Jobs in the Smog:

Firm Location and Workers' Exposure to Pollution in African Cities*

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Abstract

Air pollution within African cities is high but unevenly distributed. In principle, individuals could mitigate the severe health risk by working in the less polluted parts of the city. In practice, we show that pollution avoidance is challenging because firms locate on the busiest and most polluted roads searching for customer visibility. Both workers and entrepreneurs bear the cost of this pollution exposure, but the benefits are unequally distributed: profits are much higher in polluted areas, while compensating differentials in wages are minimal. An information experiment reveals limited awareness of pollution, suggesting that workers might be undercompensated for their exposure. JEL Codes: Q53, Q56, O12, L23, J31

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1 Introduction

African cities are among the most polluted in the world, with air pollution levels now posing a health threat on par with diseases like HIV or malaria in many African countries (Greenstone and Jack, 2015, Greenstone and Hasenkopf, 2023). These high pollution levels are likely to persist in the medium term. However, their adverse health effects could be mitigated if individual exposure to pollution was reduced through adaptation or avoidance strategies.[1]

In this paper, we collect new data from urban areas in Uganda to study pollution exposure at workplaces, which is where most people in African cities spend the majority of their waking hours.[2] Adaptation to pollution is difficult in these settings: production often occurs outdoors or in poorly insulated buildings, and the cost of investments in air purifiers can be prohibitively high. On the other hand, avoidance might be a more viable strategy since air pollution varies widely across space, even within the city.[3] In principle, workers could avoid the air pollution by working in the cleaner parts of the city.

The key contribution of our paper is to show that, in practice, avoiding air pollution is very challenging for manufacturing workers in Ugandan cities. Entrepreneurs tend to locate their businesses in the most polluted parts of the city, which we show are also the most profitable ones, as road traffic bundles pollution exposure with access to customers. As a result, employment opportunities are concentrated in these highly polluted areas—*jobs are in the smog*—leaving workers with few options to avoid exposure to harmful air quality.

To situate our study in the broader context, we begin by showing that cities in developing countries feature some of the world's highest levels of pollution, caused at least in part by rising motorization and poor infrastructure that ultimately lead to traffic congestion.[4] Uganda is no exception: Ugandan cities today are on average as polluted as Chinese cities.

We collect geo-coded PM2.5 measurements in a sample of 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. Importantly, this local analysis would not be possible with standard satellite data, as the level of geographical aggregation in those datasets would not capture differences in pollution levels within neighborhoods, which we show are substantial.

[1] The literature has highlighted the important role of adaptation investments (such as air purifiers) and avoidance behavior through location choices or labor supply decisions in limiting the negative health effects of pollution in low- and middle-income countries. See Greenstone et al. (2021), Hanna and Oliva (2015), Aragon et al. (2017), Hoffmann and Rud (2024), Khanna et al. (2021) and Chen et al. (2022).

[2] More generally, the literature has shown that workers in developing countries spend longer hours at the workplace than in higher income countries (Bick et al., 2018).

[3] See, for instance, Karner et al. (2010), Kim et al. (2004) and Guo et al. (2010).

[4] 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).

We combine the pollution data with our own geo-coded survey of more than 1,000 manufacturing firms. For each firm, we collect measures of productivity such as profits, a standard and vetted managerial ability index (following McKenzie and Woodruff, 2017), as well as a range of questions about location choice. For the workers of our firms, we gather information on their background characteristics, the hours they work, and their wages. In addition, for both entrepreneurs and workers, we ask several questions on pollution avoidance behaviors and adaptation investments, as well as awareness of pollution as a problem.[5] Finally, we have access to the geo-coded universe of Ugandan roads.

Equipped with this data, the empirical analysis proceeds in five steps. We begin by documenting the extent of spatial heterogeneity in air pollution *within the city*. To do so, we divide our sample area in grid cells of 500 meters $\times$ 500 meters (following Ahlfeldt et al., 2015, Michaels et al., 2021) and aggregate the PM2.5 measurements at the grid-cell level.[6] We find large spatial heterogeneity: in the average sub-county (which corresponds to a large neighborhood of a city), grid cells with pollution levels similar to Dhaka in Bangladesh coexist with others with pollution levels similar to Milan in Italy. We further show that air pollution in a grid cell is highly correlated with the presence of large roads: grid cells with major roads are significantly more polluted, and this remains true even within sub-counties.[7]

Second, we study where firms locate within the city. We find that most entrepreneurs sort into polluted grid cells, locating along the largest and most polluted roads. We rule out that the correlation between firm density and pollution is driven by reverse causality by showing that firms themselves are not the source of pollution.

Third, we study the economic returns from locating near large (and polluted) roads. We find that, in addition to being more polluted, grid cells with major roads feature significantly higher profits, even controlling for a rich set of observables: that is, there is a large *profit pollution premium.* In our road data, each road has an ordinal size going from 1 (smallest) to 5 (largest). An increase of one unit in the median road size in the grid cell (e.g., going from secondary to primary road) is associated with an increase in profits of 15%. While the profit pollution premium is large, the corresponding *wage pollution premium* for employees is small: an increase of one unit in the median road size in the cell only leads to a 2.5% increase in wages. Therefore, workers only get a small share of the benefits from locating on larger roads.[8]

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

[6]Focusing on grid cells of 500 meters $\times$ 500 meters is also justified by the fact that emissions for most traffic pollutants decay to background levels within 570 meters (Karner et al., 2010).

[7]We also verify that the spatial heterogeneity in air pollution is mainly driven by road traffic being larger on main roads, which is consistent with the literature (Karner et al., 2010).

[8]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. As we find that the wage pollution premium is close to zero, any positive selection of workers into more polluted areas would imply that the real wage premium is even lower than what we

Fourth, we study the mechanisms leading to the large profit pollution premium. We show that road traffic bundles pollution exposure with customer access: firms are small and sell locally through face-to-face interactions as they have limited other means to access customers; therefore, by locating on large (and polluted) roads, they can gain visibility to consumers and increase their profits. Using the latest firm census of Uganda covering the entire population of firms, we validate the role of customer access in driving location choice, by showing that the sorting on larger roads is stronger in sectors where face-to-face interactions with consumers are more important, and is stronger for smaller firms, which may struggle to access customers otherwise.

Finally, the extent to which exposure to pollution translates into productivity and health costs depends on whether entrepreneurs engage in any adaptation investments or strategies to protect their workers from pollution. We show that any such adaptation is very limited and, importantly, is not higher in more polluted areas. We notice instead that firm owners with higher managerial ability protect their workers more, through both provision of equipment and organizational practices to avoid exposure.[9]

We interpret the evidence using a stylized model. We consider an economy with multiple locations, each differing only in its road traffic. Traffic not only generates pollution but also drives customer flow to businesses. A firm's output at any given location is a function of both customer access and the number of firms at that location, through standard agglomeration forces. The economy is populated by entrepreneurs who decide where to establish their firms, trading-off the location's profitability with the pollution exposure. Workers search for jobs subject to matching frictions. They match randomly with entrepreneurs and share production surplus through Nash Bargaining.

The model serves three purposes. *First*, it provides a structural equation showing that the *wage pollution premium* is given by the sum of the compensating differentials from pollution exposure and the *profit pollution premium* multiplied by the relative bargaining power of workers and entrepreneurs. From this equation, we infer that both the compensating differentials and the bargaining power of workers must be small. If this were not the case, it would be impossible for the model to generate the small *wage pollution premium* alongside the large *profit pollution premium* which we document in the data. Workers are thus bearing the cost of pollution

estimate. 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 (e.g., Le Barbanchon et al., 2020) 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.

[9]In highlighting the role of managerial ability for adaptation, we contribute to a related literature on management that has found that good management practices lead to a reduction in pollution emissions by firms (Bloom et al., 2010 and Gosnell et al., 2019) and that higher quality managers are better able to respond to shocks to worker productivity caused by exposure to pollution (Adhvaryu et al., 2022a).

exposure from the observed entrepreneurial sorting without reaping many of the benefits.

Second, we use the model as a measurement framework to quantify the extent of entrepreneurial sorting. We find that the observed distribution of firms has meaningful aggregate and distributional implications: relative to a benchmark in which firms were randomly allocated across space (within the same sub-county), the average annual profits for entrepreneurs are $195 higher (an increase of 7.1%), while workers' wages are only 11$ higher (a 1.3% increase). These earnings come at the cost of higher exposure to pollution, which we estimate (using WHO guidelines and Ebenstein et al., 2017) could decrease life-expectancy by almost two months for both firm owners and workers. Under standard assumptions on the value of an extra year of life expectancy, these results imply that entrepreneurs are much better off locating in the highly polluted areas; workers instead are at best indifferent between the current layout of jobs and one where jobs are evenly distributed within the sub-county, and could even be better off with less jobs in the smog.[10] These results are purely in the realm of accounting, since they keep the spatial distribution of pollution, profits, and wages constant.

Our *third* model exercise is thus to clarify under which conditions and on which aspects these accounting results could be informative for firm relocation policies, such as the ones currently considered by the Ugandan government to decongest urban areas. In general, as long as there are positive agglomeration externalities, equilibrium forces would dampen the accounting results. However, we show that one key takeaway is robust: entrepreneurs are the ones who would be most affected by any relocation policy since they capture most of the benefits of jobs being in the smog. Instead, workers would be roughly indifferent in any equilibria.

Finally, we design an information experiment to test individuals' awareness of pollution. Understanding this is important: given that workers are at best indifferent between locations with high and low pollution, increasing their awareness of pollution might be enough to trigger meaningful changes in their choices of where to work or increase the wage they demand as compensation for working in polluted areas. The experiment consists in providing some initial information on the spatial distribution of pollution within the city, and then testing whether this increases willingness to pay (WTP) for more information.[11] We find that information frictions are significant in this setting. This opens up the possibility that workers might be undercompensated for the health risk from exposure to pollution, thus exacerbating disparity in outcomes between more and less polluted areas.[12] We conclude by discussing the potential

[10] In these calculations, we are assuming 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, even if firms were to actively avoid polluted areas by moving to grid cells at the 10th percentile of air pollution, this 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.

[11] Hanna et al. (2021) use a similar experimental design to study the effect of providing masks or increasing participants' compensation on WTP for air quality alerts in Mexico city.

[12] A related literature studies disparities in pollution exposure in the United States, finding that poorer and

importance of information policies for reducing exposure to pollution and its costs for workers.

Related literature. Taken together, our results uncover the key role of firm location choices in driving exposure to air pollution for workers in developing countries. In doing so, our primary contribution is to a growing literature at the intersection of environmental and development economics that seeks to understand the determinants of individuals' exposure to air pollution in lower- and middle-income countries. This literature has studied the demand for clean air and adaptation investments by households (Greenstone et al., 2021), as well as individual's avoidance of air pollution through either labor supply decisions (Hanna and Oliva, 2015, Aragon et al., 2017, Hoffmann and Rud, 2024) or migration and residential sorting decisions (Khanna et al., 2021, Chen et al., 2022), including also the role of the transportation network in facilitating adaptation through changes in travel patterns (Barwick et al., 2024).[13] We contribute by unveiling and explaining the role of firm location choices within developing country cities in leading to exposure to pollution of workers.

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. Our evidence of limited awareness of pollution shows that information frictions also play an important role in determining low willingness to pay for environmental quality however, so that this may be inefficiently low.

Second, we contribute to the literature on employee-manager relationships and the role of organizational practices internal to the firm for determining workers' productivity, wages, health and safety (Boudreau, 2024, Harju et al., 2021, Jager et al., 2021, Adhvaryu et al., 2022b). Our contribution is to uncover a potential conflict of interest between entrepreneurs and workers related to firm location: while the entrepreneur receives substantial compensation (in terms of profits) for locating in polluted areas, workers bear the net costs of the pollution.

Third, we bring new evidence to the literature studying firms' location choice and environmental amenities. This literature has shown that firms respond to environmental regulation by sorting *away* from regulated areas (Levinson, 1996, Greenstone, 2002, Wang et al., 2019) and that flood-affected firms move away from flood-prone areas (Balboni et al., 2023). We contribute by showing how the spatial distribution of within-city pollution indirectly affects

less educated areas are more exposed (Colmer et al., 2020).

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

the location of non-polluting firms in African cities, as in this context the pollution disamenity is positively correlated with access to customers.[14]

Finally, we contribute to a classic literature that emphasizes the role of access to customers and agglomeration forces as major drivers of firm location choice (Marshall, 1920, Ellison et al., 2010, Combes and Gobillon, 2015 and Glaeser and Xiong, 2017). A growing body of work has focused on access to demand for small firms in developing countries, highlighting that information frictions are a critical source of inefficiency (Lagakos, 2016, Jensen and Miller, 2018, Startz, 2024, Bassi et al., 2024) and that lack of managerial or marketing ability creates a barrier to accessing new markets (Anderson et al., 2018, Hjort et al., 2020). As a consequence, small firms tend to sell locally. Vitali (2024) studies the role of consumer search and demand externalities for firm agglomeration in our same setting. We contribute by highlighting how exposure to traffic pollution is another negative consequence of firms struggling to tap into broader markets and having to locate on congested roads to access customers.

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 used to guide the interpretation of our results. Section 7 shows the results of the experiment to test for information frictions on pollution, and Section 8 concludes. Additional details are in the Online Appendix.

2 Air Pollution and Urbanization in Uganda

In this section, we discuss pollution emissions, urbanization and motorization in Uganda, to show the relevance of our setting.

Air pollution levels in Uganda. Uganda features levels of pollution comparable to China and well above the recommendations by the US Environmental Protection Agency (EPA): Average annual PM2.5 concentration was 40.8 micrograms per cubic meter (μ/m^3) in 2018 and 29.1 μ/m^3 in 2019, three to four times higher than the suggested EPA annual standard of 12 μ/m^3.[15] 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. Further, a recent WHO study emphasizes that

[14] A related paper is Gollin et al. (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.

[15] 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`.

air pollution disproportionately affects urban areas in Uganda, with PM2.5 concentrations 40% higher than in rural areas (WHO, 2016).

Urbanization, motorization and pollution emissions. Road traffic is widely recognized as a common source of PM2.5. 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 has now reached over 1.5 million (UBOS, 2016). 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.[16] The issue is acknowledged by Ugandan policy makers, but no comprehensive solution exists yet.[17]

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 firm location choice 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 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 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 collect PM2.5 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

[16]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 PM2.5 concentrations in Kampala and Jinja, two Ugandan cities.

[17]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.

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.[18] 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 (the capital city).[19]

3.2 Pollution Measurements

We create a unique database of PM2.5 measures with geo-coordinates and time stamps that we collected in partnership with AirQo.[20]

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 areas.[21]

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.[22] The average number of PM2.5 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 were also active 24 hours a day and produced an average of 30 (median 31) measurements an hour for a total of 119,011 data points in our sampled sub-counties.[23]

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

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

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

[20] 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.

[21] 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.

[22] 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.

[23] 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.

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 PM2.5 readings by hour of the day, from both stationary and mobile monitors. The figure shows that: (i) the stationary and mobile measurements track each other closely, which reassures us about the quality of our data; (ii) average levels of PM2.5 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;[24] (iii) there is a strong cyclicality in pollution within the day with peaks at rush-hour in both mornings and evenings, which indicates that the main source of pollution in these urban areas is road traffic rather than economic activity, something that we explore further and confirm again 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 B8.[25]

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.[26] 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

[24] These numbers are also consistent with measurements of PM2.5 in Kampala between 2018 and 2021 by Atuyambe et al. (2024), averaging at 39 $\mu g/m^3$.

[25] Appendix Figure B6 shows that the average PM2.5 readings of mobile and stationary monitors in the same sub-county are positively correlated (the correlation is 0.34, 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 were potentially hundreds of meters away from the stationary monitors at times.

[26] 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 mechanization and pollution perceptions and daptation.

their GPS coordinates, so that we virtually have geo-coded data on the universe of firms in our sampled sub-counties and sectors.[27] 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.[28]

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, age, experience etc.) including measures of workers' time use at the firm. 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.[29]

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 levels 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 7. We were able to

[27]Appendix Figure B7 plots the firms in the listing in one of the study sub-counties.

[28]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. For instance, in carpentry, this is doors. 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.

[29]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.

successfully interview about 68% of the target sample of firms.[30]

Descriptives on basic firm characteristics. Appendix Table B1 reports basic descriptives for the 1,027 firms in our survey sample and their employees. The key take-away is that 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), thus confirming that air pollution exposure at the firm premises is potentially very relevant in this context.

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*.[31] 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.[32]

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

[30]Appendix Table B2 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.

[31]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.

[32]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 B3 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.

