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Searching for customers, finding pollution

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Searching for Customers, Finding Pollution*

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Abstract

In developing countries, most manufacturing firms are small and located in high-density urban areas, often near congested streets. To study the determinants and implications of this location choice, we collect a novel firm survey and detailed air pollution measurements within Ugandan cities. We find that firms locate on the busiest roads searching for customer visibility, but in doing so they expose their workers to substantial pollution. This sorting pattern increases profits, but with severe health costs: if firms were randomly located across space, annual profits would decrease by $195 for the average firm, but its workers' life expectancy would increase by two months.

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1 Introduction

In the cities of high income countries, goods are sold, but not produced: manufacturing production has long relocated away from city centers in search of scale, cheaper land prices, and easier accessibility. In low income countries, production is organized in a different way. Coming as no surprise to whomever has set foot in East Africa, most firms are small and located inside the city, often clustered near the busiest roads. Workers produce goods outdoor, sometimes literally on the side of the road, and sell them to final customers passing by the firm premises.

In this paper, we investigate empirically the determinants and implications of this organization of production and we show that it comes with an important cost: it exposes workers to high levels of air pollution, with dire health consequences. The story we tell is a simple one. Facing low customer demand and equipped with limited tools to advertise their products and build a brand reputation, small firms locate near the busiest city roads in search of customer visibility. These same roads, however, due to poor infrastructure, chaotic city planning and growing traffic congestion, are also the most polluted parts of the city. As a result, while firms are only searching for customers, they also find, bundled with customer demand, exposure to air pollution: road traffic generates both.

Our main contribution is to collect a unique dataset to characterize firm location choices within Ugandan cities and their consequences for exposure to air pollution and workers' health. Matching a novel firm survey with high-resolution pollution measurements, we document and quantify the trade-offs faced by firm owners. We find that, even within cities, there are very large spatial differences in air pollution which are strongly correlated with differences in customer access, hence profitability. Facing this trade-off, most firms sort towards the most polluted areas, increasing their profits and value added, but leading to severe health costs: the annual profits and value added per worker of the typical firm are, respectively, \$195 and \$42 higher than if it was randomly located within the city, but the life-expectancy of its workers could be two months lower. This trade-off is relevant for understanding the welfare costs of the informal organization of production in low income countries and, as we discuss, could shape the effectiveness of development and industrial policies.

To situate our study in the broader context, we begin by discussing global trends in urbanization, pollution, and its health consequences. The key takeaway is that cities in the developing world feature some of the world's highest levels of pollution, with such levels rising over time as a result of motorization, poor infrastructure and poor urban planning that ultimately lead to traffic congestion (Grossman and Krueger 1995; Akbar et al. 2018; Harari 2020).[1] The high and

[1] For instance, in Uganda, the setting of our study, between 2013 and 2019 over 800,000 vehicles were added to the country's vehicle fleet. Kreindler (2018) 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).

increasing pollution generates severe consequences for both health and productivity.[2] These effects are plausibly more severe in developing countries due to poor healthcare systems. Uganda is no exception: Ugandan cities today are as polluted as Chinese cities.

While country-level evidence on pollution emissions in low income countries is abundant and household-level evidence on adaptation is growing, to the best of our knowledge we lack firm-level evidence on exposure to pollution and how it is driven by firm location choice. We fill this evidence gap. We gather detailed geo-coded pollution measurements in a representative sample of urban areas throughout Uganda, using both mobile and stationary monitors. The resulting high frequency data allows us to document spatial variation in pollution within the city, and to precisely estimate temporal fluctuations in pollution within the day. We combine the pollution data with a representative geo-coded survey of more than 1,000 firms in small-scale manufacturing and their employees that we conducted at the same time as our pollution measurements. For each firm, we have detailed measures of productivity such as profits and value added per worker, a standard and vetted managerial ability score, as well as a range of questions about location choice, pollution avoidance behaviors and adaptation investments, and awareness of both pollution levels and pollution as a problem. Finally, we have access to the geo-coded universe of Ugandan roads.

To guide and interpret the empirical analysis, we develop a stylized, partial equilibrium, firm-location model. We consider the problem of an entrepreneur, endowed with a given managerial ability, who maximizes profits by making three decisions: (i) where to locate; (ii) how many workers to hire; and (iii) whether to mitigate the effects of pollution by investing in protective equipment or other organizational strategies to limit exposure (adaptation). The key outcomes of interest are the location and adaptation choices, and the resulting exposure to pollution at the workplace. If locations only differ in their pollution, entrepreneurs should avoid the most polluted areas since these entail direct health costs, higher cost of labor (compensating differentials), higher non-health disamenities (e.g., smell) and possibly lower productivity (through lower workers' health). A trade-off instead emerges if locations differ not only in their pollution levels, but also in their profitability, driven by customer access. Entrepreneurs may then choose to sort towards the most polluted locations if they are more profitable and the additional profits are sufficiently large to compensate them for their own disamenity and health cost. The impact of location choice on pollution exposure is itself modulated by any mitigation actions taken to adapt. Managerial ability can affect all these choices both through complementarities with location-specific profitability, as well as through a potentially lower cost of protective investments for higher ability managers.

Guided by the model, we use our data to establish the main empirical results on how the

[2] Recent research has established the negative health and productivity effects of pollution exposure. On health effects, see Chay and Greenstone (2003), Ebenstein et al. (2015) and Deryugina et al. (2019). On productivity effects, see Graff Zivin and Neidell (2012), Chang et al. (2016), Adhvaryu et al. (2022) and Fu et al. (2021).

informal nature of production in low-income countries shapes exposure to pollution. To study location choice in practice, we divide the cities in our sample in grid cells of 500 meters $\times$ 500 meters following the literature (Ahlfeldt et al. 2015, Michaels et al. 2021). We then aggregate our key variables of interest – pollution, firm density and road size – at the grid cell level. The analysis is then organized in three steps.

