers of road per road size, both for our sampled area (grid) and the whole country. Source: WFP on OSM.

Table B6: Returns from Locating on Polluted Roads

	(1) log(Profit)	(2) log(Profit)	(3) Nb Customers	(4) Log(Price)	(5) Log(Input Price)	(6) Input Accessibility	(7) log(Salary)	(8) log(Rent)
Avg log(Pollution) Resid./Cell	0.234	0.250	0.0635	-0.0518	0.0951	-0.0238	-0.0402	0.00743
	(0.0855)	(0.0825)	(0.2109)	(0.0493)	(0.0557)	(0.0086)	(0.0333)	(0.0714)
Man. Score		0.196	0.428	0.0618	0.106	0.0107	0.0563	0.0854
		(0.0378)	(0.119)	(0.0215)	(0.0396)	(0.00710)	(0.0230)	(0.0422)
log(Size Premises)								0.0369
								(0.0238)
N	591	591	475	450	3621	4126	1359	411
R2	0.417	0.441	0.291	0.948	0.391	0.142	0.370	0.405
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sub-county FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Level of Observation	Firm	Firm	Firm	Firm	Firm x Input	Firm x Input	Employee	Firm
SE clustering	Bootstrap	Bootstrap	Bootstrap	Bootstrap	Bootstrap	Bootstrap	Bootstrap	Bootstrap
Employee Controls							Yes	
Input FE					Yes	Yes		

Notes: OLS regression coefficients, standard errors displayed in parentheses. Man. Score is a standardized index of managerial ability constructed using our survey (see Appendix A.1 for details). We control for log distance to the main city in the region. We also control for a dummy for whether the grid cell is incomplete (i.e., 500m x 500m), its area, as well as a dummy for whether it is in our main surveyed area. All specifications include sector and sub-county fixed effects. Employee controls include education, age, age squared, any vocational training (dummy), cognitive ability (measured through a Raven matrices test), employee tenure. We control for missing managerial score (dummy) and missing employee controls (dummies). The top and bottom one percent of all monetary dependent variables are trimmed. For regressions at the Firm x Input level, we include input fixed effects, as well as controls for the quantity of input purchased and the input unit. Input Accessibility is a standardized index of seven variables reflecting input accessibility. Analogous regressions for each individual variable can be found in Appendix Table B9. The procedure to construct pollution residuals is detailed in Section 4.1. The number of observations is lower in Table B6 than Table 4 because, as described in Section 3.2, information on pollution is available in 32 of our 52 sampled sub-counties, while road size is available in all sub-counties. Pollution standard errors are bootstrapped 400 times following the procedure described in Footnote 38.

Table B7: Workers' Returns on Experience as a Function of Road Size

	(1) Log Salary	(2) Log Salary	(3) Log Salary	(4) Log Salary	(5) Log Salary
Median Road Size/Cell	0.0250	0.0204	0.0199	0.0277	0.0287
	(0.0152)	(0.0337)	(0.0310)	(0.0193)	(0.0160)
Manscore	0.0842	0.0843	0.0842	0.0841	0.0844
	(0.0192)	(0.0192)	(0.0192)	(0.0193)	(0.0191)
Years Educ	0.0164	0.0164	0.0151	0.0164	0.0164
	(0.00389)	(0.00389)	(0.00819)	(0.00387)	(0.00388)
Age	0.0560	0.0557	0.0560	0.0559	0.0558
	(0.00832)	(0.00852)	(0.00835)	(0.00850)	(0.00836)
Vocational Training	0.0604	0.0602	0.0604	0.0609	0.133
	(0.0454)	(0.0453)	(0.0455)	(0.0451)	(0.0889)
Firm Tenure	0.0188	0.0188	0.0188	0.0206	0.0189
	(0.00475)	(0.00478)	(0.00474)	(0.00721)	(0.00469)
Age * Median Road Size/Cell		0.000171			
		(0.00107)			
Years Educ * Median Road Size/Cell			0.000560		
			(0.00282)		
Firm Tenure * Median Road Size/Cell				-0.000793	
				(0.00318)	
Vocational * Median Road Size/Cell					-0.0317
					(0.0381)
N	2272	2272	2272	2272	2272
R2	0.392	0.392	0.392	0.392	0.393
Sector FE	Yes	Yes	Yes	Yes	Yes
Sub-county FE	Yes	Yes	Yes	Yes	Yes
Employee Controls	Yes	Yes	Yes	Yes	Yes
Level of Observation	Employee	Employee	Employee	Employee	Employee
SE clustering	Grid Cell	Grid Cell	Grid Cell	Grid Cell	Grid Cell

Notes: OLS regression coefficients, standard errors clustered at the grid cell level and displayed in parentheses. Man. Score is a standardized index of managerial ability constructed using our survey (see Appendix A.1 for details). We control for log distance to the main city in the region and a dummy for whether the grid cell contains any road. We also control for a dummy for whether the grid cell is incomplete (i.e., 500m x 500m), its area, as well as a dummy for whether it is in our main surveyed area. All specifications include sector, sub-county and input fixed effects. We control for missing managerial score (dummy) and missing employee controls (dummy). The top and bottom one percent of the monetary dependent variables are trimmed. All specifications include sector and sub-county fixed effects as well as employee controls. Road size goes from 1 (Trail/Track) to 5 (Highway). The variable *Firm Tenure* corresponds to the number of years the worker has been working at the firm and the variable *Vocational Training* is a dummy equal to 1 if the worker previously received vocational training.