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 PM2.5

As described in Section 3, we collected measures of PM2.5 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 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.[33]

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

$$ln(PM2.5)_{k,h,d} = a + b \times hour_h + c \times date_d + \lambda_k + \epsilon_{k,h,d} \tag{1}$$

where $ln(PM2.5_{k,h,d})$ is the log of the PM2.5 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:

$$e_{\hat{m,h,d}} = ln(PM2.5)_{m,h,d} - (\hat{a} + \hat{b} \times hour_h + \hat{c} \times date_d). \tag{2}$$

$e_{\hat{m,h,d}}$ 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.

[33]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.

4.2 Grid-Cell Approach

We adopt a grid-cell approach to create neighborhood-level measures of firm density, pollution, and road size. The next 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.[34] Each road, pollution measure, and firm are attributed to a cell using their geo-coordinates.[35]

We then compute the following variables for each grid cell: (i) the average residual pollution $e_{\hat{m,h,d}}$—constructed as described above—for all the observations m recorded within the cell; (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).[36]

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.[37] 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 Results

We build on the data structure described in Sections 3 and 4 to establish our core empirical results. While these results constitute the backbone of our contribution, we leave to Section 7 a careful interpretation of their magnitudes.

We proceed in five steps. We begin by studying (i) the spatial heterogeneity in air pollution within neighborhoods and how this is correlated with the presence of large roads, and (ii) the location choice of firm owners. Then, (iii) we compute the returns from locating near large (and

[34] For more details on the calculation of the grid cells and the robustness of our approach see Appendix A.2.

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

[36] 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).

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

polluted) roads for firm owners and employees, and (iv) explore the mechanisms leading to the large profit premium of being located near large roads. Finally, (v) we describe adaptation to pollution within the firm.

5.1 Large Spatial Heterogeneity in Pollution, Driven by Road Traffic

We begin by showing the extent of spatial heterogeneity in air pollution within sub-counties.

Spatial heterogeneity in air pollution. Panel (a) of Figure 3 reports the distribution of air pollution across grid cells of the average sub-county, after netting out any temporal variation and aggregating the pollution data at the grid-cell level following the procedure described in the previous section.[38] To facilitate interpretation, we report as vertical lines the average levels of PM2.5 concentration in several major capital cities. The figure confirms that there is substantial local spatial heterogeneity in air pollution: within the same sub-county, there are grid cells with average levels of pollution comparable to Milan (i.e., 23 μ/m^3), which is a moderately polluted city, as well as grid-cells with very high levels of pollution comparable to Dhaka (i.e., 83 μ/m^3), which is one of the most polluted capitals in the world.

To further highlight the local nature of heterogeneity in pollution, panel (b) shows the distribution of the maximum decrease in average PM2.5 levels that could be achieved by moving 500 meters, 1,000 meters and 2,000 meters away from each grid-cell of the average sub-county. This confirms that it is common for highly polluted grid cells to be just next to low polluted grid cells: for instance, for 25% of grid cells, there would be a reduction of PM2.5 levels of about 21 μ/m^3 or more by moving away only 500 meters (in other words moving to the neighboring grid cell), which is close to the reduction in average air pollution of going from Beijing to Milan.

Comparison with satellite data. Standard satellite data on air pollution would be unsuitable to conduct our analysis, as their granularity is too coarse. We show this in Appendix A.3, where we confirm that while our pollution measurements are strongly positively correlated with satellite data, there is almost no variation left in the satellite data once we remove sub-county fixed effects. This highlights the importance of our measurement exercise.

[38] To compute the distribution for the average sub-county, we first net out the temporal variation from our individual measurements to create residuals $e_{m,\hat{h},d}$, as explained in Section 4.1. We then average these residuals at the grid-cell c level $e^{c\,\bar{\hat{}}}_{m,h,d}$ and remove the sub-county average $e^{c,\bar{s}}_{m,h,d}$, to net out across sub-county differences and compute within-sub-county distributions. To transform our recentered residuals from log to levels, we add the log average air pollution measured by our monitors, before taking the exponential:

$$\tilde{\text{poll}}_c^{\text{recentered}} = \exp\left(e^{c\,\bar{\hat{}}}_{m,h,d} - e^{c,\bar{s}}_{m,h,d} + \log \bar{\text{poll}}_{\text{measured}}\right)$$

Figure 3 then plots the distribution of $\tilde{\text{poll}}_c^{\text{recentered}}$, which corresponds to the distribution of grid-cell level PM2.5 for the average sub-county.

Larger roads are more polluted. Having established that there is substantial spatial heterogeneity in local pollution, we assess whether larger roads are more polluted due to their more sustained flows of vehicles. We run the following regression for grid cell j in sub-county s in region r:

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

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. In addition, we control for log distance to the main city in the region, $log(dist)_r$, to make sure that we do not just capture the fact that areas closer to the city center are both more polluted and more productive (and so have larger roads).[39] To account for spatial correlation, we use Spatial Heteroskedastic and Autocorrelation Consistent (SHAC) standard errors (Conley, 1999), using the routine developed by Hsiang (2010).[40]

Our key coefficient of interest is α_1. A positive estimate would indicate that areas closer to larger roads are more polluted. To interpret α_1 as the causal effect of road traffic on pollution, we need two identifying assumptions. The first is that the location (and size) of roads is predetermined relative to contemporaneous sources of pollution emissions, such as large factories; the second is that the firms in our sample are not the sources of PM2.5 pollution themselves. On these two assumptions, we note that: (i) as we discuss further below, pollution peaks at rush hour rather than during working hours, which is consistent with pollution coming from traffic rather than the firms themselves or other sources of economic activity; (ii) the nature of the production process in small scale manufacturing firms like the ones in our sample is such that they do not produce substantial emissions of PM2.5;[41] and (iii) as discussed in Section refsec:Background-2, the core of the road infrastructure in Uganda was built in the 1960s while the firms in our sample are 10 years old on average, which alleviates concerns related to the endogenous placement of roads based on the current layout of local economic activity.[42]

The results are presented 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. Adding sub-county fixed effects in column 2 barely affects the

[39] 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 effect of road size on pollution are a lower bound.

[40] When including sub-county fixed effects, we first demean both left- and right-hand side variables.

[41] Only about 4% of the firms in our sample use generators, which could be potential sources of pollution.

[42] Notice that if 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.

results, thus confirming that there is a strong relationship between road size and 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.[43]

To better gauge the extent to which local heterogeneity in air pollution is driven by heterogeneity in road size, in panels (c) and (d) of Figure 3 we draw the same distributions as in panels (a) and (b), but exploiting only heterogeneity in *predicted* air pollution levels from equation 3. Naturally, the extent of the within-sub-county dispersion is reduced, as we are only focusing on the component of PM2.5 that is explained by road size, but the local spatial heterogeneity remains substantial, thus confirming that variation in local road size is an important predictor of variation in air pollution levels.[44]

Air pollution is due to road traffic. Next, we validate the assumption that pollution is mainly due to road traffic rather than the firms themselves. The left panel of Figure 1 shows that pollution peaks between 6-9am and 7-9pm, times corresponding to rush hour in Uganda. The right panel plots the share of workers at the firm premises by hour of the day, and shows that production activity instead peaks between 10am and 3pm. These patterns suggest that the main source of pollution emissions is road traffic. Levels of pollution are still substantially above EPA standards even in the late morning and early afternoon however, thus implying that exposure to pollution at the firm premises can have a significant effect on worker health.[45]

5.2 Firms Locate Near Large and Polluted Roads

We study where firms locate within the city. As we have argued that air pollution originates from road traffic and the location of roads is pre-determined with respect to our firm sample, in our preferred specification we study the correlation between firm density and the presence of large roads. Since major roads are more polluted, these results will be informative of whether firms sort into more polluted areas. Specifically, we run a grid-level regression similar to equation 3

[43]In columns 3 and 4 of Table 1, 4,604 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. Standard errors are clustered at the grid-cell level in columns 3-4.

[44]Panel (d) shows that for about 50% of grid cells, there would be no improvement in predicted PM2.5 levels from moving away even 2,000 meters. This is because such grid cells have the smallest roads in the sub-county, and so by construction no further improvement in pollution levels is possible. We verify that such grid cells on average have significantly lower pollution levels than grid cells from which it is possible to find other locations with lower predicted pollution levels.

[45]We conduct one further test in Appendix Figure B12: we split the stationary monitors by whether they fall in a grid cell with at least one firm, or whether they have no firms nearby. If firms are a 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.

but with firm density on the left hand side. However, 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. We find similar results when looking at 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%. Column 4 shows that a 1% increase in pollution residual 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. 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.

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.

Firm location choice exposes workers to pollution. This sorting pattern of entrepreneurs implies that most jobs are in the highly polluted locations: the median employee works in a neighborhood with PM2.5 levels of about 56 $\mu g/m^3$, even though much cleaner locations are available nearby (Figure 3).In addition, pollution exposure can be exacerbated by the fact that workers in this context operate mostly outdoor and in the immediate vicinity of the road side. Our survey shows direct evidence of this: Panel E of Table 4 reveals that 64% of firms produce only outside or mostly outside, and only 16% of firms produce entirely inside.

5.3 Returns from Locating Near Large and Polluted Roads

We next study the benefits for entrepreneurs and workers of locating near large and polluted roads.

Large profit premium of locating near large roads. We first study whether locating near larger roads provides higher profits. 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. We can, however, 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 any residual

unobserved firm characteristics correlated with firm productivity do not also predict location choice within urban areas. Although this may sound like a strong assumption, we provide evidence in its favor later in this section.

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

$$y_{i,j,s,r} = \beta_0 + \beta_1 MedianRoad_j + \beta_2 ManScore_i + \lambda_l + \delta_s + \eta log(dist)_r + \upsilon_{i,j,s,r}, \qquad (4)$$

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 λ_l, sub-county fixed effects and distance from the major city in the region, as in equation 3. Standard errors are adjusted for spatial correlation.

Our main coefficient of interest is β_1. A positive estimate when the outcome is profit would indicate that firms located near major roads are more profitable. Similarly to equation 3, our first identifying assumption is that roads are pre-determined with respect to firm location. As mentioned above, the second, and potentially stronger, identifying assumption is that, conditional on sub-county and sector fixed effects and on our index of managerial ability, there is no selection of more productive firms near larger roads.

The results are in Table 3. 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 15.5%, a result significant at the 1% level. Column 2 shows that adding the managerial ability index as a control barely affects the estimate of β_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): that is, there is a large *profit pollution premium*. In Appendix Table B4, 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.[46]

Small wage premium of locating near large roads. We compare the profit pollution premium with the corresponding *wage pollution premium*, by estimating regressions like equation

[46]The number of observations is lower in Table B4 than Table 3 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.

4, but at the worker level and with monthly wages on the left hand side. Column 3 of Table 3 shows that employees working near larger roads earn higher wages, after controlling for a rich set of worker controls, but the magnitude is 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 much smaller than the one in columns 1 and 2 for firm owner's profits, thus indicating that workers only get a small share of the benefits from locating on larger roads.

5.4 Why Are There Pollution Premia? Mechanisms and Robustness

We explore potential mechanisms for the large estimated profit pollution premium, by studying how access to customers, access to other inputs and land rental values vary near large roads. We then return to the discussion of the assumption of no selection of entrepreneurs (and workers) near larger roads based on productivity, and present several related robustness checks.

Large roads provide access to customers. Our survey data suggest that the profit pollution premium reflects primarily better access to customers on larger roads for small informal firms, which lack the means to access customers otherwise. First, to study the role of demand, we asked firms how many customers they typically have on a very good day and a very bad day. We create the average number of daily customers, and use this as dependent variable in column 4 of Table 3. 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.[47]

Consistent with these results, in Table 4 we further support 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 on marketing, common strategies to communicate quality and gain visibility to customers are simply to talk to the customer directly and have 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.[48]

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

[47]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.

[48]In line with this, Appendix Figure B13 shows that lack of demand is the main perceived constraint to growth in our survey.

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 4 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.[49]

Large roads do not provide better access to intermediate inputs. In columns 7-8 of Table 3, 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.[50] These results confirm that the profitability premium of large roads is not due to cheaper or easier access to intermediates. In turn, this further supports the interpretation of these benefits coming from better access to customers.

Net profitability benefits of large roads despite higher rental prices. Finally, in column 9 of Table 3, we focus on the relationship between road size and rental prices, by exploiting our survey questions about the rental value and the size of the business premises.[51] The result shows that increasing median road size by one unit leads to an increase in rental expenditure of about 11%: prime locations, that give access to customers, are more expensive. Consistent with this, Panel C of Table 4 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 (shown in columns 1-2). This is expected given that the effect on wages is small, and rental expenditures are only a small share of the overall firm costs.[52]

[49] 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 B14 reports the distribution of all 18 possible reasons for location choice. Access to customers is clearly the primary reason.

[50] The regressions in columns 6 and 7 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. In Appendix Table B5, we show that the null relationship in column 7 holds for all individual components of the input accessibility index.

[51] 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.

[52] 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.

Why are the profitability benefits not eroded away by higher rents? There are two main mechanisms that may 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 such 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 Tables A8 and A9, we show that firm owners are not only aware of the productivity and health costs of air pollution, but also perceive the positive correlation of road traffic, profitability and air pollution. In addition to air pollution, another disamenity of these profitable locations is their distance to the owner's home: Appendix Table B6 shows that owners whose firm is located on larger roads face a longer commute, and in line with this are more likely to commute using a motorized vehicle.[53] These disamenities may hold rents down. A second explanation for the partial passthrough of profits into rents is rooted in failures 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 or amenities, which shape the distribution of population density and economic activity across the city.

Validity of assumption of no selection on unobservables and robustness. We highlight three further points on the validity of the assumption of no selection on larger roads based on unobservable productivity in equation 4. First, in Appendix A.4 we show that: (i) there is no statistical correlation between road size and observable proxies of firm productivity, 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;[54] (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 profitability returns from locating near larger roads are not stronger for higher ability managers, thus justifying the lack of strong sorting based on productivity.

Second, 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 B6 are consistent with heterogeneity in taste

[53]This suggests that residential areas are located further away from the large and busy roads on average, which is consistent with recent work on the residential disamenity value of highways in the U.S (Brinkman and Lin, 2024). Vitali (2024) finds a similar result that firm owners operating in the city center of Kampala commute for longer than those operating in the outskirts of the city. A large literature examines the role of taste for commuting on labor market outcomes. See, for instance, Le Barbanchon et al. (2020).

[54]The lack of correlation between large roads and output quality as well as input prices/accessibility documented in Table 3 is in line with these results, and further alleviates concerns of selection on unobservable productivity.

for commuting being an important explanation for why some entrepreneurs locate further from the large roads and closer to home.

Third, in Appendix A.6 we show that there is positive assortative matching on age and education between firm owners and workers. So, if the results in Table 3 party reflect the selection of more productive entrepreneurs—and therefore more productive workers—into polluted areas, this would imply that both the profit pollution premium and the wage pollution premium are overestimated. This is particularly noteworthy for the wage pollution premium: since we already estimate it to be small, this would only strengthen our claim that workers get little compensation for locating on larger roads.[55] We will come back to this point in the model, where we show that our evidence rejects any large compensating differentials for workers.

Additional evidence from the Uganda census of business establishments. To further validate the role of access to customers as a mechanism for firm location choices, we present additional evidence from the latest Census of Business Establishments of Uganda from 2010, which covers the universe of firms. This allows us to study how firm location choices vary across different sectors and firms of different sizes. In doing so, we can test whether locating near large roads is more prevalent in sectors where face-to-face interactions with consumers are more important, and whether the sorting near larger roads is less prevalent among larger firms, which might be 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.[56]

In practice, we extend our grid-cell approach to all sub-counties in the entire country, and for each grid cell we calculate firm density by sector, and median road size. We then run specifications based on equation 3 but using the firm census and clustering standard errors at the sub-county level. The results are reported in Table 5. For comparison, column 1 reports the sorting regression from the manufacturing firms in our own survey, so this is the same specification as column 3 of Table 2, restricting to firms in carpentry and metal fabrication.[57] The sorting regression for manufacturing using the Uganda census is in column 2: the coefficient is remarkably similar to column 1, which is reassuring. To study the role of firm size, in column 3 we restrict the firm density in manufacturing in the Uganda census to firms with at least 10 employees. We find that the strength of the sorting on major roads among large firms is only *one third* that of the average firm: large firms are better able to break away from polluted

[55] In Appendix A.6 we also show that there is no evidence that workers sort into polluted areas based on their pollution awareness, thus ruling out that compensation for pollution exposure is low because polluted areas attract workers who are less aware of pollution as a problem.

[56] The census is more appropriate than our survey to conduct this heterogeneity analysis for two reasons: (i) our survey covers only three sectors; (ii) as only a small share of firms in Uganda has more than 10 workers, in our survey data we lack statistical power to conduct heterogeneity by firm size: in our survey, less than 10% of firms have more than 10 workers.

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

roads.