First, we show that road traffic bundles customer access and pollution exposure: grid cells with major roads are more polluted, but also feature higher profits per worker, even controlling for a rich set of observables. Location choice thus entails a trade-off between pollution exposure, which we verify to be mainly driven by road traffic, and access to customers. We also use our survey data to argue that the benefits can be explained primarily by the fact that, as it is typically the case across the developing world, firms sell locally through face-to-face interactions and do not have any other means to access customers than to be as visible as possible to them. Therefore, proximity to busy roads is essential.

Second, we show that, facing the described trade-off between pollution exposure and access to customers, most entrepreneurs sort in polluted grid cells, locating along the largest and most polluted roads. This is true even within small geographical units within the city (sub-counties), and we rule out that it is driven by reverse causality by showing that firms themselves are not the source of pollution.

Importantly, proxies for firm productivity, such as our managerial ability score, do *not* predict firm location choice within the city, building confidence that the correlation between local pollution and profitability reflects a causal relationship (generated by road traffic). This of course raises the question of what generates heterogeneity in location choice, as not all firms locate in the most polluted areas. While proxies for firm productivity do not predict location choice, we find that locating along the major roads entails a longer commute. Preferences over commuting and other related accessibility considerations can then be an explanation for why some firms avoid the major roads.[3] We also show that our results are robust to the bounding exercises suggested by Oster (2019), which confirm that any role of selection on unobservables in explaining the positive correlation between pollution and profitability is limited.[4]

Through the lenses of the model, these results show that the profitability benefit of locating in busy areas outweighs the cost of exposure to pollution, similarly for both high and low ability managers. We further use our survey to corroborate the mechanism: firm owners report to struggle to access customers and to locate near busy roads precisely to gain customer visibility.

Third, having established that firms sort towards the most polluted locations within the

[3]The role of taste for commuting in determining labor market outcomes has been established in the literature (Le Barbanchon et al., 2020).

[4]We also notice one cannot easily estimate the causal relationship between location and profitability using experimental methods, as that would involve paying firms to move or manipulate where roads are built, which are both difficult experiments to implement in practice.

city, we study whether they adapt to pollution by mitigating exposure, and how this behavior varies by managerial ability. We show that mitigation is very limited: only 5% of firm owners provide pollution protective equipment to their workers, and approximately 13% allow workers flexibility in working hours and commuting times to limit pollution exposure. Nonetheless, this behavior varies significantly across entrepreneurs, with those of higher managerial ability being more likely to mitigate pollution exposure.

In the last part of the paper, we discuss the broader implications of our empirical results. We begin by using back of the envelope calculations to quantify the magnitude of the described trade-off and show how it affects welfare inequality. To interpret the cost of pollution, we convert pollution exposure into predicted life-expectancy effects following results in the literature (Ebenstein et al., 2017). Using the estimated grid-cell level elasticities between road size, profits, wages, and pollution, and the empirical distribution of road size across grid cells within sub-counties, we compare the outcomes of the average firm in the observed allocation with those under a (counterfactual) spatial allocation where firms are allocated randomly to grid-cells (again within sub-county).[5] The random allocation would increase life-expectancy by almost two months, but come at the cost of a decline in annual value added per worker of $42 for the average firm; a large decline considering that per capita GDP in Uganda was $60 per month in 2018. The monetary benefits of locating in high polluted areas, however, are not shared equally within the firm: most of the benefits accrue to firm owners as locating in a polluted area increases their profits by more than the workers' wages. To further highlight the strength of the trade-off between profitability and exposure to pollution, we show that a policy that induced firm owners to move so as to generate the random allocation within the city described above, and compensated them for their forgone earnings due to the move, would not be cost-effective by WHO standards: the required payments to firm owners would be too high relative to the benefit in terms of increased life expectancy.

The results of these back of the envelope calculations summarize the key message of the paper: the informal nature of production in low-income countries leads firm owners to locate in severely polluted areas thus exposing themselves and their workers to high level of pollution, with plausibly dire health consequences.

We then discuss and study which policies could help to mitigate the health cost. While we document large profitability benefits from locating in polluted areas, the low level of mitigation and the high health costs open up the possibility that firm owners may underestimate pollution. Eliciting firm owners' beliefs about the distribution of pollution and profitability within the city, we confirm that firm owners in fact are aware, at least in part, of the trade-off between pollution and profitability caused by large roads, but also tend to underestimate pollution

[5]It is important to notice that these should be interpreted as partial equilibrium counterfactuals, calculating the marginal effect of relocating only one firm owner.

levels. We thus conduct an information RCT where we randomly reveal information about local levels of pollution and find that this increases willingness to pay for more information about pollution levels in other areas of the city. This result is consistent with the presence of information frictions and speaks to the potential importance of information campaigns in increasing pollution awareness and resulting mitigation, especially given their low cost.

However, given the strength of the relationship between locating near large roads and profitability, it is plausible to think that most owners, even if fully aware of the pollution cost, would still sort towards polluted areas. Therefore, we conclude the paper by discussing the benefits of "big push" policies, such as large urban planning interventions or industrial parks, which can lead firms to relocate by changing the joint distribution of pollution and profitability within the city.

Taken together, our results highlight the importance of considering the organization of manufacturing production in low income countries to understand and address exposure to pollution of workers in developing cities.

In doing so, 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 for buyers and sellers (Lagakos 2016, Jensen and Miller 2018, Startz 2021) 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 (2022) studies the role of consumer search and demand externalities as drivers of firm agglomeration in our same setting. We contribute by highlighting exposure to traffic pollution as another negative consequence of firms struggling to tap into new markets and having to cluster on busy roads to access local demand.

Second, we bring new evidence to the literature studying firms' location choice with regard to environmental amenities. This literature has shown that firms respond to environmental regulations by sorting away from regulated areas (Levinson 1996, Greenstone 2002, Wang et al. 2019). We contribute by showing how the spatial distribution of within-city pollution indirectly affects the location of non-polluting firms, as the pollution disamenity is positively correlated with access to customers.