Table B8: Owners' Training and Experience as a Function of Road Size

	(1) Attended Formal Business Training	(2) Attended Formal Vocational Training	(3) Previously worked as Employee
Median Road Size / cell	0.0133	-0.0100	0.00264
	(0.0134)	(0.0154)	(0.0122)
Manscore	0.0513	0.0319	0.0114
	(0.0124)	(0.0168)	(0.0144)
N	976	987	992
R2	0.108	0.193	0.183
Mean Dep. Var	.16	.35	.84
Sector FE	Yes	Yes	Yes
Sub-county FE	Yes	Yes	Yes
Level of Observation	Firm	Firm	Firm
SE clustering	Grid Cell	Grid Cell	Grid Cell

Notes: OLS regression coefficients, standard errors clustered at the grid cell level and displayed in parentheses. Man. Score is a standardized index of managerial ability constructed using our survey (see Appendix A.1 for details). We control for log distance to the main city in the region and a dummy for whether the grid cell contains any road. We also control for a dummy for whether the grid cell is incomplete (i.e., 500m x 500m), its area, as well as a dummy for whether it is in our main surveyed area. All specifications include sector and sub-county fixed effects. We control for missing managerial score (dummy). Road size goes from 1 (Trail/Track) to 5 (Highway). The variable *Attended Formal Business Training* is a dummy equal to 1 if the owner previously attended formal business training. The variable *Attended Formal Vocational Training* is a dummy equal to 1 if the owner previously attended formal vocational training. The variable *Previously worked as Employee* is a dummy equal to 1 if the owner previously worked as an employee.

Table B9: Input Accessibility near Large Roads

	(1) Input Quality	(2) Direct Suppliers	(3) Replace. Supplier	(4) Nb Suppliers	(5) Size Supplier	(6) Rel. Size Supplier	(7) Modern Supplier
Median Road Size/Cell	0.00416	-0.00308	-0.0216	0.00435	0.00390	0.00387	0.00357
	(0.00375)	(0.00648)	(0.0173)	(0.00787)	(0.0106)	(0.00870)	(0.00811)
Man. Score	0.00660	-0.00574	-0.0301	0.0501	0.0598	0.0335	0.0205
	(0.00390)	(0.00789)	(0.0176)	(0.00959)	(0.0122)	(0.0105)	(0.00977)
N	5763	5800	5776	5711	5071	5767	5741
R2	0.110	0.106	0.162	0.188	0.256	0.218	0.243
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sub-county FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Level of Observation	Firm	Firm	Firm	Firm	Firm	Firm	Firm
SE clustering	Grid Cell	Grid Cell	Grid Cell	Grid Cell	Grid Cell	Grid Cell	Grid Cell
Input FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: OLS regression coefficients, standard errors clustered at the grid cell level and displayed in parentheses. Man. Score is a standardized index of managerial ability constructed using our survey (see Appendix A.1 for details). We control for log distance to the main city in the region and a dummy for whether the grid cell contains any road. We also control for a dummy for whether the grid cell is incomplete (i.e., 500m x 500m), its area, as well as a dummy for whether it is in our main surveyed area. All specifications include sector, sub-county and input fixed effects. We control for missing managerial score (dummy). Road size goes from 1 (Trail/Track) to 5 (Highway). The variable *Input Accessibility* in Table 4 Column 6 is a weighted average of the dependent variables in this table. *Input Quality* is a dummy variable equal to 1 if the firm reported using the highest quality input available in the past 3 months for this input. *Direct Suppliers* is a dummy variable equal to 1 if the firm reported finding new domestic suppliers of this input in a way that may be facilitated by its location near large roads (by going to fairs/exhibitions, by waiting for the supplier to come to the firm, or by visiting a neighborhood where suppliers are). *Replace. Supplier* is a dummy variable equal to 1 if the firm reported taking less than median time (1-2 days) to find a new supplier for this input. *Nb Suppliers* is a standardized continous variable from 0 to 1 corresponding to the firm's number of suppliers for this input during the last year. *Size Supplier* is a standardized continous variable from 0 to 1 corresponding to the size (number of employees) of the firm's typical supplier for this input. *Rel. Size Supplier* is a standardized continous variable from 0 to 1 corresponding to the relative size of the representative firm's suppliers of this input, compared to other suppliers of this input.