In columns 2 to 7 we then study sectoral heterogeneity, finding that: (i) agricultural firms sort *away* from large roads, which is expected given that land is more expensive along large roads; (ii) in retail the sorting on large roads is almost twice as strong as in manufacturing, which is again consistent with the role of customer access in driving firm location choice; (iii) the sorting on large roads is as strong in manufacturing as in low skilled services (like hairdressing), while high skilled services (like banking or consulting) are less likely than manufacturing to sort on large roads. These results are notable in three ways: first, they show that the extent to which workers are exposed to pollution varies across sectors, with important policy implications for who is most exposed; second, they show that manufacturing firms in low-income countries behave like low-skilled 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. Third, they suggest that if small manufacturing firms were able to grow and behave more like high-skilled services, the pollution exposure of their workers would decrease.

5.5 Limited Adaptation but Increasing in Managerial Ability

The negative health consequences from working in polluted areas could in principle be reduced through in-place adaptation. We use our survey data to study the adaptation that takes place, and whether this differs for high- and low-ability owners. The results, discussed in detail in Appendix A.5, show two key takeaways. First, we find both limited investment in protective equipment and low prevalence of organizational strategies to limit exposure, such as employees adjusting their work hours to limit exposure to pollution during commute.[58] Importantly, adaptation is not higher in more polluted areas, confirming that the reason why wages are only marginally higher near larger roads is not that workers receive more protection from air pollution. Second, we find that managers of higher ability protect their workers more. Overall, these results indicate that while there is a significant role of managerial ability for adaptation, the currently low levels of adaptation are unlikely to meaningfully reduce actual exposure to pollution for workers.

Taken together, the results of this section establish the key message of the paper: given the informal nature of production in low-income countries, firm owners choose to locate in the polluted areas to access customers, thus exposing their workers to substantial pollution. While firm owners reap the economic benefits of this location choice, workers receive little compensation or protection for the exposure.

[58]This result on limited labor supply responses is consistent with the evidence in Hoffmann and Rud (2024) that at low levels of income labor supply is less responsive to pollution.

6 Conceptual Framework and Results' Interpretation

Next, we introduce a stylized framework in order to: (i) clarify the interpretation of the profit pollution and wage pollution premia; (ii) discuss what the magnitudes of our empirical results imply for the aggregate effects of the observed location choice on income, pollution exposure, and health; and (iii) discuss how our results can inform the aggregate effects of firm relocation policies.

6.1 Environment

We consider a one-period economy, partitioned in many locations $j \in \mathbb{J}$. Each location is characterized by an exogenous traffic shifter τ_j—which could capture local features such as the existing road network—and by an endogenous mass of firms/entrepreneurs n_j satisfying: $\sum_{j\in\mathbb{J}} n_j = 1$. Road traffic in a location is given by a Cobb-Douglas aggregator of τ_j and n_j: $t_j(n_j) = n_j^{\nu}\tau_j^{1-\nu}$, where the parameter ν modulates the role of firms as a source of traffic themselves. Traffic turns into pollution with a "unit conversion" constant ψ: $p_j = \psi t_j$, thus dictating the spatial distribution of air pollution.[59]

The economy is inhabited by entrepreneurs, with heterogeneous ability z satisfying $E(z) = 0$, and by homogenous workers. Entrepreneurs and workers have the same utility function given by $u(x,p) = x - p$,where x is income (either profit or wages) and p is pollution exposure (the pollution level of the location they work in).

Entrepreneurs further draw a vector of preference shocks for each location from a type-I extreme value distribution. Each entrepreneur then chooses the location to maximize her utility, thus solving

$$\max_{j\in\mathbb{J}} u\left(\pi_j(z,n_j), p_j(n_j)\right) + \varepsilon_j(z).$$

where $\varepsilon_j(z)$ is the draw of preference shocks for entrepreneur z, $p_j(n_j)$ is the pollution in location j given the (endogenous) distribution of firms, and $\pi_j(z,n_j)$ are the (equilibrium) profits, which we define below.[60]

Workers search for jobs in a frictional labor market with random search and one-to-one matching (as in Diamond, 1982, Mortensen, 1982 and Pissarides, 1985). Workers then go to the location where they are matched with an entrepreneur, hence where they have a job.

A filled job—i.e., a match in location j between an entrepreneur of type z and a worker—produces output according to the production production $D_j(n_j)+z$, where $D_j(n_j)$ is a demand

[59]For simplicity, we assume that pollution is only a function of local traffic with no spatial spillovers.

[60]Consistent with the limited role of in-place adaptation documented in Section 5, we assume that entrepreneurs (and workers) cannot engage in adaptation investments to reduce exposure.

shifter capturing location characteristics. We assume that

$$D_j(n_j) = (t_j(n_j))^{1-\eta} n_j^{\eta}. \tag{5}$$

A location productivity increases in the amount of traffic and in the mass of firms, with η modulating the relative weight of these two elements. Along the lines of the discussion of Section 5, traffic increases firm output since it increases visibility to customers. The mass of firms could also increase firm output through standard agglomeration effects, on either the demand side (i.e., by generating more traffic) or supply side (e.g., by facilitating access to inputs). Replacing the equation for traffic $t_j(n_j)$ into equation (5) gives

$$D_j(n_j) = \tau_j^{(1-\eta)(1-\nu)} n_j^{\eta(1\nu)+\nu}, \tag{6}$$

which shows that the distribution of firms could affect output either directly, or through its effect on traffic.

As standard in this type of frameworks, the surplus from a match is shared between the entrepreneur and the worker through Nash bargaining, where their relative bargaining power is given by $1-\beta$ and β, respectively.

Finally, to close the description of the environment, we outline the four value functions: E for an entrepreneur with a filled job, V for a vacancy (an entrepreneur that did not match with a worker), W for a worker and U for an unemployed (a worker not matched with a job):

$$\begin{aligned}
E_j(z, n_j) &= \pi_j(z, n_j) - p_j(n_j) \\
V_j(z, n_j) &= -p_j(n_j) \\
W_j(z, n_j) &= w_j(z) - p_j(n_j) \\
U &= 0.
\end{aligned}$$

A few comments are in order. First, firm profits are defined as output minus wage: $\pi_j(z, n_j) \equiv D_j(n_j) + z - w_j(z)$. Second, we are excluding the preference shocks from the values since they are already realized once an entrepreneur has chosen a location j. Third, we are assuming that entrepreneurs are stuck in a location even if they do not match with a worker. For this reason, the value of a job not filled (V) is negative since the entrepreneur does not make any flow profits and has to suffer the cost of pollution. The value of unemployment, instead, is 0 since workers do not earn any wage, but also do not suffer the cost of pollution exposure (as they only move to a specific location j once they find a job there).

6.2 Firm Sorting and Wages

Next, we describe the equilibrium wages and the sorting of firms across space.

Workers' wage. Nash Bargaining implies that the wage for a job of an entrepreneur z in location j is

$$w_j(z, n_j) = \underbrace{p_j(n_j) + U}_{\text{Outside option}} + \underbrace{\beta}_{\text{Bargaining Power}} \underbrace{(D_j(n_j) + z - p_j(n_j) - U)}_{\text{Job Surplus}},$$

workers are paid their outside option and a share β of the surplus that is generated by a match, which is $E_j(z, n_j) + W_j(z, n_j) - V_j(z, n_j) - U$.

Entrepreneurs' location choice. Given the properties of the extreme value distribution, the share of entrepreneurs of type z choosing location j is

$$\mu_j(z, n_j) = \frac{\exp\left(\lambda E_j(z, n_j) + (1-\lambda) V_j(z, n_j)\right)^{\frac{1}{\sigma}}}{\sum_{k \in \mathbb{J}} \exp\left(\lambda E_j(z, n_j) + (1-\lambda) V_j(z, n_j)\right)^{\frac{1}{\sigma}}}$$

where σ is (related to) the variance of the preference shocks and λ is the probability that a job is filled.[61] Replacing the values $E_j(z, n_j)$ and $V_j(z, n_j)$, the equilibrium wage $w_j(z, n_j)$, and simplifying, we get

$$\mu_j(z, n_j) = \frac{\exp\left(\lambda(1-\beta) D_j(n_j) - (1 + \lambda(1-\beta)) p_j(n_j)\right)^{\frac{1}{\sigma}}}{\sum_{k \in \mathbb{J}} \exp\left(\lambda(1-\beta) D_j(n_j) - (1 + \lambda(1-\beta)) p_j(n_j)\right)^{\frac{1}{\sigma}}}. \tag{7}$$

Equation (7) describes the sorting pattern in the economy. Entrepreneurs sort towards locations that provide high output and low pollution exposure. Importantly, equation (7) also shows that, given the assumed functional forms, the sorting patterns are identical for entrepreneurs with different z—-thus matching the empirical evidence of Section 5 that, within sub-county, there is no evidence of differential sorting based on managerial ability.

6.3 Interpreting the Empirical Results Through the Model

Next, we use these results to interpret the empirical evidence through the lens of the model.

[61] As standard in frameworks based on Diamond (1982), Mortensen (1982) and Pissarides (1985), the probability λ would depend on the shape of the matching function and on the relative mass of workers and entrepreneurs. Since it is beyond the scope of this paper to compute model counterfactuals in equilibrium, we leave λ as an exogenous parameter.

Structural counterparts of empirical specifications. Consider any two locations j and k where we assume that j is more polluted than k. The average gap in profits and wages—i.e., the *profit pollution premium* and *wage pollution premium*—are given by

$$\underbrace{E\left[\pi_j\left(z,n_j\right)\right]-E\left[\pi_k\left(z,n_k\right)\right]}_{\text{Profit Pollution Premium}} = (1-\beta)\underbrace{\left[\left(D_j\left(n_j\right)-p_j\left(n_j\right)\right)-\left(D_k\left(n_k\right)-p_k\left(n_k\right)\right)\right]}_{\text{Surplus Gap}} \tag{8}$$

$$\underbrace{E\left[w_j\left(z,n_j\right)\right]-E\left[w_k\left(z,n_k\right)\right]}_{\text{Wage Pollution Premium}} = \underbrace{p_j\left(n_j\right)-p_k\left(n_k\right)}_{\text{Compensating Differential}} + \frac{\beta}{1-\beta}\underbrace{\left(E\left[\pi_j\left(z,n_j\right)\right]-E\left[\pi_k\left(z,n_k\right)\right]\right)}_{\text{Profit Pollution Premium}}, \tag{9}$$

where we have used the fact that $E(z)=0$ and that sorting across location does not depend on z.

Equations (8) and (9) offer the structural counterparts of regression equation 4 for profits and wages, respectively. Together, they suggest that both the compensating differential and the bargaining power of workers are small relative to the surplus offered by more polluted locations. The reason is simple. In the data, we find large profit pollution premium (an increase in median road size in the grid cell by one unit is associated with a 15% increase in profits) and small wage pollution premium (the same increase in road size leads only to a 2.5% increase in wages). Equation (9) shows that the wage pollution premium is given by the sum of the compensating differential and the profit pollution premium multiplied by the ratio between the bargaining power of workers and entrepreneurs $\left(\frac{\beta}{1-\beta}\right)$. As a result, it must be that both $p_j\left(n_j\right)-p_k\left(n_k\right)$ and β are small. Otherwise, it would be impossible to rationalize such a small wage pollution premium.[62]

Aggregate effects of the sorting pattern. Next, we use the model as a guide to quantify the aggregate effects of the observed distribution of firms and pollution on pollution exposure, income, and heath. Our main objects of interest are the average values for workers and for active entrepreneurs (i.e., those with a filled job): $\mathbb{W}$ and $\mathbb{E}$. They are simply the weighted average of the individual values defined above, weighted by the distribution of firms across locations and the distribution of entrepreneurs in each location j, defined as $G_j(z)$:

$$\mathbb{W}\left(\{n_j\}_{j\in\mathbb{J}}\right) \equiv \sum_{j\in\mathbb{J}}\left(n_j\int W_j\left(z,n_j\right)dG_j\left(z\right)\right) \tag{10}$$

$$\mathbb{E}\left(\{n_j\}_{j\in\mathbb{J}}\right) \equiv \sum_{j\in\mathbb{J}}\left(n_j\int E_j\left(z,n_j\right)dG_j\left(z\right)\right). \tag{11}$$

[62] The model assumes that workers are homogeneous. As discussed in Section 5, if our estimated wage pollution premium partly captures the sorting of more productive workers to more polluted areas, this would imply that the true wage pollution premium—and therefore the true compensating differentials and workers' bargaining power—are even lower than we estimate.

These values depend on the distribution of firms across space through two channels. First, through weighting: locations with more firms and workers (higher n_j) are more relevant in the aggregate. Second, through equilibrium effects: the distribution of firms may affects the equilibrium traffic, pollution and production surplus.

Accounting for the weighting channel. As a first useful step, in this section we keep constant the observable average wages and profits in each location, $\{\hat{w}_j, \hat{\pi}_j\}_{j\in\mathbb{J}}$, and the local measured pollution, $\hat{p}_j$. We can then easily quantify the aggregate importance of their observed spatial dispersion— i.e., we quantify the role of the distribution of firms across space through only the *weighting* channel without allowing for equilibrium effects. The exercise, summarized in Table 6, is to calculate

$$\begin{aligned}
\hat{\mathbb{W}}\left(\{n_j\}_{j\in\mathbb{J}}\right) &= \underbrace{\sum_{j\in\mathbb{J}} n_j \hat{w}_j}_{\text{Average Wage}} - \underbrace{\sum_{j\in\mathbb{J}} n_j \hat{p}_j}_{\text{Average Pollution Cost}} \\
\hat{\mathbb{E}}\left(\{n_j\}_{j\in\mathbb{J}}\right) &= \underbrace{\sum_{j\in\mathbb{J}} n_j \hat{\pi}_j}_{\text{Average Profit}} - \underbrace{\sum_{j\in\mathbb{J}} n_j \hat{p}_j}_{\text{Average Pollution Cost}} ,
\end{aligned}$$

and its components for different distributions n_j. Intuitively, this corresponds to comparing how these values change as we move from the actual spatial distribution of firms (and jobs) to counterfactual distributions where firms (and jobs) were to relocate, while not allowing for equilibrium effects. To do so, we need to measure entrepreneurial sorting, and then average profits, wages, and pollution for each location, which is relatively straightforward. The main challenge is to then turn the pollution measures into a monetary utility cost that can enter into the utility function. We next describe how we conduct this measurement exercise.

Using the elasticities shown in Table 1, column 1, and Table 3, columns 2 and 3, we predict pollution, profits and salary from road traffic in each grid cell in our sample.[63] To transform measured pollution into an interpretable health measure, we use the elasticity of 0.98 years of loss of life expectancy (LLE) for every $10\mu g/m^3$ of PM2.5 above the WHO guidelines (Ebenstein et al., 2017).

Figure B15 plots the pooled distributions of within-sub-county predicted grid-cell level deviations (compared to the sub-county average) for pollution and value added per worker (which corresponds to firm output in the model).[64] We see that there is substantial heterogeneity in

[63]Road size is available for all our sampled sub counties and we normalize road size by average road size in the sub-county, so that we are effectively looking at within-sub-county distributions. We restrict observations to grid cells containing at least one road. More details on how we predict profits, salary and pollution can be found in Appendix A.7.

[64]In practice, we first compute percentage deviations for each grid cell relative to the the sub-county mean, and then rescale it using the medians for our entire sample to go from percentage deviations to interpretable

the pollution and profitability of available locations, even within sub-counties. For example, moving from the 10th to the 90th percentile of the pollution distribution would increase annual value added per worker by more than \$250, but at the cost of more than one year of life expectancy.

To quantify the impact of the *actual* distribution of firms, we compare the predicted firm-level value added per worker and health costs under firms' actual location against those same costs and benefits under a hypothetical random spatial distribution of firms within their sub-county.[65] We repeat the same procedure for value added per worker. Results are presented in the first column of Table 6. Panel A shows the inputs used in the calculations and Panel B the main results. The difference in exposure between the actual and the random allocation is $1.6\mu g/m^3$ of PM2.5, which translates into an increase in life-expectancy of almost two months. However, random location would also mean lower access to customers, hence lower profitability and annual value added per worker, which we estimate would be \$42 lower. Crucially, this average number hides substantial heterogeneity as the benefits from sorting to polluted areas are unequally distributed: workers' wages are only \$11 higher (column 3, Panel B), while entrepreneurs' profits are \$195 higher (column 2, Panel B).