Third, we contribute to a classic literature on the role of managers for firm productivity (Bloom and Van Reenen 2007, 2011; Bloom et al. 2013; Bruhn et al. 2018) and employees' welfare through both financial (Song et al. 2019, Card et al. 2013) and non-financial (Sorkin 2018, Morchio and Moser 2020) amenities. This literature has established that good management practices lead to a reduction in pollution emissions by firms (Bloom et al. 2010b 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., 2022). Our contribution is to study the role of managers in preventing workers' exposure to pollution in equilibrium, as well as the role of managerial ability in responding to information shocks about air pollution. Our result shows that, in low-income and informal economies, inequality in worker welfare across firms is likely to be larger than inequality in earnings, due to the negative relationship that we document between exposure to pollution and managerial ability driven by adaptation.

Fourth, we contribute to the environmental economics literature by emphasizing the importance of exposure to pollution at the workplace. Most of this literature has studied how individual households value clean air (Chay and Greenstone 2005, Currie et al. 2015) and may therefore protect themselves against air pollution (Deschenes et al. 2017, Ito and Zhang 2020), or choose to migrate away from polluted locations, both across (Kahn and Walsh 2015, Banzhaf and Walsh 2008, Khanna et al. 2021, Chen et al. 2022) and within (Heblich et al. 2021) cities.[6] In this paper we show that the discrepancy between residential and productive amenities leads firms to locate near highly polluted areas in African cities, thus exposing workers to pollution in a way that cannot be captured by looking at household level decisions only.

The rest of the paper is organized as follows. Section 2 presents background information on the context of our study. Section 3 describes the sample and data sources. Section 4 presents the model used to guide the interpretation of the results, while in Section 5 we present the data construction for the empirical analysis. The results are then presented in Section 6. Section 7 discusses the quantitative implications of our results and Section 8 concludes. Additional details are in the Appendix.

2 Pollution and Urbanization in Uganda

In this section, we discuss trends in urbanization, motorization and pollution emissions in Uganda, to show the relevance of our setting. We also discuss the negative impact of pollution on health and productivity, to highlight the importance of pollution exposure as a key driver of economic development and individual welfare in low income countries.

Pollution levels in Uganda. Uganda features high levels of pollution comparable to China and well above the recommendations by the US Environmental Protection Agency (EPA): average annual PM2.5 concentration was 50.5 micrograms per cubic meter in 2017, more than four times higher than the suggested EPA annual standard of 12 micrograms per cubic meter.[7]

[6] A related literature studies the role of transportation networks in facilitating adaptation to pollution and heat events through changes in travel patterns (Barwick et al., 2022).

[7] Source: World Bank: https://data.worldbank.org/indicator/EN.ATM.PM25.MC.M3?name_desc=true&view=map. 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:

Appendix Figure A8 also show that: (i) pollution in Uganda is not only very high, but has also been *increasing* in recent years, while pollution has been declining in China, India and the US; (ii) Uganda exhibits pollution levels and trends that are broadly comparable to other African countries such as Nigeria and Ghana. Further, a recent WHO study (WHO, 2016) emphasizes that air pollution disproportionally affects urban areas in Uganda with PM2.5 concentrations 40% higher than in rural areas.

Health and productivity effects of pollution. The impacts of air pollution on health and productivity are well established. PM2.5 has been shown to be the deadliest component of air pollution (Pope and Dockery, 2006). Early work shows how exogenous changes in pollution affect infant mortality (Chay and Greenstone 2003), and mortality due to cardiorespiratory diseases (Ebenstein et al. 2015). Deryugina et al. (2019) estimate that a 1 microgram per cubic meter increase in PM2.5 leads to 0.69 more deaths per million elderly over the following three days. Anderson (2020) identifies a causal link between long-term exposure to air pollution from road traffic and adult mortality.

Pollution also negatively affects labor supply as first shown for the US by Ostro (1983) and Hausman et al. (1984). Hanna and Oliva (2015) exploit a natural experiment to identify a negative causal effect of air pollution on labor supply in Mexico, and Aragon et al. (2017) show similar results for Peru. On the intensive margin, numerous studies document the negative effects of particulate matter on worker productivity in both developed and developing countries (Graff Zivin and Neidell 2012, Chang et al. 2016, Adhvaryu et al. 2022 and Fu et al. 2021).

Urbanization, motorization and pollution emissions. Road traffic is widely recognized as a common source of PM2.5. With rapid urbanization and increasing motorization, the challenges brought by air pollution in the developing world can only be expected to rise. Across Africa, the urban population is expected to triple by 2050 (Collier 2017). Like other African countries, Uganda has experienced rapid urbanization 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 A9), together with unpaved roads and limited coordinated land use or transport planning, make motorization one of the main sources of pollution in urban Uganda.[8]

//www.epa.gov/pm-pollution/particulate-matter-pm-basics.

[8]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

The issue is acknowledged by Ugandan policy makers, but no comprehensive solution exists yet. 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 A10. While this policy was effective, the average age of newly registered vehicles still remained high at over 7 years in 2018. A Bus Rapid Transit (BRT) project for Kampala, with pre feasibility studies completed in 2010, is still pending.

3 Sampling Strategy, Data, and Descriptives

The extent to which the aggregate increases in motorization and air pollution described in Section 2 impact health, productivity and welfare ultimately depends on individuals' exposure. Motivated by the observation that firms in low income countries seem to cluster in the most congested parts of cities, our goal in this paper is to study the role of the organization of production – and more specifically of firm location choice – in mediating workers' exposure to pollution in urban Uganda.

Towards this goal, we need to build a specific data infrastructure, which we describe in this section. 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-level survey data to study the economic benefits and costs associated with different locations, as well as firm's perceptions of pollution and adaptation strategies.

3.1 Sampling Strategy

We collected pollution measurements and a novel firm survey in a representative sample of urban and semi-urban areas across three of the four macro-regions of Uganda: Central, Western, and Eastern regions. The pollution measurements and the firm survey are both geo-located and were collected in the same geographical 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 sections of a city, so that there are multiple sub-counties within a city.[9] 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).[10]

driving up PM2.5 concentrations in Kampala and Jinja, two Ugandan cities.

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

[10]Appendix Figure A11 shows the final sample of sub-counties.