Table B10: Owners' Location Choice - Proximity to Home

	(1) Log dist work	(2) <2km from work	(3) <1km from work	(4) Motorized to work
Median Road Size/Cell	0.0364	-0.0222	-0.0296	0.0476
	(0.0246)	(0.0175)	(0.0150)	(0.0157)
N	988	988	988	988
R2	0.183	0.160	0.176	0.231
Sector FE	Yes	Yes	Yes	Yes
Sub-county FE	Yes	Yes	Yes	Yes
Level of Observation	Firm	Firm	Firm	Firm
SE clustering	Grid Cell	Grid Cell	Grid Cell	Grid Cell

Notes: OLS regression coefficients, standard errors clustered at the grid cell level and displayed in parentheses. Road size goes from 1 (Trail/Track) to 5 (Highway) and is averaged within a grid cell. We control for log distance to the main city in the region and a dummy for whether the grid cell contains any road (dummy). We also control for a dummy for whether the grid cell is incomplete (i.e., 500m x 500m), its area, as well as a dummy for whether it is in our main surveyed area. All specifications include sector and sub-county fixed effects. In our baseline survey, we asked firm owners how far they live from work (in km) and how they go to work. Log distance to work is the log of reported distance to work +1. Median (q1) distance to work is 2km (1km). Mean distance to work is 4.4 km.

Table B11: Workers' Location Choice - Proximity to Home

	(1) Log dist work	(2) <2km from work	(3) <1km from work	(4) Motorized to work
Median Road Size/Cell	0.0331	-0.0245	-0.0307	0.0415
	(0.0223)	(0.0138)	(0.0150)	(0.0141)
Manscore	-0.0233	0.00589	0.00851	0.00652
	(0.0208)	(0.0142)	(0.0167)	(0.0160)
N	1997	1997	1997	2050
R2	0.187	0.160	0.150	0.254
Sector FE	Yes	Yes	Yes	Yes
Sub-county FE	Yes	Yes	Yes	Yes
Employee Controls	Yes	Yes	Yes	Yes
Level of Observation	Employee	Employee	Employee	Employee
SE clustering	Grid Cell	Grid Cell	Grid Cell	Grid Cell

Notes: OLS regression coefficients, standard errors clustered at the grid cell level and displayed in parentheses. Road size goes from 1 (Trail/Track) to 5 (Highway) and is averaged within a grid cell. We control for log distance to the main city in the region and a dummy for whether the grid cell contains any road (dummy). We also control for a dummy for whether the grid cell is incomplete (i.e., 500m x 500m), its area, as well as a dummy for whether it is in our main surveyed area. All specifications include sector and sub-county fixed effects. In our baseline survey, we asked workers how far they live from work (in km) and how they go to work. Log distance to work is the log of reported distance to work +1. Median (q1) distance to work is 2km (1km). Mean distance to work is 6.1 km.

Table B12: Balance Table - Pollution and Profitability Information Experiments

	Control			Treatment			
	n	mean	sd	n	mean	sd	p-value
Panel A: Pollution							
Manscore	245	-0.00	0.97	225	-0.05	0.93	0.40
Profit (UDX)	254	961512.64	946345.84	236	982486.92	1049180.95	0.20
Revenues (UDX)	252	5961898.15	6387247.66	237	5796015.94	6135613.15	0.79
Nb Employees	258	4.83	3.18	241	4.84	3.54	1.00
Firm Age (years)	255	10.40	9.61	240	10.19	8.87	0.52
Owner Age (years)	249	39.05	10.59	231	38.93	10.84	0.60
Owner Education	250	10.15	3.48	231	9.93	3.44	0.55
Poll. Protective Equipment	257	0.04	0.20	240	0.04	0.20	0.80
Joint							0.66
Panel B: Profitability							
Manscore	286	-0.17	0.98	298	-0.01	0.95	0.16
Profit (UDX)	302	1000063.54	968484.19	307	1024759.46	1085408.65	0.37
Revenues (UDX)	304	5687665.84	5706429.62	311	5613090.77	5785423.42	0.87
Nb Employees	304	4.45	3.07	311	4.66	2.80	0.44
Firm Age (years)	304	9.13	8.43	307	10.41	9.65	0.27
Owner Age (years)	292	38.29	9.83	302	37.60	10.91	0.24
Owner Education	291	9.75	3.61	303	9.91	3.48	0.74
Poll. Protective Equipment	303	0.05	0.21	311	0.03	0.16	0.44
Joint							0.25

Notes: The samples in panels A and B correspond to the two samples of firms used for the pollution and profitability information experiments, respectively. 499 and 615 firms out of the 1,027 were included in the pollution and profitability experiments, respectively. The treatment assignment was stratified by sector and sub-county. The displayed p-values are for the predictive power of the variable on the treatment status, controlling for stratification variables and with robust standard errors. Profits and revenues are trimmed at the top and bottom 1%. The joint p-values are from a joint F-test of significance of all the variables considered for the balance checks in predicting treatment assignment, again controlling for stratification variables and with robust standard errors.