As an alternative benchmark, we show the potential gains from pollution avoidance by comparing the predicted value added and health costs of firms' actual location versus those if firms were to actively *avoid* polluted roads (while keeping constant profits, wages, and pollution, as before). We find that moving all firms to grid-cells at the 10th percentile of the distribution of pollution (and value added) within their sub-county would increase life-expectancy by six months, but at the cost of a decline in annual value added per worker of \$139 (Panel B).[66]

To compute $\hat{\mathbb{W}}\left(\{n_j\}_{j\in\mathbb{J}}\right)$ and $\hat{\mathbb{E}}\left(\{n_j\}_{j\in\mathbb{J}}\right)$,we still need one final, challenging, step: to express life-expectancy in monetary value so that we can compare the positive effect on earnings with the negative one on health. We rely on the WHO guidelines in terms of cost-effectiveness for health policies. We assign a monetary value to the increase in life-expectancy of 1.89 months by calculating the cost of a hypothetical "health intervention" with this same health impact of 1.89 months and which would be deemed cost-effective by the WHO. The WHO guidelines (Iino et al., 2022) indicate that a policy investment should cost no more than 3 times GDP percapita for one year of life saved. Given that per capita GDP in Uganda is \$720 at the time of the study, for the increase in life expectancy of 1.89 months to be cost-effective, the policy should

magnitudes.

[65]In practice, we compare the average predicted pollution across all grid cells in a sub-county to the average exposure from the observed location of all the firms in our initial listing, which we compute by weighting the grid-cell average pollution by the number of firms actually located in each cell.

[66]We notice that moving to a grid-cell at the 10th percentile of pollution exposure would not require firms in the average sub-county to move very far: it would entail a move between 408 meters and 1,102 meters for the average firm. For comparison, the average worker (entrepreneur) in the sample commutes a distance of 2.4km (4.3km) from their home to the firm every day. Consistent with this, in the calculations in this section we are implicitly assuming that relocation does not affect commuting costs.

cost at most \$340. We can then compare this value to the present discounted value of total earnings lost from relocation discounted at either a 5% or 10% interest rate, which gives \$758 or \$453, respectively. From this calculation we learn that, summed over both entrepreneurs and workers, the current allocation provides a higher value than the alternative random allocation (Panel C, column 1). However, the results are strikingly different if we compare entrepreneurs and workers. The health benefit from reduced exposure to pollution of \$340 is the same, but the cost in terms of lost earnings would be only \$196 for workers and \$3,516 for entrepreneurs.[67] According to this calculation, *workers would be better off with less jobs in the smog* (Panel C, columns 2 and 3).[68]

6.4 The Aggregate Effects of Firm Relocation Policies

The exercises in the previous Section are purely in the realm of accounting, and useful mainly to conclude that the spatial distribution of firms has potentially meaningful aggregate effects. They cannot be interpreted as structural counterfactuals since they keep the spatial distribution of wages, pollution, and profits constant. In this section, we go one step further and use the model as a tool to discuss the effects of firm relocation policies, while not going as far as structurally estimating it. These policies are relevant as they are being actively considered by the Ugandan government in this setting.[69]

To do this, we rewrite equations (10) and (11) in terms of model primitives rather than observable empirical objects. To simplify the expressions, we use the fact that $E(z) = 0$ and that the firm location choices are not a function of entrepreneurial ability— $G_j(z) = G(z)$ for all $j \in \mathbb{J}$. We also substitute into the firm output and pollution the traffic equation and equation (5). Doing this, gives:

$$\mathbb{W}\left(\{n_j\}_{j\in\mathbb{J}}\right) \equiv \beta \sum_{j\in\mathbb{J}} n_j \left(\tau_j^{(1-\eta)(1-\nu)} n_j^{\eta(1-\nu)+\nu} - \psi n_j^{\nu} \tau_j^{1-\nu}\right) \tag{12}$$

$$\mathbb{E}\left(\{n_j\}_{j\in\mathbb{J}}\right) \equiv (1-\beta) \sum_{j\in\mathbb{J}} n_j \left(\tau_j^{(1-\eta)(1-\nu)} n_j^{\eta(1-\nu)+\nu} - \psi n_j^{\nu} \tau_j^{1-\nu}\right) - \psi n_j^{\nu} \tau_j^{1-\nu}. \tag{13}$$

From these equations we get two main takeaways.

[67] Discounted at 5% interest rate.

[68] We investigate the sensitivity of these results in Panel C of Table 6, which shows that the lack of cost effectiveness of the policy for the average individual is robust to: (i) using actual pollution instead of predicted pollution in the calculations for a 0.95 discount rate and (ii) using the lower bound of the elasticity of profits to road size from the most conservative specification which accounts for selection on unobservables, following the approach described in Appendix A.4 for firm owners. Only under a 0.90 discount rate and measured rather than predicted pollution would the policy be almost cost effective for the average individual (but would never be cost effective for owners).

[69] For instance, the Kampala Capital City Authority has started to relocate firm clusters away from congested central roads as part of decongestion and road modernization programs (see: `https://www.kcca.go.ug/uDocs/Proposed%20relocation%20of%20kasubi%20market.pdf`)

The first takeaway is that any firm relocation would have a minimal effect on workers' average value, irrespective of any agglomeration force. This is because, in equilibrium, workers are compensated for their exposure to pollution but we argued that most likely receive only a minor portion of the production surplus (β is small).

The second takeaway is that the partial equilibrium exercises done in the previous section would correspond to the aggregate effects of firm relocation if and only $\eta = \nu = 0$ —i.e., if differences in profitability and pollution across locations are unaffected by the distribution of firms. In Section 5, we have discussed that our empirical evidence suggests that traffic and pollution are not caused by firms themselves, hence assuming $\nu = 0$ seems plausible. On the contrary, recent work in this same context by Vitali (2024) suggests the existence of agglomeration externalities ($\eta > 0$). This would imply that the partial equilibrium effects on profitability might be an overestimate of the general equilibrium ones. The reason is that the empirical results are partially driven by agglomeration forces making more polluted and denser areas more profitable. Of course, the argument would be reversed if $\eta < 0$.

Taken together, these results imply that while the extent to which firms are affected by relocation policies (and therefore the extent to which they might be willing to move) depends on the strength of agglomeration effects, this is not the case for workers: regardless of agglomeration effects, they would remain at best indifferent, or would even be slightly better off moving to a cleaner area. This is a key takeaway from our study.

7 Testing for Awareness of Pollution

The model and the analysis of the previous sections implicitly assume that firm owners and workers are aware of pollution levels and of the health costs of pollution. However, if individuals underestimate pollution, providing more information may affect location choices and wage setting, and particularly so for workers: given they are close to indifferent, removing even small information frictions may induce them to look for jobs in cleaner parts of the city or to demand higher compensation for the higher *perceived* pollution. In this section, we design an experiment to show that information frictions are indeed significant in this setting.

A simple information experiment. We test for information frictions on pollution levels using an experiment where we estimate 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. 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. 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.[70]

As motivation for the experiment, in Appendix A.8, we show that while firm owners are aware that pollution is higher on larger (and more profitable) streets, they underestimate pollution levels near their firm relative to other areas of their sub-county.[71] The information experiment then goes as follows. First, we ask all firm owners to estimate the relative levels of pollution and customer demand (i.e., profitability) at the premises of their firm (*low, average, high*), compared to other locations in their sub-county. Second, we randomly divide all firms with available information on actual pollution in their grid-cell into a treatment group that receives 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 does not receive any information. Similarly, we divide all firms with available information on actual profitability into a treatment group that receives additional information on local relative profitability, and a control group.[72] Thus, there are two separate information experiments, each with its own treatment and control groups. The two treatments are independent.[73]. Third, we ask all firm owners (in both treated 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 offer them 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 offer them for a *medium* price (UGX $2,000$). If at least one map is

[70]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.

[71]In Appendix A.8 we also show that: (i) firm owners and workers are aware, at least in part, of the negative impact of pollution on health and productivity; and (ii) the perceived costs of pollution are relatively higher in firms ran by higher ability managers, which is consistent with the results in Appendix A.5.

[72]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 (1st tercile), average (2nd tercile) or high (3rd tercile) within the sub-county.

[73]Firms with available information on both relative pollution and profitability can be part of both experiments. The randomization is 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 exclude 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 B8 shows the sample sizes and balance checks for the two experiments.

still not purchased at this price, we make one last offer at a *low* price (UGX $1,000$). Thus, the elicitation of willingness to pay for the maps is incentivized and the stakes are relevant. We create two sets of outcomes: a dummy if the owner is willing to pay the high price for the pollution/profitability map, and a variable taking values 0 to 3, depending on whether the owner is 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 7. Column 1 shows that providing information on local pollution increases the probability that the firm owner is 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 are 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 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.[74] 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 uncover the presence of significant information frictions on pollution, and are notable in two ways. First, they open up the possibility that workers might be undercompensated for the health risk from exposure to pollution, since they might not be fully aware of the spatial distribution of pollution. Second, they highlight how simple information interventions may have meaningful distributional effects. Admittedly, while they may be a promising way to change attitudes and increase adaptation investments, it is unlikely that information interventions would directly affect the location choices of entrepreneurs, due to the strength of the profit pollution premium documented in Section 5. At the same time, such interventions might have a meaningful impact on workers' choices of where to work and the wages they demand to work in polluted areas, thus reducing pollution exposure and its costs for workers.

[74]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.8 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.

8 Conclusion

Air pollution is becoming a critical health challenge in much of sub-Saharan Africa, where life expectancy may already be over two years lower due to the high levels of air pollution.[75] This raises the important question of who is most exposed and which policies can help limit exposure.

Our contribution is to show that in Ugandan cities it is difficult for manufacturing workers to avoid pollution at work, as *most jobs are in the smog*: even though there is large spatial variation in pollution levels within the city, small manufacturing firms end up locating along the most congested and polluted roads, as this is where the customers are. For owners, the profitability benefits from this location choice substantially outweigh the costs in terms of loss of life expectancy. Workers instead bear the costs of such exposure without reaping many of the benefits, as compensating differentials are small, and any adaptation investments limited.

Our results have several important implications for environmental policy. First, they imply that actual exposure to pollution in developing country cities is even higher than what might be predicted by looking at city-level averages of PM2.5, as workers and firms cluster in the most polluted parts of the city. This highlights again the critical importance of interventions to reduce pollution emissions—such as congestion pricing (Kreindler, 2024), enforcement of pollution standards for vehicles (Jacobsen et al., 2023), and creation of efficient public transportation systems (Gendron-Carrier et al., 2022; Kreindler et al., 2023)—as *first-best* policies.

Second, the results of an information experiment show that awareness of pollution levels is limited in this context. This opens up the possibility that workers, in addition to being exposed to high levels of pollution, are also undercompensated for such exposure. Removing the information gaps is therefore critical for environmental justice, as it would enable workers to make informed decisions about where to work. This points to the importance of information campaigns as an additional policy tool to reduce exposure. A recent literature has started to evaluate the effects of information provision on adaptation and avoidance (Hanna et al., 2021). Our findings highlight the importance of this new line of research.

Finally, given the strength of the bundling between pollution and profitability created by large roads, it is unlikely that information interventions targeted at entrepreneurs would lead them to relocate their firm. Bigger push policies are likely to be needed. However, these would be *second-best* policies, as they might lead to profitability losses for firms. Recent papers have started to evaluate the impact of firm relocation policies, finding that this leads to a reduction in pollution emissions in the city but is costly for firms (Gechter and Kala, 2024). Shedding light on the general equilibrium effects of different urban planning policies and how they can best induce firms to relocate away from city centers while maintaining the benefits of access to customers and agglomeration effects remains another promising avenue for future research.

[75] See the Air Quality Life Index by the EPIC center of the University of Chicago.

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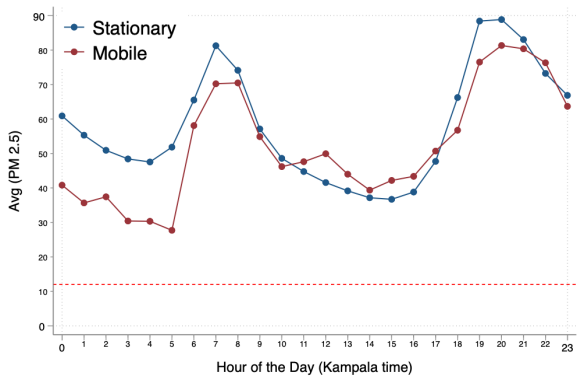
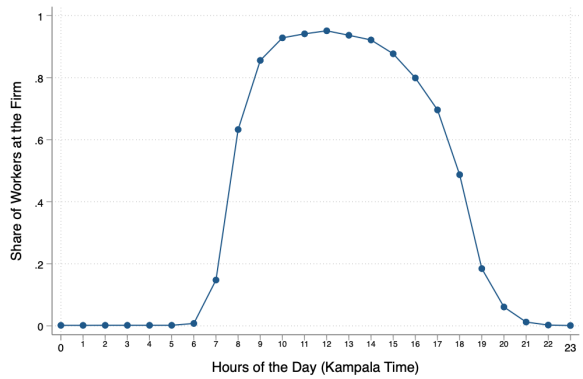
Figure 1: Cyclicality of Pollution and Production Within the Day

(a) Cyclicality of Pollution

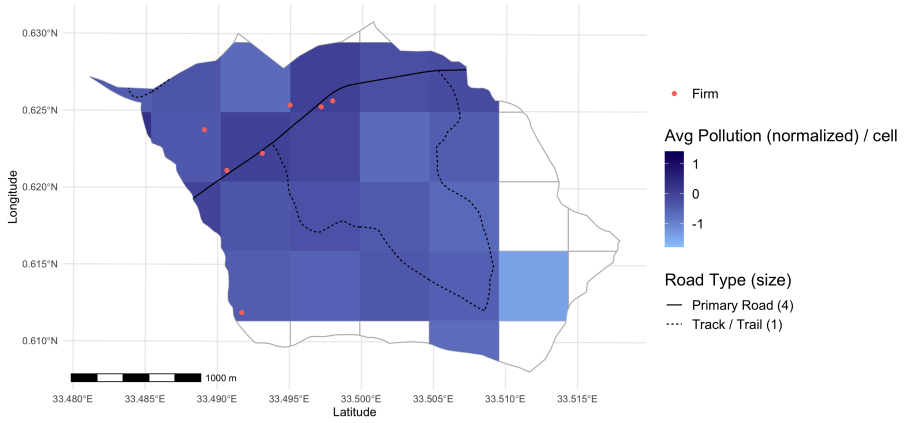


(b) Cyclicality of Production



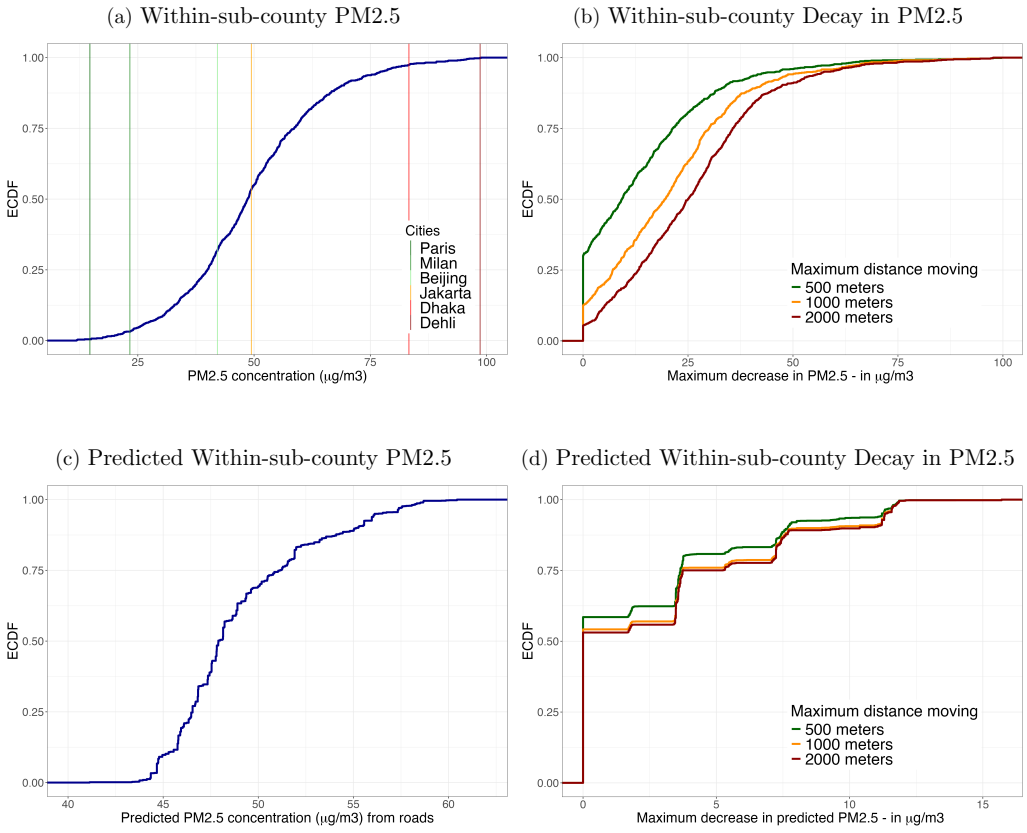
Notes: The left panel shows pollution cyclicality during the day, as measured by our stationary and mobile monitors. The red dotted line corresponds to the 2021 EPA guideline for average annual PM2.5 exposure. The right panel shows the share of employees who report working by hour of the day. In our 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: Large Within-sub-county Spatial Variation in Pollution



Notes: Panels (a) and (b) represent pollution dispersion across 500 × 500m grid cells within the average sub-county with our pollution data (net out from temporal variation). To aggregate across sub-counties, we recenter pollution measurements to net out across sub-counties median pollution differences. We then add back the average pollution in our data, $47.9\mu g/m^3$ for readability. Panels (c) and (d) present an analogous exercise for pollution as predicted by our estimate of pollution elasticity on roads, restricting to grid cells with at least one road. On panel (d), the predicted pollution in grid cells with 0 gain from moving 500 meters is 4.9 $\mu g/m^3$ lower than in grid cells with strictly positive predicted gain. Selected world city pollution averages come from the IQAIR (2019) report.