3.2 Pollution Measurements

We create a unique database of pollution measures with geo-coordinates and time stamps that we collected in partnership with AirQo.[11]

Stationary and mobile measurements. Pollution measurements come from two distinct types of monitors, which we refer to as *stationary* and *mobile* monitors. The former were attached to a number of 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.[12]

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.[13] 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 in our sampled sub-counties.[14]

By moving across space, the mobile monitors allow us to measure the spatial variation in pollution at a granular level within the city. By virtue of being fixed in one location, stationary monitors allow us to precisely measure the time variation in pollution. In Section 5, 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 pollution readings by hour of the day, from both stationary and mobile monitors. The figure reveals 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 micrograms per cubic meter, which is substantially higher than the EPA annual average

[11] 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.

[12] Appendix Figure A12 shows pictures of a stationary and mobile monitor. Okure et al. (2021) summarizes the technical details of monitors and processes used for data collection.

[13] 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.

[14] 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 2.345 km and 95% of measurements are within 7km from a stationary monitor.

concentration guideline of 12 $\mu g/m^3$ and lines up well with the average of 50 micrograms per cubic meter for Uganda reported by the World Bank in 2017 and mentioned in Section 2; (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 6. 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 A17.[15]

3.3 Firm Survey

The second data source is a novel firm survey that we conducted in Uganda. 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 Uganda, in partnership with the Ministry of Trade. Within each target sub-county, urban and semi-urban parishes were surveyed. The survey is described in detail in Bassi et al. (2021). Here we summarize again the key elements of the sampling and survey design, and then focus on those aspects that were specifically designed for this study.[16] 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. As revealed by the latest Census of Business Establishments conducted by the Uganda Bureau of Statistics in 2010, these are sectors that: (i) employ a large share of workers, covering approximately 33% of manufacturing employment, and (ii) are not dominated by micro-enterprises. The first criterion implies that we target sectors that are important for policy, whereas the second criterion allows us to focus on labor relationships within the firm, which is a key focus of this paper.

We conducted a door-to-door listing of all the firms in our three sectors in the 52 sampled sub-counties, identifying close to 3,000 firms. For each firm in the listing, we recorded their sector of operation and GPS coordinates. This means that we virtually have geo-coded data

[15] Appendix Figure A13 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.

[16] Bassi et al. (2021) study the role of the rental market for mechanization and productivity. The two studies share the same survey but 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 adaptation.

on the universe of firms in our sampled sub-counties and sectors.[17]

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[18] and all the employees working on the main product.[19] Compliance with the survey was high at over 90% and all the results from our survey are appropriately weighted to reflect our sampling strategy.

Survey design. Our initial survey was designed to study firm performance, firm location choices, adaptation to pollution and awareness of pollution as a problem, as well as the role of managerial ability. On *firm performance*, we collected information on revenues, profits, number of employees as well as wages. On *firm location*, in addition to collecting GPS coordinates, we asked the firm owner to indicate the reasons behind their location choice, including detailed information on how firms access customers (e.g., whether orders are placed through walk-ins, expenditures on marketing etc.). 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 premises and how they commute to work. On *adaptation to pollution*, we asked detailed questions about any investments made by the firm owner to protect their workers from pollution exposure, such as providing masks and other protective gear. We also asked about organizational strategies to protect workers from pollution, such as allowing flexibility in commuting times and work schedules to avoid exposure to traffic pollution at rush hour. Importantly, we asked employees about whether they feel that managers are taking active steps to protect them from pollution exposure. 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 quality*, we follow McKenzie and Woodruff (2017), who build on the work of Bloom and Van Reenen (2007) to adapt standard management surveys to the context of small firms in developing countries. In particular, we create a standardized index of managerial ability by aggregating a wide range of questions about marketing practices, stock management of inputs, recording of transactions, financial performance review, business planning and forecasting. The index should be interpreted as a summary measure of overall management ability.[20] We also collected detailed information on other owner and worker characteristics (e.g., education, age, experience etc.) as well as measures of workers' time use at the firm.

[17] Appendix Figure A14 plots the firms in the listing in one of the study sub-counties.

[18] In our sample, firm owners also actively manage the firm operations in most cases. Therefore, we use the terms "firm owners", "entrepreneurs" and "managers" interchangeably in the paper.

[19] More precisely, as discussed in Bassi et al. (2021), 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. See Bassi et al. (2021) for more details.

[20] We validate the index in Bassi et al. (2021), where we show that it is a strong predictor of revenues per worker. The exact construction of the index is detailed in Appendix A.1

Follow-up survey and information experiment. We followed up again with our sample of firms in early 2022 with a phone survey in order to: (i) test the firm owners' awareness about pollution levels and profitability in their neighborhood, which we were able to do by asking firm owners about their perception of pollution and access to customers in the area near their firm relative to other areas of their sub-county, and comparing these to the actual levels as measured in 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* on willingness to pay for information on local pollution levels, which is described in more detail in section 7.2. We were able to successfully interview about 68% of the target sample of firms.[21] 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.

Descriptives on basic firm characteristics. Table 1 reports basic descriptives for the 1,027 firms in our survey sample and their employees. The key take-away from the table is that these are established and regular activities providing remunerative employment: the average firm has been in business for 10 years and has about five employees. Average monthly profits are $244, while employees make about $71 dollar per month. To put these numbers into perspective, per capita GDP in Uganda was $60 per month in 2018.

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 following the United Nations Spatial Data Infrastructure (UNSDI) for Transport standards.[22] The WFP shape-file distinguishes between five distinct road types in Uganda: *track/trail*, *tertiary roads*, *secondary roads*, *primary roads*, and *highways*, by converting Open Street Map (OSM)'s highway tag.[23] The geo-referenced nature of the dataset allows us to match roads with both the pollution and firm survey data. We create an ordinal measure of road size. To do so, we rank road types by size so that *track/trail* are assigned the value 1, and *highways* are 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*

[21] Appendix Table A14 reports the predictors of attrition and, reassuringly, shows that the index of managerial ability, being located near major roads, and treatment assignment for the willingness to pay experiment are all insignificant predictors of attrition.