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		
	(0.0117)	(0.0161)		
Closest Road Size			0.0988	0.0597
			(0.0156)	(0.0334)
N	972	972	52965	52965
R2	.3511	.1631	.1591	.0334
Sub-county FE	Yes		Yes	
Level of Observation	Grid Cell	Grid Cell	Poll. measure	Poll. measure
SE clustering	SHAC	SHAC	Grid Cell	Grid Cell

Notes: OLS regression coefficients, SHAC standard errors in parentheses. SHAC standard errors are Bartlett (spatial weighting kernel decaying linearly in distance) and the distance cutoff for spatial correlation is 5km. We control for log distance to the main city in the region. 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	
		(0.0536)		(0.143)		(0.137)	
Avg Man. Score					0.00908	0.00786	
					(0.0664)	(0.0679)	
log(Pollution) Resid.							0.121
							(0.0451)
N	972	972	420	420	420	420	52965
R2	.2983	.3048	.4426	.4365	.485	.4795	.4643
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	SHAC	SHAC	SHAC	SHAC	SHAC	Grid Cell

Notes: OLS regression coefficients. SHAC standard errors are displayed in parentheses. SHAC standard errors are Bartlett (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. Regressions at the pollution measure level have the same geographical coverage as regressions at the grid cell level. Road size goes from 1 (Trail/Track) to 5 (Highway). The procedure to construct pollution residuals is detailed in section 4.1.

Table 3: 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)
Median 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 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. 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 aretrimmed. 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 B5. We compute output quality as the standardized sum of various component z-scores, as detailed in Bassi et al. (2022)'s supplemental appendix, and we control for produce_main and produce_type. In column 6 we only include firms producing the main product.

Table 4: 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	4.5
More thefts of products	4.1
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
Panel E: Production location	
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: The questions reported in Panels B and C, as well as the 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, D and E 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 5: Correlation Between Firm Density and Road Size in the Ugandan Firm Census

Dep. Var:			Log(Firm Density)				
Sample:	Our survey	UBOS	UBOS	UBOS	UBOS	UBOS	UBOS
Sector:	Manuf (Weld + Carp.)	Manuf	Manuf (> 10 emp.)	Agr	Retail	Low Skill Serv	High Skill Serv
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Median Road Size/Cell	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
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	Grid Cell
SE clustering	SHAC	Sub-county	Sub-county	Sub-county	Sub-county	Sub-county	Sub-county

Notes: OLS regression coefficients. Standard errors are 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. Road size goes from 1 (Trail/Track) to 5 (Highway).

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

	Per Person (1)	Owner (2)	Workers (3)
Panel A: Inputs			
External Parameters			
Loss Life Expectancy Elasticity to $10\mu g/m^3$ PM2.5 (years)	0.98	0.98	0.98
Average Life Expectancy	63	63	63
Expected working life (years)	40	40	40
GDP per capita ($)	720	720	720
WHO cost-effectiveness guidelines - 1 year LE	2160	2160	2160
Estimated Elasticities and Quantities from Our Data			
Elasticity of Pollution to Road Size	0.0767	0.0767	0.0767
Elasticity of Earnings to Road Size		0.145	0.0294
Average Annual Earnings ($)	1203.1	2923.2	852
Average Pollution Exposure ($\mu g/m^3$ PM2.5)	47.9	47.9	47.9
Panel B: Results			
Move to Random Location Within the Same Sub-county			
Δ PM2.5 Exposure ($\mu g/m^3$)	-1.61	-1.61	-1.61
Δ Life Expectancy (Months)	+1.89	+1.89	+1.89
Δ Annual Earnings ($)	-42.1	-195.2	-10.9
NPV Δ Lifelong Earnings ($\beta = 0.95$; Over 40 years) ($)	-758.7	-3516.2	-196
NPV Δ Lifelong Earnings ($\beta = 0.90$; Over 40 years) ($)	-453	-2099.4	-117
Move to 10th Pct. Exposure Within the Same Sub-county			
Δ PM2.5 Exposure ($\mu g/m^3$)	-5.22	-5.22	-5.22
Δ Life Expectancy (Months)	+6.1	+6.1	+6.1
Δ Annual Earnings ($)	-138.8	-643.3	-35.9
NPV Δ Lifelong Earnings ($\beta = 0.95$; Over 40 years) ($)	-2500.9	-11590.1	-645.9
NPV Δ Lifelong Earnings ($\beta = 0.90$; Over 40 years) ($)	-1493.1	-6919.8	-385.6
Panel C: Net Surplus From Intervention (WHO Guidelines)			
Move to Random Location Within the Same Sub-county			
(i) Main			
- $\beta = 0.95$; Over 40 years ($)	-418	-3176	145
- $\beta = 0.90$; Over 40 years ($)	-112	-1759	224
(ii) Sensitivity: Measured Pollution (Rather Than Predicted)			
- $\beta = 0.95$; Over 40 years ($)	-335	-3092	228
- $\beta = 0.90$; Over 40 years ($)	-29	-1675	307
(iii) Sensitivity: Oster Lower Bound on the Elasticity of Profits to Roads			
- $\beta = 0.95$; Over 40 years ($)		-2942	
- $\beta = 0.90$; Over 40 years ($)		-1619	

Notes: We take the Loss of Life Expectancy (LLE) elasticity of 0.98 for each $10\mu g/m^3$ of PM2.5 above WHO levels from the Air Quality Life Index (AQLI), which uses Ebenstein et al. (2017)'s estimates. Elasticities and earnings at baseline can be found in Tables B1, 1 and 3. Average pollution exposure at baseline is computed by weighting grid cell predicted pollution by the number of firms in each grid cell. We assume that workers and firm owners' lifelong earnings are over 40 years. The Oster lower bound estimate on the elasticity of profits to road size is taken from column 4 of Appendix Table A2. The counterfactual in the bottom half of Panel B corresponds to moving to a grid-cell at the 10th percentile of the distribution of predicted pollution exposure within the same sub-county where the firm is located. We rule out in-place adaptation given the small levels of adaptation documented in Table A4.

Table 7: 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: Robust standard errors are 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 (see Section 7 for more details on treatment assignment). 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.

Online Appendix

The Online Appendix is divided in two 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 our grid-cell approach; Section A.3 reports the comparison with satellite data; Section A.4 discusses the robustness of the estimated profitability returns from locating on large roads to sorting on productivity; Section A.5 gives details of our results on adaptation; Section A.6 shows that worker sorting across firms plays a limited role in explaining the adaptation results; Section A.7 presents additional details on our counterfactual exercises; and Section A.8 shows additional results on perceptions about pollution that motivate and complement the experiment.

Second, in Appendix B 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 et al. (2019). The index comprises of several component scores including scores for marketing, stock, recording, financial and forecasting abilities of firm owners/managers.[76] 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,

[76] Our approach differs from de Mel et al. (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).

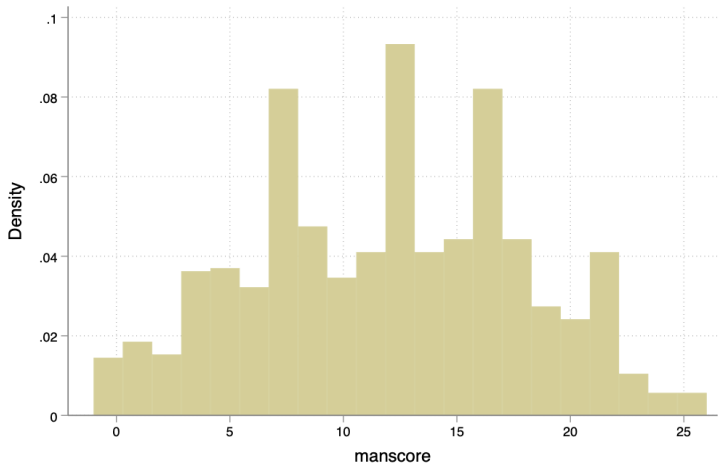
- The *forecasting* score ranges from a minimum score of 0 to a maximum of +5. The score is calculated by adding one point for each of the following activities reported by the firm owner/manager at the time of the survey:

  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.[77] In our analysis we standardize the managerial ability index across all firms in our sample.

[77]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



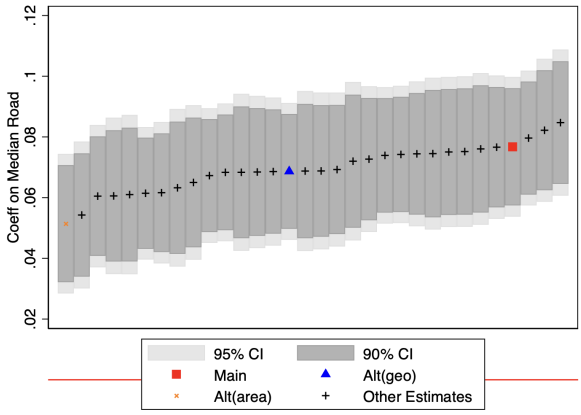
Notes: This figure shows the distribution of our managerial ability index for all firms in our survey (not standardized).

A.2 Grid Construction and Robustness Checks

As described in Section 4.2, we adopt a grid cell approach in order to create neighborhood-level measures of firm density, pollution and road size. Do do so, we draw a rectangle (grid) containing 500m x 500m cells covering all 179 urban and semi-urban parishes in our 52 sampled sub-counties, as well as all neighboring parishes containing at least one surveyed firm.

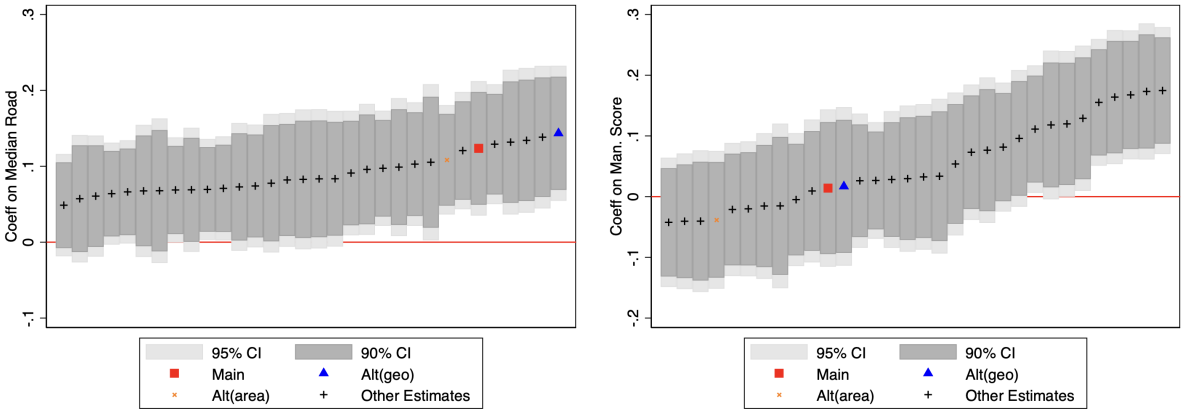
By default in the software used to generate the grids, the bottom-left grid cell matches the bottom-left corner of the smallest rectangle covering these sampled parishes. The grid starting point (i.e., coordinates of the bottom-left corner) may mechanically affect the aggregation of firms, pollution and road measures at the grid cell level. To address the arbitrariness of such starting point, we check that our results are robust to alternative starting points of the covering grid. More specifically, to mirror the software default, we build one grid such that the top-right corner (as opposed to the bottom-left corner) of the smallest rectangle covering these parishes matches a full grid cell, as well as 30 random starting points for the covering grid. Among these, we also highlight results for the randomized grid with the largest average and median grid cell area, to ensure that our results are robust when the distribution of grid cell areas is closest to the ideal one, i.e., the one where all grid cells have a size of exactly 500m x 500m. Of course, we note that reaching the ideal distribution is not possible given that the area of the sampled parishes cannot be divided exactly in grid cells by 500m x 500m. We present below our main coefficients susceptible of being affected by these changes. Overall, we see that our main results are robust to these alternative starting points for the calculation of the grid cells.

Figure A2: Average Log Pollution Residual/Cell on Median Road Size/Cell (Table 1, col 1)



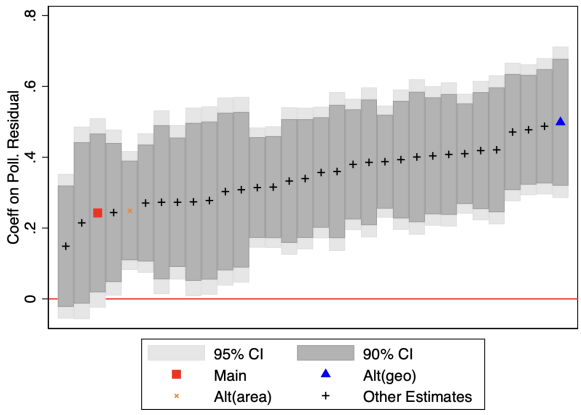
Notes: We run the specification in Table 1, Column 1 for different starting points of the covering grid. The red square is the estimate from our main specification. The blue triangle corresponds to the mirroring specification as described in Appendix A.2. The orange cross corresponds to the randomized grid with the largest average and median grid cell area as described in Appendix A.2, and black crosses represent coefficients for the 29 other randomly picked starting points for the grid. 90% and 95% confidence intervals are displayed.

Figure A3: Log Firm Density per Grid Cell on Median Road Size and Average Managerial Score (Table 2, col 5)



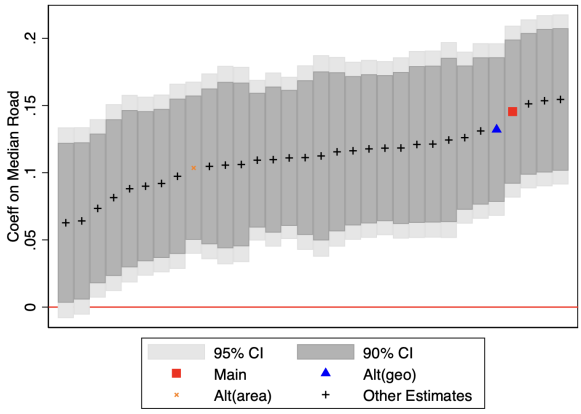
Notes: We run the specification in Table 2, Column 5 for different starting points of the covering grid. The red square is the estimate from our main specification. The blue triangle corresponds to the mirroring specification as described in Appendix A.2. The orange cross corresponds to the randomized grid with the largest average and median grid cell area as described in Appendix A.2, and black crosses represent coefficients for the 29 other randomly picked starting points for the grid. 90% and 95% confidence intervals are displayed.

Figure A4: Log Firm Density per Grid Cell on Average Log Pollution Residual (Table 2, col 6)



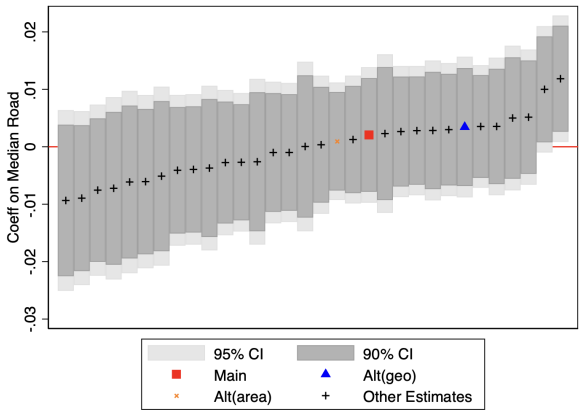
Notes: We run the specification in Table 2, Column 6 for different starting points of the covering grid. The red square is the estimate from our main specification. The blue triangle corresponds to the mirroring specification as described in Appendix A.2. The orange cross corresponds to the randomized grid with the largest average and median grid cell area as described in Appendix A.2, and black crosses represent coefficients for the 29 other randomly picked starting points for the grid. 90% and 95% confidence intervals are displayed.

Figure A5: Log(Profit) on Median Road Size/Cell (Table 3, col 1)



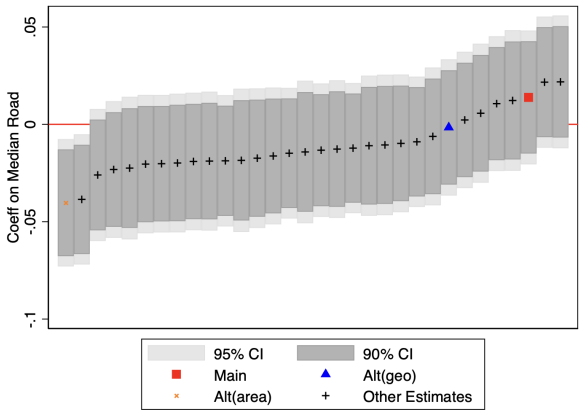
Notes: We run the specification in Table 3, Column 1 for different starting points of the covering grid. The red square is the estimate from our main specification. The blue triangle corresponds to the mirroring specification as described in Appendix A.2. The orange cross corresponds to the randomized grid with the largest average and median grid cell area as described in Appendix A.2, and black crosses represent coefficients for the 29 other randomly picked starting points for the grid. 90% and 95% confidence intervals are displayed.

Figure A6: Manager's Use of Protective Equipment in the Firm on Median Road Size/Cell (Table A4, col 1)



Notes: We run the specification in Table A4, Column 1 for different starting points of the covering grid. The red square is the estimate from our main specification. The blue triangle corresponds to the mirroring specification as described in Appendix A.2. The orange cross corresponds to the randomized grid with the largest average and median grid cell area as described in Appendix A.2, and black crosses represent coefficients for the 29 other randomly picked starting points for the grid. 90% and 95% confidence intervals are displayed.

Figure A7: Protection of Employees from Pollution on Median Road Size/Cell (Table A4, col 2)



Notes: We run the specification in Table A4,Column 2 for different starting points of the covering grid. The red square is the estimate from our main specification. The blue triangle corresponds to the mirroring specification as described in Appendix A.2. The orange cross corresponds to the randomized grid with the largest average and median grid cell area as described in Appendix A.2, and black crosses represent coefficients for the 29 other randomly picked starting points for the grid. 90% and 95% confidence intervals are displayed.

A.3 Comparison of Satellite and On the Ground Pollution Measurements

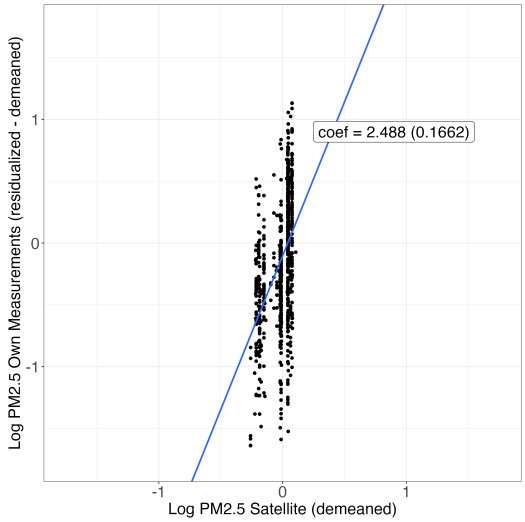
We measure air pollution using on the ground monitors rather than relying on satellite estimates. We show that (i) our measurements are highly correlated with satellite data overall and that (ii) unlike our measurements, satellite data does not feature substantial within-sub-county variation, making it unsuitable to the study of local pollution heterogeneity.

We retrieve PM2.5 satellite estimates from van Donkelaar et al. (2021)'s 2018 global dataset (V5.GL.02) in our sample areas.[78] We map the satellite data to the grid-cells in our sample and compare them with grid-cell averaged PM2.5 from our own measurements. To recover grid-cell average PM2.5 levels from our own measurements, we start by residualizing log pollution at the measurement level to net out day and time fixed effects. We then average the residuals at the grid-cell level to obtain the grid-level average on-the-ground pollution used in our main analysis. To compare these residuals to PM2.5 estimates from the satellite measurements, at the grid-cell level, we remove the average PM2.5 residual and add back the grid-cell level average raw log pollution. Finally, we take the exponential to recover PM2.5 levels. The results are analogous when using our raw pollution measurements instead.

With this grid-cell level datasets in hand, we first show that our measurements are strongly correlated with satellite estimates. Figure A8 displays the grid-cell level relationship between satellite-estimated (x-axis) and our own (y-axis) log PM2.5. Variables are demeaned by their national average. The correlation between the two sources is strongly positive and statistically significant (2.48 (0.16)). In Figure A9, we repeat the exercise but demeaning each variable by their sub-county's average. While our measurements retain within sub-county variation, this is not the case for satellite estimates as all points shrink to around 0 on x-axis.

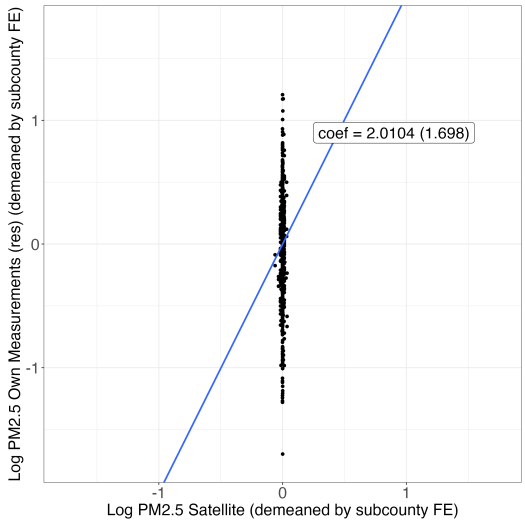
[78] van Donkelaar et al. (2021) combine Aerosol Optical Depth retrievals from the NASA MODIS, MISR, and Sea WIFS instruments to estimate PM2.5 levels.

Figure A8: Our Ground PM2.5 Measurements are Strongly Correlated with Satellite Estimates



Notes: Satellite data come from van Donkelaar et al. (2021). We restrict the sample to grid-cells with average raw PM2.5 from our own measurements below $150\mu g/m^3$ (99.5^{th} percentile at $142.3\mu g/m^3$). We subtract national grid-cell averages to both measures.

Figure A9: Satellite PM2.5 Estimates Do Not Feature Significant Within Sub-County Variation



Notes: Satellite data come from van Donkelaar et al. (2021). We restrict the sample to grid-cells with average raw PM2.5 from our own measurements below $150\mu g/m^3$ (99.5^{th} percentile at $142.3\mu g/m^3$). We subtract sub-county grid-cell averages to both measures.

A.4 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 3.

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.[79] We also show robustness to using the more conservative assumption of $R_{max} = 2 \times \tilde{R}$ and even $R_{max} = 3 \times \tilde{R}$,

[79] 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 $\tilde{R}$.

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 3. 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 0.144-0.142, which remains very close to the magnitude of the elasticity in the main specification of Table 3, 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 3 changes very little once we control for our index of managerial ability in column 2 of Table 3: 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 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 3 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 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. 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	0.142	0.141	0.136
N	967	967	967	967
R2 baseline (within subcounty & sector)	0.0938	0.106	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 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. 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.5 Adaptation Results: Details

We use our survey data to study the adaptation that takes place, and whether this differs for high- and low-ability owners. We estimate firm- and worker-level regressions analogous to equation 4 but with various measures of adaptation from our survey as outcomes.[80]

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.[81] 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.[82] 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.6,

[80] As shown in Table 2 and discussed more in detail in Appendix A.4, 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.

[81] Appendix Figure A10 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 A10 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 et al. (2017) show that richer individuals in China are more likely to invest in lumpy pollution-abating technologies such as air filters.

[82] 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.[83]

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 4 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.

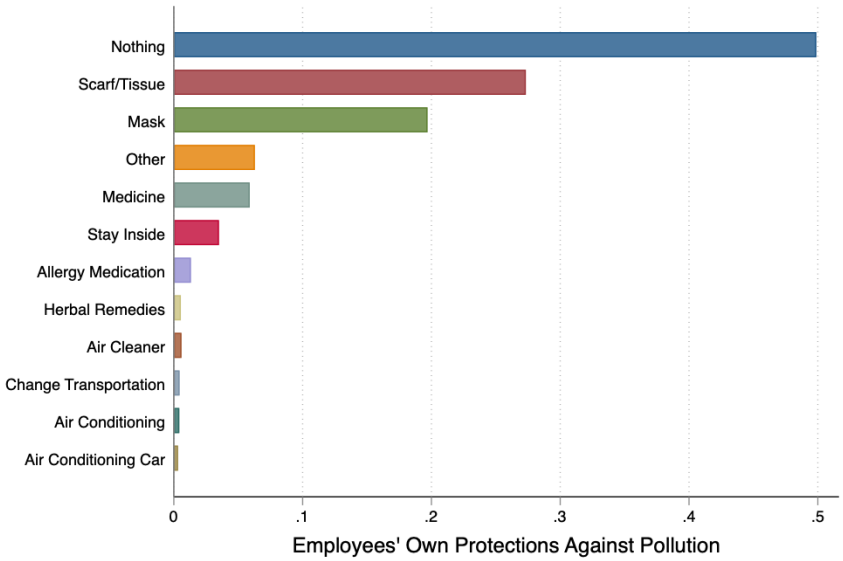
[83]It is worth noting that columns 2-5 of table A4 are obtained from a survey of workers, and do not use, apart from the independent variable (i.e., managerial ability), any information provided by firm owners. Therefore, our results cannot be contaminated by any reporting bias correlated with managerial 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 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 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 A10: 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.6 Limited Role of Worker Sorting in Explaining the Results

As discussed in section A.5, the inclusion of worker-level controls in the regressions in Tables A4 and A8 barely affects the coefficient on the managerial ability index. This is consistent with the sorting of workers to managers not being a driver of the results in these two tables.

We conduct further checks to shed more light on the potential role of sorting 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.[84] 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.[85] The lack of sorting on our pre-determined measure of employee pollution awareness limits concerns that the specifications in Tables A4 and A8 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 columns 3-6 of Table A8 (odd columns). This further reassures us that the results on owners' adaptation are not primarily driven by sorting.

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 3, by ruling out that compensation for pollution exposure is low because polluted areas attract workers who are less aware of pollution as a problem.

[84] 18% of workers report that pollution was an important consideration in their location decision.

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

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 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 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 the dependent variables in columns 3-6 of Table A8 (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 the dependent variables in columns 3-6 of Table A8 (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
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.7 Counterfactual Exercise: Predicting Pollution and Profits

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 3, respectively. Here we give more details on the calculations.

Predicting Profits

In Table 3, column 2, we estimated 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) (where we ignore the error term for simplicity):

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

This is equivalent to normalizing the dependent and independent variables by their sub-county average, denoted by an upper bar and super-script s:

$$\log Y_{i,c} - \overline{\log Y_{i,c}}^s = \underbrace{a - \overline{a}^s}_{=0} + b \times (MedianRoad_c - \overline{MedianRoad_c}^s) + \eta \times (X_{i,c} - \overline{X_{i,c}}^s)$$

We consider a firm with average characteristics in each sub-county, such that $X_{i,c} - \overline{X_{i,c}}^s = 0$, and average characteristics at the grid-cell level c, so that Y_c is the profit in grid-cell c for a firm with average characteristics $X_{i,c}$:

$$\log Y_c - \overline{\log Y_c}^s = b \times (MedianRoad_c - \overline{MedianRoad_c}^s)$$

To predict grid-cell level profits, $\hat{\log} Y_c$, in deviation from their sub-county average, we recover the left hand side of the above equation using the estimated elasticity $\hat{b}$, such that

$$\hat{Y_c - \overline{Y_c}^s} = [\exp(\hat{b}) - 1] \times \underbrace{[MedianRoad_c - \overline{MedianRoad_c}^s]}_{\text{data}}$$

Finally, we multiply by $AvgY_c$ to get from percentage change to levels. We apply a similar methodology for predicting worker salaries (where we use the elasticity of salary to median road size from column 3 of Table 3.).

Predicting Pollution

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

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

This is equivalent to normalizing the dependent and independent variables by their sub-county average, denoted by an upper bar and super-script s:

$$res_c - \overline{res_c}^s = b \times (MedianRoad_c - \overline{MedianRoad_c}^s)$$

Unlike for profits, the dependent variable is in levels rather than in logs, so we recover the left hand side by directly using the estimated elasticity $\hat{b}$

$$res_c \hat{-} \overline{res_c}^s = \hat{b} \times \underbrace{(MedianRoad_c - \overline{MedianRoad_c}^s)}_{\text{data}}$$

However, we are interested in pollution levels, rather than pollution residuals. Remember that the following relationship holds at the mobile pollution measurement level m at time t (see Section 5.1):

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

where FE_t correspond to hour and day fixed effects estimated using the stationary monitors. To convert $res_c \hat{-} \overline{res_c}^s$ into $poll_c \hat{-} \overline{poll_c}^s + \text{avg}poll_c$, or the predicted pollution (in levels) at the grid-cell level, adjusting for deviation of the sub-county average $\overline{poll_c}^s$ compared to the overall average avg$poll_c$, for average FEs, we calculate:

$$poll_c \hat{-} \overline{poll_c}^s + \text{avg}poll_c = \exp[res_c \hat{-} \overline{res_c}^s + \text{avg } \log poll_c]$$

Finally, we use a linear relationship between PM2.5 concentration and loss of life expectancy (LLE, in months) (Ebenstein et al. 2017) to go from pollution levels to LLE:

$$L\hat{L}E_c = \frac{poll_c \hat{-} \overline{poll_c}^s}{10} * 0.98 * 12$$

Computing Counterfactuals

After predicting pollution (and LLE), profits and salary for each grid-cell in our sample, we contrast these average predicted outcomes in three scenarios. First, we compute average predicted exposure, profits and salary given the observed distribution of firms in our sample. 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 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:

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

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 outcome if all firms were to actively avoid polluted and busy roads and move to grid-cells with a median road size at the 10th percentile, within their sub-county: $\overline{\hat{Y}}^{s}_{random}$ is replaced by $\overline{\hat{Y}_{p10}}^{s}$. We then average across sub-counties as above.

A.8 Perceived Costs of Pollution and Pollution Levels

The perceived costs of pollution depend on managerial ability. In Table A8, we study firm owners' and employees' perceptions of pollution as a problem, and how this varies by managerial ability.

First, owners were asked how concerned they are with the effects of air pollution on their workers' productivity and health. Both questions were asked using a 0-5 likert scale, where higher values indicate higher concerns about pollution. Columns 1-2 show that concerns about the costs of pollution are relatively high among all firm owners, with the average score for productivity and health concerns reaching 2.9 and 3.4 out of 5, respectively. Higher ability owners report higher productivity and health concerns, although the coefficient on the managerial ability index is not significant, potentially due to the low sample size in these regressions.[86]

Analogously, workers were asked how concerned they are with the effects of pollution on the planet and on their own health (using a 1-5 scale and a 0-5 scale, respectively).[87] Columns 3-4 show that employees working for higher ability owners are significantly more concerned about the effects of pollution on the planet and on their own health. In column 5 we use as dependent variable the answer to a question about whether the worker thought the government should do more on pollution (using a 1-5 scale). We again see a positive and significant coefficient on managerial ability. Finally, workers were asked to indicate the characteristics of their ideal job, selecting from a list which included also low exposure to pollution as an option. We create a dummy equal to one if workers selected exposure to pollution among the characteristics of their ideal job, and use this as dependent variable in column 6. We find that workers employed by higher ability owners are substantially more likely to indicate exposure to pollution among the characteristics of their ideal job. Interestingly again, omitting employee controls barely alters the coefficients on our index of manager ability (not shown). This suggests that the effects are driven by higher ability owners being relatively more aware of pollution as a problem and thus affecting the perceptions of their employees, rather than by differential sorting of workers to managers of varying ability. See Appendix A.6 for more details on how we address the role of worker sorting.

Firm owners underestimate pollution but perceive its link with access to customers. We investigate whether firm owners underestimate pollution or fail to perceive the bundling of pollution and access to customers. First, we compare firm owners' perceived levels of relative pollution near their firm to actual relative pollution, as measured by our data. To construct the dependent variable in Table A9, we ask firm owners whether they think air pollution near the premises of the firm is low, average or high compared to other locations in their sub-county. The

[86] Owners were asked about their perceived costs of pollution during the follow-up phone survey.

[87] Workers were asked about their perceived costs of pollution during the baseline survey.

variable takes values 1 (low), 2 (average) or 3 (high).[88] Analogously, within each sub-county, we categorize grid-cells into low (1st tercile), average (2nd tercile) or high (3rd tercile), based on the actual measurements from our mobile pollution monitors (net of time variation, as described in Section 4.1). The dependent variable – perceived relative pollution – has a mean of 1.7. This implies that owners overall *underestimate* relative air pollution at the premises of their firm.