[22] Source: https://geonode.wfp.org/layers/ogcserver.gis.wfp.org:geonode:uga_trs_roads_osm/metadata_detail.

[23] The WFP classification is a mapping of the 18 OSM's 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.

road (4), will be 3.[24]

Appendix Table A9 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 2,754 km of roads, 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.

4 Conceptual Framework

We introduce a framework to guide and interpret the empirical analysis in the next sections.

We consider an economy inhabited by entrepreneurs and workers. Entrepreneurs have a managerial ability x_i while workers are homogeneous and simply supply labor. The economy is divided into locations $j \in \mathbb{J}$, which we interpret as city neighborhoods. Each location is characterized by a *bundle* $\mathbb{X}_j = \{p_j, w_j, R_j, z_j\}$ where p_j is the pollution level; w_j is the local wage per worker; R_j is a catch-all rental cost to be paid to set up a firm in location j, which also captures any other location specific fixed costs, such as commuting; and z_j is the location-specific productivity. Firm location may affect productivity through several channels, which are all captured in reduced form by z_j in our model. Central and busier locations are more visible to customers, thus offering higher demand, and they may also provide economies of agglomeration, for example due to interactions in the rental market (Bassi et al. 2021), demand externalities (Glaeser et al. 2001), or productivity spillovers (Arzaghi and Henderson 2008). At the same time, firm congestion could hinder productivity, either due to business stealing, or diseconomies of density such as road traffic making it harder to access suppliers.

Our setting abstracts from equilibrium considerations since we are not attempting to compute policy counterfactuals using the model. We study the location choice of a marginal entrepreneur within the city, and do not aim to characterize the full spatial equilibrium, which we take as given, nor the possible strategic interactions between firms. In general, w_j and R_j would be determined in equilibrium, but in this paper we focus on the drivers guiding location choice and exposure to pollution from the perspective of a single firm owner, taking the observed distribution of prices as given. Similarly, the location-specific productivity z_j is plausibly a function of the number of entrepreneurs located there, but studying these forces is beyond the scope of our modeling exercise.

Entrepreneur problem. The problem of each entrepreneur i is to decide where to set up a firm, how many workers to hire, and whether to invest in equipment or organizational strategies

[24] A road is defined 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 A15.

to mitigate the effects of exposure to pollution, e. We assume that the mitigation of pollution applies to the same extent to the entrepreneur and each worker in the firm, that is, that mitigation is not excludable within the firm. The maximization problem can be unpacked into a location choice, and the within-location choices. We next describe both problems.

We first take as given the location j and solve for the maximization of net profits within the location. An entrepreneur i solves

$$\pi_j(x_i;\mathbb{X}_j) = \max_{L,e\in[0,1]} \underbrace{ZL^\gamma}_{\text{Output}} - \underbrace{\chi(x_i,p)}_{\text{Amenity Cost of Pollution}} - \underbrace{w_j\omega(p)L}_{\text{Cost of Labor}} - \underbrace{\xi(x_i,e)}_{\text{Cost of Pollution Mitigation}} - \underbrace{R_j}_{\text{Rental Cost}} \quad (1)$$

$$\begin{aligned} &\text{s.t.} \\ Z =& \quad g(x_i, z_j, p) \quad \text{(Productivity)} \\ p =& \quad p_j(1-e) \quad \text{(Adaptation)} \\ w_j(L) =& \quad w_j\omega(p)L \quad \text{(Compensating Differential).} \end{aligned}$$

The first constraint shows that the overall firm productivity Z is a function of managerial productivity x_i, location-specific factors z_l, and pollution exposure p. As discussed in Section 2, a number of papers identify the negative short-run effects of pollution exposure on workers' productivity. The second constraint shows that the overall pollution exposure p depends on the location-specific pollution level p_j, which can be abated by protective investment e. The third constraint shows that the wage per worker is given by the location-specific wage level w_j multiplied by the term $\omega(p)$ capturing the fact that workers might have to be compensated for the exposure to pollution.

Overall, exposure to pollution within each location affects the entrepreneur's net profits through three margins: (i) a *productivity margin*, as pollution directly reduces firm productivity; (ii) an *amenity margin*, as the entrepreneur suffers a cost $\chi(x_i,p)$ (expressed in monetary terms) from her exposure to pollution, capturing factors such as perceived health cost, and future income losses due to worsened future health; (iii) a *compensating differential margin*, as the entrepreneur potentially has to compensate her workers more for exposure to higher pollution.

It is relevant to notice that in our model, due to the decreasing returns ($\gamma < 1$), workers would be paid below their average product, thus generating rents for firm owners. As a result, the pollution exposure of workers potentially reduces firms' profits and would not simply show up in equilibrium as a reduction in wages.[25]

Next, we turn to the location choice. Each entrepreneur i draws a vector of shocks $\varepsilon_{i,j}$, one for each location j, distributed according to a Type II Extreme Value Distribution with shape parameter σ^{-1}. These taste shocks, often used in the urban and migration literature (see e.g.,

[25] One way to interpret the decreasing returns is through either output or labor market frictions. Alfonsi et al. (2020), Bassi and Nansamba (2022) and Bassi et al. (2021) show direct evidence of these frictions in our same context.

Heise and Porzio 2022 and Khanna et al. 2021), capture several factors that may influence the firm location, such as the home location of individual i or her idiosyncratic distaste for pollution exposure. The parameter σ modulates the extent to which firm owners sort towards locations that offer higher net profits. For example, when $\sigma \to 0$, location choice is purely driven by shocks, and firm owners are uniformly distributed across space. Given the vector of shocks, the entrepreneur chooses the location that provides the highest value, thus solving

$$\max_{j \in \mathbb{J}} \varepsilon_{i,j} \pi_j \left(x_i; \mathbb{X}_j \right).$$

Pollution mitigation and location choice. Next, we characterize the solution of the problem. While all choices are jointly determined, we work through the problem backwards, first considering the optimal firm size and pollution mitigation and then the location choice.