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 (column 1). In line with this, 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.[89] 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 perceived relative profitability (column 3) and perceived relative traffic (column 4). Both variables are built similarly to the dependent variable, but using questions on perceived profitability and traffic near the premises of the firm, respectively. The coefficients are positive and statistically significant and imply that the residual correlation of perceived relative pollution and profitability is 0.336 (SE 0.0465) and 0.471 (SE 0.0434) for pollution and traffic, respectively.

These results confirm that while firm owners overall tend to underestimate relative pollution, they are aware of the correlation between pollution, road traffic, and profitability. Interestingly, we do not find that managerial ability predicts awareness of pollution throughout Table A9. 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 for productivity and health (as shown in Table A8), rather than of higher awareness of relative pollution levels per se.

[88] This information was collected in the follow-up survey.

[89] 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.

Table A8: Correlation Between Manager Quality and Managers' and Employees' Perceptions of Pollution as a Problem

	(1) Concerned Poll Productivity	(2) Concerned Poll Health	(3) Concerned Poll Planet	(4) Concerned Poll Health	(5) Gov Address Poll	(6) Ideal Job Low Poll
Median Road Size/Cell	0.0151	-0.0286	0.0691	-0.00189	-0.000193	0.0282
	(0.0474)	(0.0487)	(0.0349)	(0.0372)	(0.0350)	(0.0127)
Man. Score	0.0654	0.0300	0.310	0.210	0.119	0.0607
	(0.0507)	(0.0521)	(0.0367)	(0.0464)	(0.0411)	(0.0145)
N	652	646	2045	2044	2045	2045
R2						0.157
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Sub-county FE	Yes	Yes	Yes	Yes	Yes	Yes
Level of Observation	Firm	Firm	Employee	Employee	Employee	Employee
SE clustering	Grid Cell	Grid Cell	Grid Cell	Grid Cell	Grid Cell	Grid Cell
Employee Controls			Yes	Yes	Yes	Yes
Mean(dependent var)	2.876	3.34	3.964	3.735	4.045	.298
Answer scale	0-5	0-5	1-5	0-5	1-5	Dummy
Model	O.Probit	O.Probit	O.Probit	O.Probit	O.Probit	OLS

Notes: 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 for 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, vocational training (dummy), cognitive ability, employee tenure. We control for missing managerial score (dummy) and missing employee controls (dummies). Road size goes from 1 (Trail/Track) to 5 (Highway). The dependent variables are defined as follows: the manager is asked how concerned she is about the effects of air pollution on the productivity (col 1) and the health (col 2) of her workers; the employee is asked how concerned she is about the effects of air pollution on the health of the planet (col 3); to what extent she is concerned about the effects of air pollution on his own health (col 4); 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 (col 5); and whether her ideal job features low levels of air pollution (col 6). Columns 1-4 report ordered probit coefficients; column 5 reports OLS coefficients.

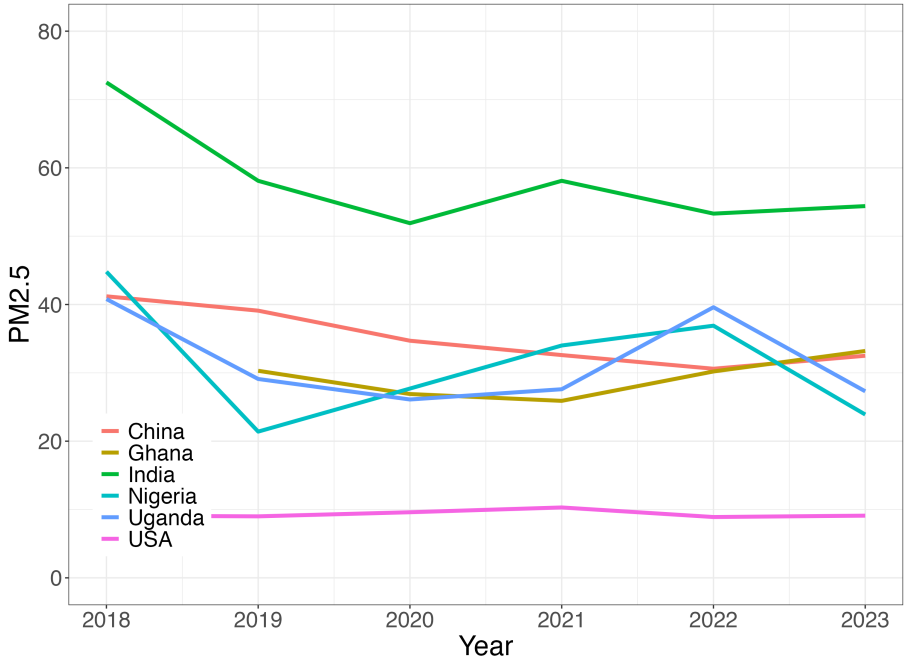
Table A9: Firm Owners Perceive the Positive Correlation Between Pollution, Profitability, and Road Traffic

	(1) Perceived Rel Poll	(2) Perceived Rel Poll	(3) Perceived Rel Poll	(4) Perceived Rel Poll
Median Road Size/Cell	0.0589	0.0378	0.0523	0.0315
	(0.0346)	(0.0501)	(0.0322)	(0.0301)
Man. Score	-0.00630	-0.0351	-0.0283	-0.0175
	(0.0334)	(0.0511)	(0.0299)	(0.0320)
Actual Rel Poll		0.0762		
		(0.0559)		
Perceived Rel Prof			0.336	
			(0.0465)	
Perceived Rel Traffic				0.471
				(0.0434)
N	677	336	677	660
R2	0.192	0.157	0.285	0.372
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
Mean Dep Var	1.689	1.689	1.689	1.689
Scale	[1;3]	[1;3]	[1;3]	[1;3]

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. 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.

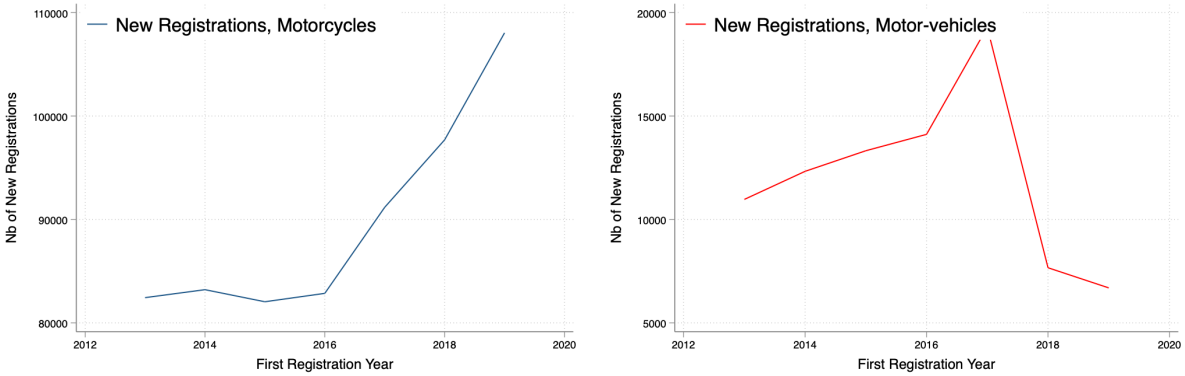
B Additional Appendix Tables and Figures

Figure B1: Average Annual Pollution Over Time in Selected Countries



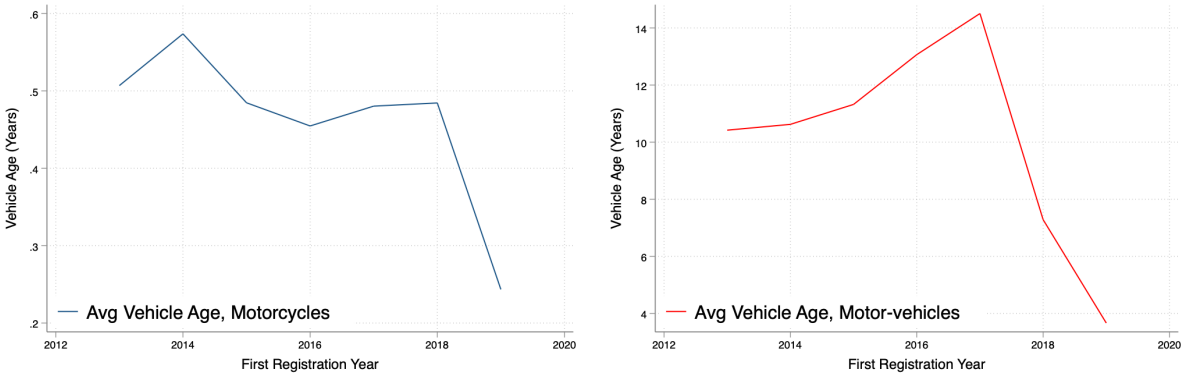
Notes: Average PM2.5 concentration (microgram per cubic meter) in selected countries over time since 2018. Source: IQAIR (2019).

Figure B2: Vehicle Registrations Over Time in Uganda



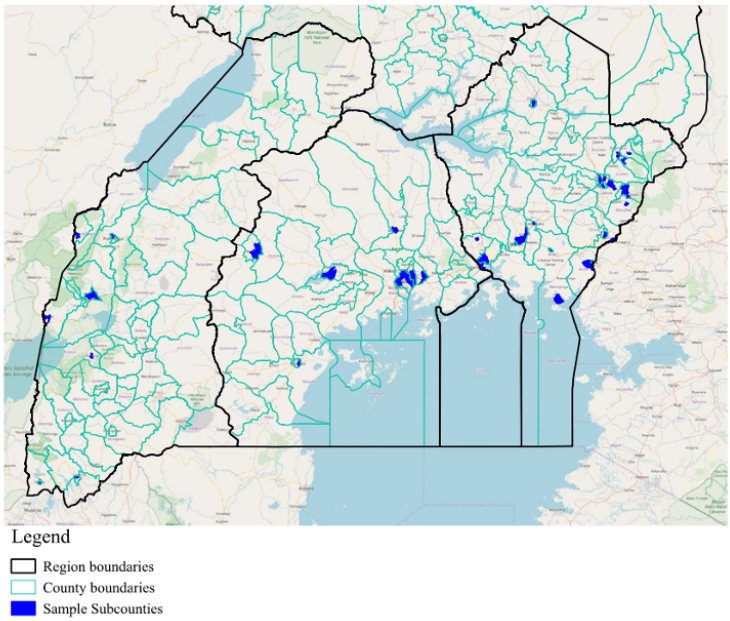
Notes: Annual number of first registrations for motorcycles (left panel) and motor-vehicles (right panel) from 2013 to 2019. The number of new motorcycle registrations has been sharply increasing since 2016. The number of newly registered motor-vehicles peaked in 2017. Source: Uganda Revenue Authority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

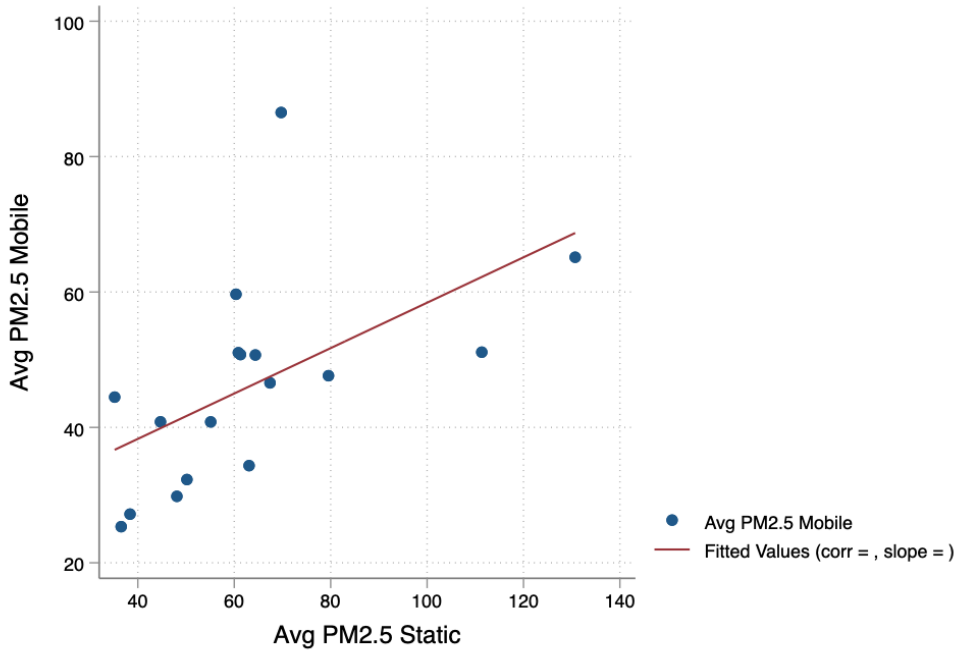


Notes: The figure shows in dark blue the sub-counties in our sample. The figure highlights that our sample region is scattered across three of the four regions of the country (Central, Eastern and Western).

Figure B5: Stationary and Mobile Monitors

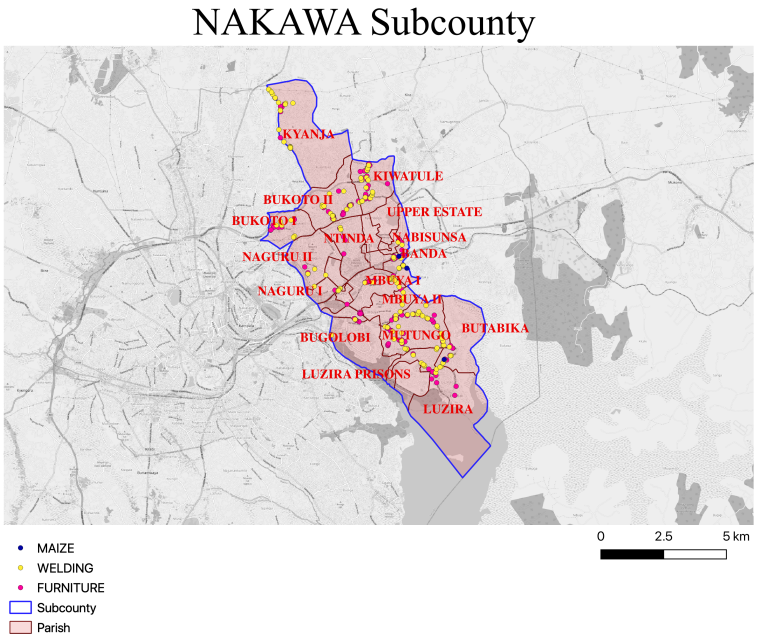
Notes: Photos of AirQo stationary (left panel) and mobile (right panel) pollution monitors.

Figure B6: Correlation Between Average Measurements from Stationary and Mobile Monitors at the Sub-county Level



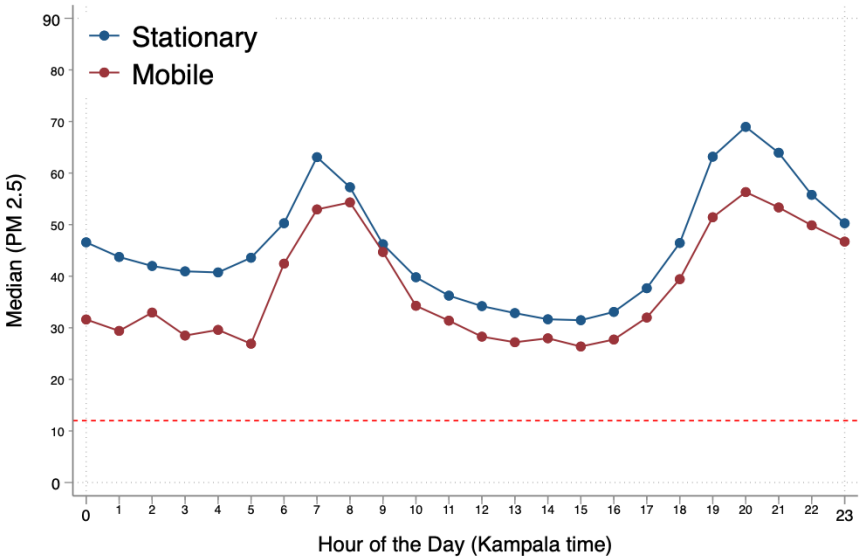
Notes: Data is from the full sample of PM2.5 measurements from the stationary and mobile monitors. We create sub-county level averages of pollution measurements from both types of monitors and plot them against each other. The figure shows that the two are positively correlated.

Figure B7: Example of Listing Exercise in One Sampled Sub-county



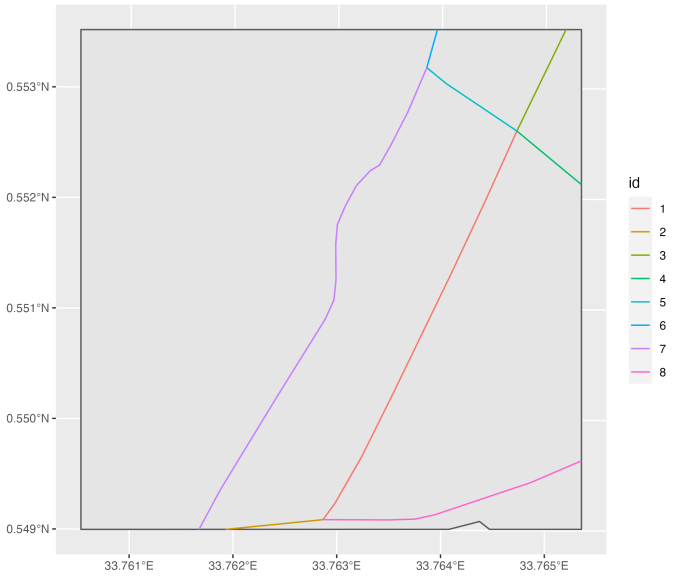
Notes: The figure shows the location of the firms identified in our initial listing in one sampled sub-county.

Figure B8: Hourly Fluctuation in Pollution Within the Day (Medians)



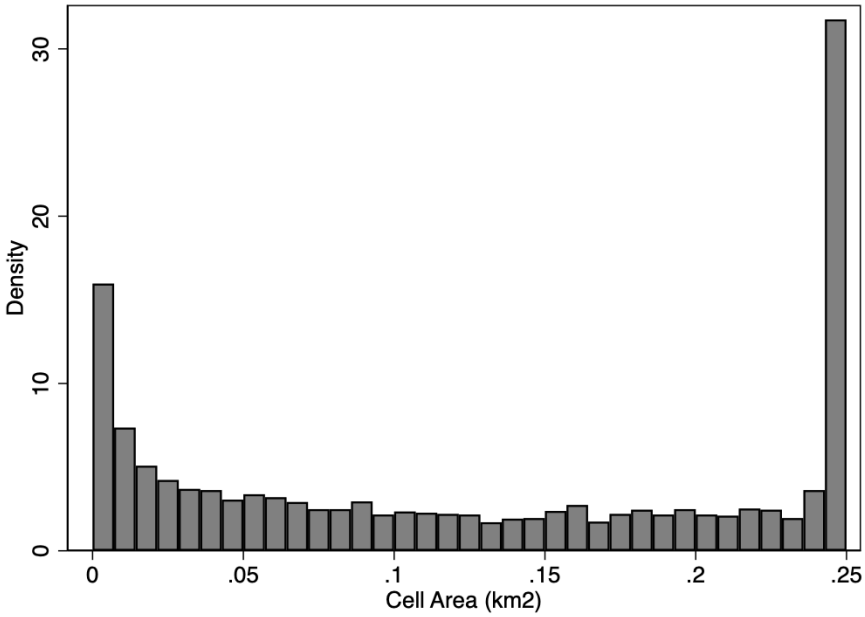
Notes: Medians of PM2.5 measurements from our stationary and mobile monitors are plotted for each hour in Kampala time. The dotted orange line corresponds to the 2021 EPA guideline for average annual PM2.5 values.

Figure B9: Illustration of Road Definition



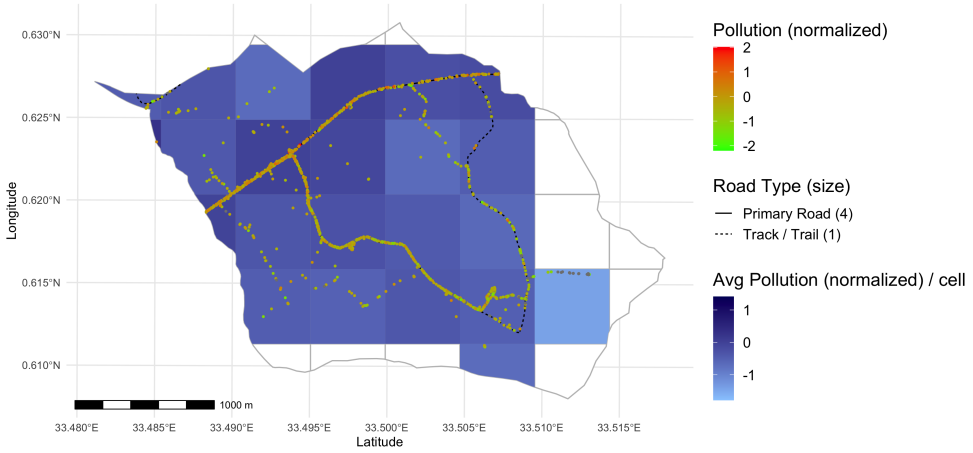
Notes: Each color represents a different road as defined in our dataset by a road segment not intersected by any other road. This grid cell, part of Bugiri Eastern Division, contains eight different roads. The median average grid cell in our sample contains 6 roads (average 11).

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

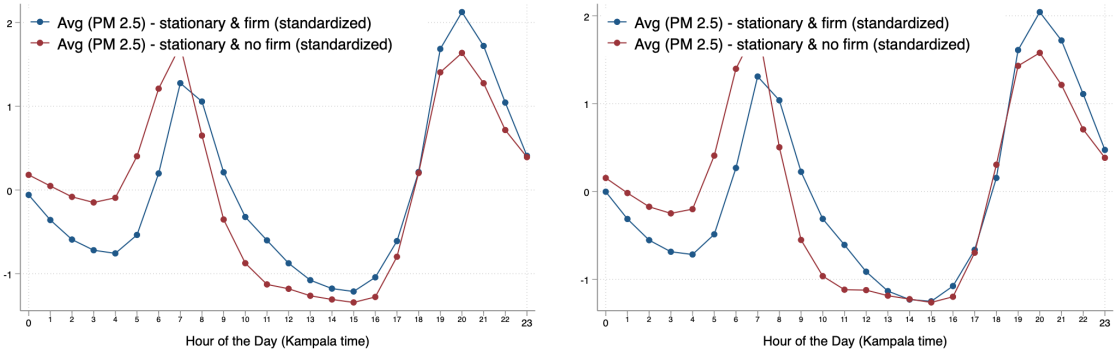


Notes: Location of roads, location of pollution measurements from mobile monitors and average pollution residual per grid cell for the sampled parish in Nakalama sub-county (Iganga District). Road sizes are defined in Section 3.4 and the computation of pollution residuals is described in Section 4.1.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

Figure B12: Cyclicality of Pollution Does Not Depend on Firm Density

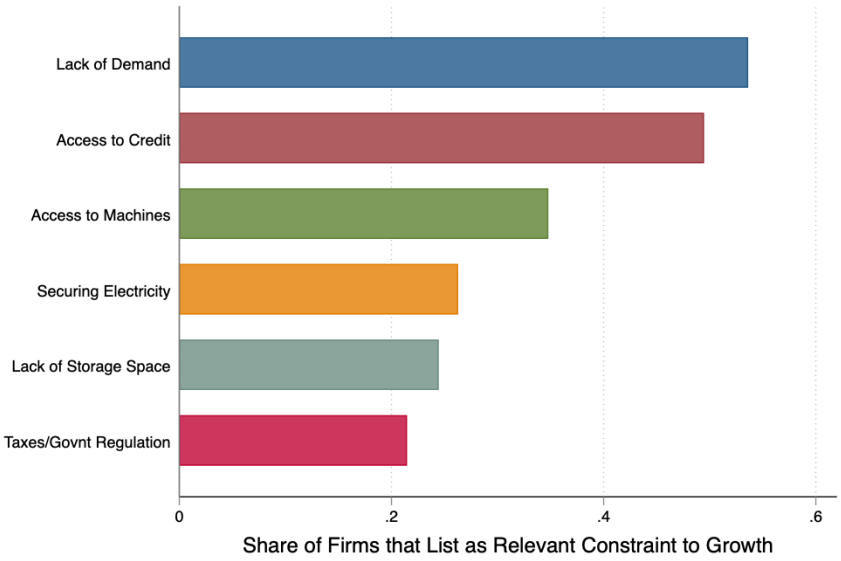
(a) Full Sample

(b) Restricting to Cells Containing at Least One Road



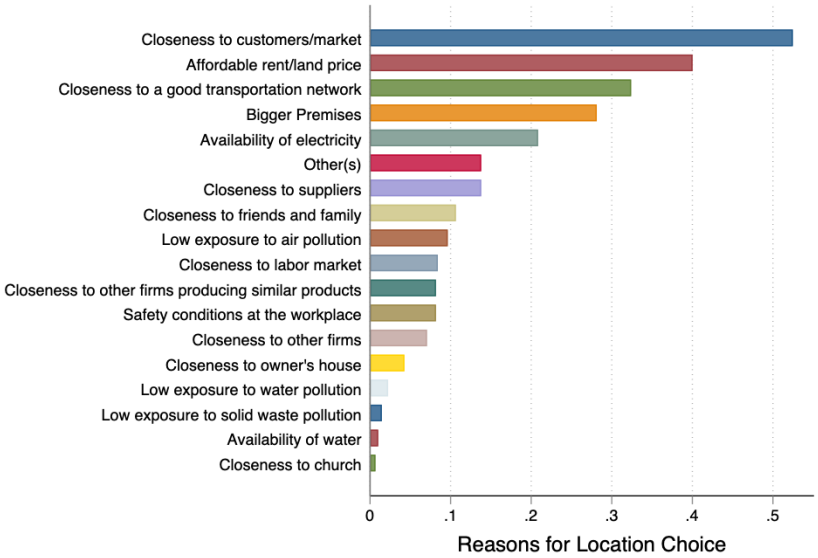
Notes: Avg (PM2.5) is the standardized mean PM2.5 measurement from stationary monitors by grid cell and hour. Grid cells with (without) firm correspond to grid cells containing at least one (no) firm from our initial listing. Normalizing PM2.5 concentrations allows us to focus on pollution cyclicality. In the right panel, the sample is restricted to grid cells containing at least one road.

Figure B13: Lack of Demand is the Main Reported Constraint to Firm Growth



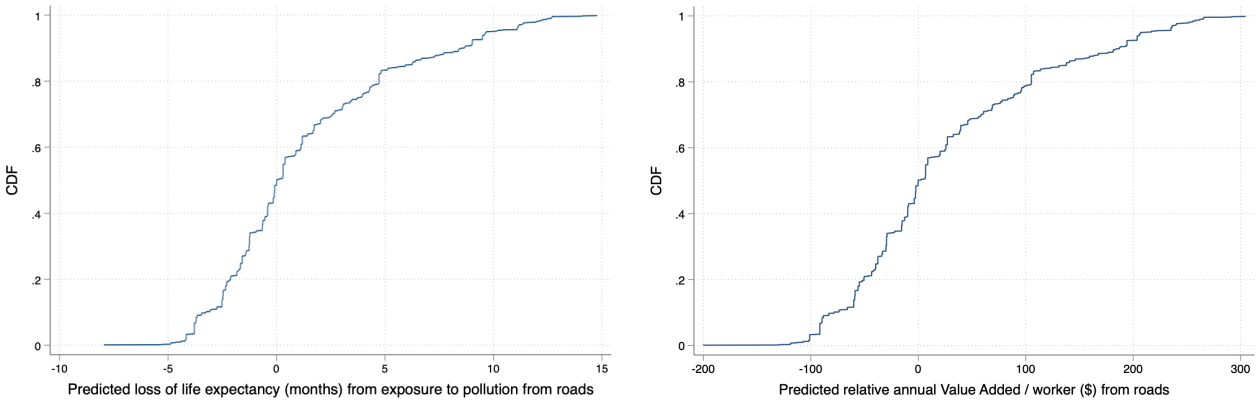
Notes: In the baseline survey, firm owners were asked about the main perceived constraint when thinking about increasing the profitability of their business. Managers could choose among a list of 14 possible constraints, indicating up to three constraints. For each potential constraint, we report the 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 B14: 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.

Figure B15: Distribution of Predicted Health Costs and Profits from Road Size



Notes: The level of observation is the grid cell. Road size at the grid cell level is defined as the size of the median road in the grid cell, as in the main analysis. The distribution of predicted loss of life expectancy from traffic on roads (left panel) is obtained by applying the estimated elasticities between pollution and road size, to the grid cells in our sample. The distribution of predicted annual value added per worker from traffic on roads (right panel) is obtained by applying the estimated elasticities between profits and road size, and salary and road size, to the grid cells in our sample. To get to value added per worker in a firm, we average predicted profits and predicted salary, weighting by the average number of employees in a firm (4.9). We multiply by 12 to go from monthly to annual value added. As these elasticities are obtained with sub-county fixed effects, in practice, we first apply the elasticities to grid cells' median road size in deviation from their sub-county's average, and then rescale it using the averages for our entire sample to go from percentage deviations to interpretable magnitudes. Data on roads is available in all sub-counties in our sample. We restrict observations to grid cells containing at least one road.

Table B1: Firm Descriptives

All Sectors	Mean	Sd
Number of firms	1,027	
Carpentry (%)	49.3	
Metal fabrication (%)	37	
Grain milling (%)	13.7	
Panel A: Firm characteristics		
Number of employees	4.9	3.1
Monthly revenues (USD)	1,481	1,645.4
Monthly profits (USD)	243.6	262
Firm age (years)	10.1	9
Panel B: Owner characteristics		
Owner is male (%)	96.1	
Owner age (years)	40.3	12.5
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	
Employee age (years)	28.5	9.3
Employee years of education	9.3	2.4
Employee hours usually worked per day for the firm	9.9	1.6
Employee monthly wage (USD)	71	48.8

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: Attrition Table - Follow-up Phone Survey

	(1) Surveyed	(2) Surveyed	(3) Surveyed
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	.679	.699	.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 7 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 B3: 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	1,280	0.011
Secondary Road	3	503	0.183	3,056	0.025
Tertiary Road	2	534	0.194	11,824	0.098
Track / Trail	1	1,039	0.377	104,996	0.866
Total		2,754	1	121,211	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 B4: 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(Poll) Resid./Cell	0.234	0.250	0.0635	-0.0518	0.0951	-0.0238	-0.0402	0.00743
	(0.132)	(0.129)	(0.352)	(0.0748)	(0.0886)	(0.0148)	(0.0649)	(0.124)
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	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 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. 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 B5. The procedure to construct pollution residuals is detailed in Section 4.1. The number of observations is lower in Table B4 than Table 3 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.

Table B5: 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 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. 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 3 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 B6: 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	0.0361	-0.0222	-0.0296	0.0476
	(0.0247)	(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 are 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).

Table B7: Robustness to Road Definition

	(1) Log(Profit)	(2) Perceived Rel Poll	(3) Poll Equipment	(4) Own Protect
Closest Road Size	0.146	0.0865	0.0117	0.00117
	(0.0305)	(0.0435)	(0.00578)	(0.0160)
Man. Score	0.232	-0.0349	0.0186	0.0453
	(0.0308)	(0.0510)	(0.00673)	(0.0181)
Actual Rel Poll		0.0453		
		(0.0531)		
N	967	336	1000	2045
R2	0.539	0.164	0.108	0.206
Sub-county FE	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
Level of Observation	Firm	Firm	Firm	Employee
SE clustering	Grid Cell	Grid Cell	Grid Cell	Grid Cell
Employee Controls				Yes
Mean(dependent var)	13.145	1.689	.047	.523
Answer scale		[1;3]	Dummy	Dummy

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 in table 3 - col 1, table A9 - col 2, table A4 - col 1 and table A4 - col 2, respectively. *Closest Road Size* is the size of the road that is the closest to the firm. Road size goes from 1 (Trail/Track) to 5 (Highway). We control for missing managerial score (dummy). Profits are trimmed at the top and bottom 1%. All specifications include sector and sub-county fixed effects and the regressions are weighted by firm weight.

Table B8: Balance Table - Pollution and Profitability Information Experiments

	Control			Treatment			
	n	mean	sd	n	mean	sd	p-value
Panel A: Pollution							
Man. Score	245	-0.00	0.97	225	-0.05	0.93	0.40
Profit (Thousand UGX)	254	961.5	946,3	236	982,5	1,049.2	0.20
Revenues (Thousand UGX)	252	5,961.9	6,387.2	237	5,796.0	6,135.6	0.79
Nb Employees	258	5.83	3.18	241	5.84	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							
Man. Score	286	-0.17	0.98	298	-0.01	0.95	0.16
Profit (Thousand UGX)	302	1,000.1	968.5	307	1,024.8	1,085.4	0.37
Revenues (Thousand UGX)	304	5,687.7	5,706.4	311	5,613.1	5,785.4	0.87
Nb Employees	304	5.45	3.07	311	5.66	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.