An entrepreneur i chooses mitigation $e^*_{i,j}$ such that

$$\underbrace{-p_j g_p \left(x_i, z_j, p_j \left(1 - e^*_{i,j} \right) \right) \left(L^*_{i,j} \right)^{\gamma}}_{\text{MB due to Productivity Increase}} + \underbrace{p_j w_{j,p} \left(p_j \left(1 - e^*_{i,j} \right) \right) L^*_{i,j}}_{\text{MB due to Wage Decline}} + \underbrace{p_j \chi_p \left(x_i, p_j \left(1 - e^*_{i,j} \right) \right)}_{\text{MB due to Amenitity Increase}} = \underbrace{\xi_e \left(x_i, e^*_{i,j} \right)}_{\text{MC of Mitigation}},$$

where $g_p(x, z, p)$, $w_p(p)$, and $\chi_p(z, p)$, are the marginal effects of an increase in pollution exposure on productivity (negative), workers' wage (positive), and pollution cost in terms of amenity value (positive); $L^*_{i,j}$ is the optimal firm size for entrepreneur i in location j which can be solved explicitly as usual; and $\xi_e(x, e)$ is the marginal cost of pollution mitigation. Pollution mitigation has three distinct benefits: (i) it increases firm productivity; (ii) it allows the firm owner to pay workers relatively less; and (iii) it reduces the own amenity cost for the firm owner. Each benefit, and the cost as well, could depend on managerial ability, thus possibly generating a correlation between mitigation and firm characteristics.[26]

Given the firm size and mitigation, we use the properties of the extreme value distribution to solve for the share of entrepreneurs of managerial ability x that choose location j:

$$\varphi(x) = \frac{\pi_j \left(x; \mathbb{X}_j \right)^{\sigma}}{\sum_{j \in \mathbb{J}} \pi_j \left(x; \mathbb{X}_j \right)^{\sigma}}.$$

For any $\sigma > 0$, entrepreneurs sort into locations that offer higher net profits.

Drivers of exposure to pollution. Pollution is a disamenity, hence one could expect entrepreneurs to avoid exposure by sorting towards less polluted locations. However, pollution may be positively correlated with customer demand due to road traffic. Areas with higher

[26] There are several reasons why managerial ability may affect the return from investing in mitigation. High ability managers may have easier access to credit to purchase protective equipment or higher ability to make organizational changes to reduce exposure, thus reducing their effective cost of mitigation. They may also higher awareness of pollution levels and its productivity and health costs, or even suffer an effectively larger productivity cost due to complementarity.

traffic, hence higher pollution, are more visible and more reachable, thus increasing the local demand and profitability. In this way road traffic bundles a good (market demand) with a bad (pollution exposure). In our model, this implies that the location productivity z_j and pollution p_j are in general positively correlated, a correlation that we will show holds in our data.

To better highlight the trade-off guiding location choice, we can then consider two locations, call them 1 and 2, one with high productivity and pollution and one with low productivity and pollution, and use equation (1) to study under which conditions an entrepreneur i is more likely to choose location 1 – or $\pi_1(x_i; \mathbb{X}_1) > \pi_2(x_i; \mathbb{X}_2)$. A few comments are in order. First, notice that there are benefits from locating in a high pollution location only if the output term net of the labor and rental cost is larger in the location 1, hence if the location-specific heterogeneity in productivity is sufficiently large to compensate for the direct negative effect of pollution, and for the possibly higher wage w_1 and rental cost R_1. Second, the firm owner will choose the high polluted location only if the amenity cost of pollution is relatively small, both the personal one, through the cost χ, and the one internalized by workers through the higher wage $\omega(p)$ needed to compensate them. Third, notice the role of mitigation. The more entrepreneurs are able to mitigate the pollution costs, the more sorting to the high pollution, high productivity locations is appealing to them. All the three channels above may vary as a function of managerial ability.

Mapping to data. To conclude this section, we discuss what we can and cannot observe in the data described in Section 3. We can directly observe firm profitability, the cost of labor, and managerial ability, and some direct measure of rental costs, namely the rental cost of the firm premises, as well as the length and mode of commuting. We can also measure investment in adaptation equipment and organizational strategies. We can instead only approximate the perceived amenity cost of pollution using the estimated effect of pollution on health, which we take from the literature. Finally, we have direct information on firm owner's perceptions about access to demand and pollution levels in different parts of the city, as well as about their awareness of the health and productivity costs of pollution. This is important, as all choices described in this section ultimately depend on firm owners' perceptions about the relative benefits and costs. As we will verify below, firm owners' perceptions are broadly aligned with reality (although pollution levels are underestimated).

5 Empirical Strategy and Data Construction

Our overall empirical goal is to show that the informal nature of production in low-income countries leads firm owners to locate in severely polluted areas thus exposing themselves and their workers to high level of pollution, with plausibly dire health consequences.

Towards this broad goal, in this section we develop the empirical framework that enables us to characterize the joint spatial distribution of pollution and economic activity and identify the key trade-offs that guide firm location choice and exposure to pollution, which we have illustrated with the conceptual framework of Section 4. We show how to transform the data described in Section 3 to make it amenable to a spatial empirical analysis. Specifically, we determine a notion of location, corresponding to the neighborhoods j in the model, and calculate for each of them a measure of pollution levels p_j and profitability z_j. To do so, we first residualize the pollution measurements to extract a measure of average local pollution. We then project all our firm-level and pollution variables on small geographic units generating a "location-level" dataset that we will use in the empirical analysis of the next sections.

5.1 Recovering Residual Spatial Variation in PM2.5

As described in Section 3, we collected measures of PM2.5 concentration from both stationary and mobile monitors. To construct measures of spatial variation in pollution within the city, we exploit 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 city 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.[27]

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:

$$ln(PM2.5)_{k,h,d} = a + b{\times}hour_h + c \times date_d + \lambda_k + \epsilon_{k,h,d} \tag{2}$$

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:

[27]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.

$$e_{\hat{m,h,d}} = ln(PM2.5)_{m,h,d} - (\hat{a} + \hat{b} \times hour_h + \hat{c} \times date_d). \quad (3)$$

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

5.2 Grid Cell Approach

To create the neighborhood-level measures of firm density, pollution and road size, we adopt a grid cell approach. The next administrative unit after sub-counties are parishes. Specifically, our 52 sub-counties comprise 179 sampled parishes. Following Ahlfeldt et al. (2015), Carozzi and Roth (2020) 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.[28] Each road, pollution measure and firm are attributed to a cell using their geo-coordinates.[29]

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 the firms and not only those that we eventually selected for the survey.[30]

Figures 2, 3, and 4 illustrate how our sampled parishes are split into grid cells, and provide visual evidence (just from one sub-county) that firms are clustered close to major roads (Figure 2), that such roads are more polluted (Figure 3), leading to firm density being higher in grid cells with higher average pollution (Figure 4). Next, we show that these results hold in general.

6 Results

Equipped with the empirical framework developed in Section 5, we here use the constructed data to establish the core empirical results. While these results constitute the backbone of our

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

[29]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.

[30]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 A16. Besides, in regressions including grid-level variables, we control for whether the grid cell has an area of less than 0.25 square km (dummy), as well as for grid cell size (linear control).

contribution, we leave to Section 7 a careful description of their magnitudes and a discussion of their broader implications for economic development.

We proceed in three steps. First, we study the relationship between local profitability (net of wages, rent and other operating costs) and pollution, to establish that they are positively related as road traffic plausibly determines both. Second, we study the location choice of firm owners within the city and show that, on average, they sort towards major polluted roads and they do so to access customers. Taken together, these two results establish the key message of the paper: given the informal nature of production in low-income countries, firm owners face a trade-off between profitability and exposure to pollution, and most owners choose to locate in the polluted areas to access customers, thus exposing their workers to substantial pollution. In Section 7, we will show that this trade-off is quantitatively relevant and we will discuss its implications for development and industrial policies. Finally, we study heterogeneity by managerial ability in location choice and adaptation behavior and show that high-skilled managers do not avoid pollution more, but better adapt to it.

6.1 Bundling: Road Traffic Bundles Pollution with Customers

To establish that road traffic bundles a good (access to customers) with a bad (pollution exposure), we proceed in four steps. First, we establish that large roads are more polluted. Second, we find evidence that this pollution is generated by road traffic and not by firms. Third, we show that firms located near larger roads have higher revenues as well as net profits, conditional on a rich set of controls. Finally, we explore the mechanism linking pollution to profitability using our rich survey data and argue that it is primarily due to access to market demand.

Larger roads are more polluted. We run the following regression at the grid cell level, for grid cell j in sub-county s in region r:

$$ResidPollution_{j,s,r} = \alpha_0 + \alpha_1 MedianRoad_j + \delta_s + \theta log(dist)_r + \nu_{j,s,r}, \tag{4}$$

where $ResidPollution_{j,s,r}$ is the average residual (log) pollution in the grid cell, calculated as discussed in Section 5.1. $MedianRoad_j$ is the median road size in the grid cell. δ_s are sub-county fixed effects, as we are interested in documenting variation in pollution and firm location choices *within* relatively small urban areas rather than between cities. 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.[31] To

[31]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.

account for spatial correlation, we use Spatial Heteroskedastic and Autocorrelation Consistent (SHAC) standard errors (Conley, 1999), using the routine developed by Hsiang (2010).[32]

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 identifying assumption 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 potentially polluting economic activities such as large factories; (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;[33] and (iii) as discussed in Section 2, the core of the road infrastructure in Uganda was built in the 1960s, which further alleviates potential concerns related to the endogenous placement of roads based on the current layout of local economic activity.[34]

The results are shown in Table 2: an increase in median road size in the cell of one unit is associated with an increase in residual pollution of about 7-8%, a result significant at the 1% level. Comparing column 1 with column 2 we note that the coefficient is barely affected by the introduction of sub-county fixed effects, thus implying that the relationship is driven by variation within as opposed to across sub-counties. In columns 3 and 4, we check that these results are robust to conducting the analysis at the level of the individual pollution measurement rather than the grid cell, by estimating the same equation 4 using variation across all the observed GPS coordinates m, rather than aggregating at the grid level. To do so, we replace the median road size in the cell with a variable capturing the size of the road closest to the pollution measurement. Reassuringly, the results are similar.[35]

Pollution is due to road traffic. Next, we argue that the geographic variation in pollution is mainly due to road traffic rather than the firms themselves. We study the cyclicality of pollution across hours of the day: the left panel of Figure 1 shows that pollution peaks between

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

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

[34] 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. Our main 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.

[35] In columns 3 and 4 of Table 2, 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.

6-9am and 7-9pm, times that correspond 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 at a different time of the day, 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 productivity and health.[36]

Firms benefit from locating near larger roads. We next study whether locating near larger roads provides higher net profits. The ideal experiment to answer this question 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 very difficult to observe firms moving across locations as those moves are extremely 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, and rental cost within urban areas, 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. 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:

$$y_{i,j,s,r} = \beta_0 + \beta_1 MedianRoad_j + \beta_2 ManScore_i + \lambda_l + \delta_s + \eta log(dist)_r + \upsilon_{i,j,s,r}, \tag{5}$$

where $y_{i,j,s,r}$ is the outcome of firm i, such as log net 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 4. Standard errors are adjusted for spatial correlation.

Our main coefficient of interest is β_1. A positive estimate when the outcome is net profit would indicate that firms located near major roads are more profitable. Similarly to equation 4, our first identifying assumption is that roads are pre-determined with respect to firm location. As shown in Table 1, the average firm has been in business for 10 years, while the main road network was built in the 1960s. As mentioned above, the second, and potentially stronger, identifying assumption is that, conditional on sub-county and sector fixed effects and on our

[36] We conduct one further test in Appendix Figure A18: we split the stationary monitors by whether they fall in a grid cell where there is 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 across the two sets of monitors, and this remains true when we restrict the sample to grid cells with at least one road.

index of managerial ability, there is no selection of more productive firms in the proximity of larger roads.

The results are shown in Table 3. Columns 1-3 show that there are clear net profitability benefits from being located 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 revenues and profits, as expected given the prior literature on returns to management skills (Bloom and Van Reenen 2007, 2011; McKenzie and Woodruff 2017). As long as observable and unobservables determinants of profitability are correlated, this result already suggests that any scope for selection on unobservables to bias our results is limited. Column 3 then shows that this corresponds to higher profits per worker too, thus confirming that locations near major roads are more productive, in a profit per worker sense.

In the rest of the table, we unpack such profitability benefits. 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. We find that firms located near larger roads report significantly more customers. The average firm has four customers per day so the magnitude corresponds to a 6% increase in the number of customers associated with an increase in median road size by one unit. In line with this, column 5 shows that revenues are also higher. Column 6 shows that employees working near larger roads earn higher wages, although the magnitude of the coefficient is much smaller when compared to the one in columns 1 and 2 for firm owner's profits. This remains true even once we add a rich set of worker controls in column 7.[37] Finally, in column 8 we study whether the profitability benefits come at the expenses of higher land prices. It is not obvious that this would be the case as there could be negative effects of pollution on land prices if pollution is perceived as a dis-amenity. To shed light on this, we exploit our survey questions about the rental value and the size of the business premises.[38] 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. It is relevant to notice that, despite the higher rental and wage cost, the overall net profit effect (shown in columns 1-3) is positive. This result is expected, given that the effect on revenues is much larger than the effect on wages and rental expenditures are only a small share of the overall firm costs.[39]

[37]The effect on salary could be due to compensating differentials from the higher exposure to pollution. Alternatively, as firms located near larger roads have higher revenues, this may also reflect rent sharing motivations, at least in part.

[38]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.

[39]In our sample, the rental expenditures of the median (average) firm is 5% (11%) of this firm's monthly

Finally, it is worthwhile to highlight again that all the results just discussed are estimated exploiting variation across grid cells *within* sub-county. Recall that a grid cell is a square of $500m \times 500m$, and that a typical sub-county only includes approximately 72 grid cells. Therefore, our results are capturing the benefits from location choice within cities and neighborhoods rather than between them.

Taken together, the results in Table 3 confirm that there are direct and tangible benefits to firms from being located on busy roads with high traffic (and high pollution). In Appendix Table A10, 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. This confirms that there are tangible benefits of being located in more polluted areas.[40]

We highlight two further points on the validity of the assumption of no selection on larger roads based on unobservable productivity in equation 5. First, in Appendix A.3 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; (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. These results support the claim that location choice is not driven by underlying firm characteristics related to 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. In the model in Section 4, such remaining determinants of firm location choice are captured by the taste shocks $\varepsilon_{i,j}$. There may be many sources of such residual variation, which are typically hard to observe. One example, which we may to some extent observe, is taste for commuting: Appendix Table A11 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. 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 2020).[41] Heterogeneity in taste for commuting can then be an explanation for why some entrepreneurs locate further from the large roads and closer to home.

revenues, among firms renting their premises.

[40]The number of observations is lower in Table A10 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.

[41]Vitali (2022) 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).

Road traffic provides access to customers. Having shown that firms on larger roads are more profitable, we next use our survey data to support the interpretation that large (and polluted) roads provide access to customers.

Panel A of Table 4 shows that only 7% of managers spend any money on marketing, and when asked about strategies they adopt to communicate the quality of their products to customers, about 60% say that they just talk to the customers directly. While firms rarely adopt broader marketing strategies, 69% of them have products on display, and 65% report doing so specifically to attract customers (as opposed to having them in stock to sell them quickly or as the result of past orders). In line with this, sales are conducted mostly through face-to-face interactions: about 93% of firms sell directly to final consumers (as opposed to wholesale retailers) and 80% of orders are placed directly through walk-ins by customers. Very few firms engage in shipping to customers. As firms sell mostly through face-to-face interactions and do not market their products widely, this suggests that firms lack the means to attract customers to their location. Therefore, by locating on large roads and putting up finished products on display, firms can gain visibility to potential customers driving down the road. We also asked firm owners about the benefits, if any, for a firm to be located near a major road.

Panel B shows that gaining visibility to new customers is the most important perceived benefit, indicated by about 76% of respondents as the main benefit. For comparison, 6% of firms indicate opportunities to interact with other producers as the main benefit. Taken together, the evidence from our survey is thus consistent with the productivity benefits of being located near major roads arising mainly from better access to customers.

6.2 Location Choice: Sorting to Polluted (High Demand) Areas

Having established that firm owners face a trade-off between profitability and exposure to pollution, we study where they locate within the city. Linking back to the model, the results in the previous sub-section show that: (i) there are net profitability benefits of locating near large roads, after taking into account any direct productivity effects of pollution, wages and rental cost; (ii) firms do not differentially sort across space based on their underlying productivity. In this sub-section, we study the extent to which firm owners locate in polluted areas. Whether managers decide to locate in such high productivity but high pollution areas then depends on: (i) the perceived amenity cost of pollution, once any compensating adaptation investments have taken place; (ii) any firm owner-specific taste shocks for the different locations (potentially reflecting a distaste for commuting as discussed above).

We run a grid-level regression similar to equation 4 but with firm density in the grid cell on the left hand side to test whether firm density is higher or lower near major roads. As we find that major roads are more polluted, these results will be informative of whether firms sort into more polluted areas, which we also verify directly by replacing the median road size in the cell with the average residual pollution in the cell. The results are shown in Table 5.

On the extensive margin, in columns 1 and 2 the dependent variable is a dummy equal to one if the grid cell has at least one firm. The results show that cells with larger roads (column 1) and more polluted grid cells (column 2) are more likely to have at least one firm. We find similar results when looking at the intensive margin. Columns 3-4 use as outcome the log of the firm density in the cell. Column 3 shows that an increase in median road size of one unit is associated with an increase in firm density of 14%. Column 4 shows that a 1% increase in pollution residual is associated with a 0.3% 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.

To confirm the absence of heterogeneity in location choice based on managerial ability, in columns 5 and 6 of Table 5 we add the average managerial ability in the cell as a regressor. The coefficient on the average managerial ability is positive but small in magnitude and not significant in both specifications. This is in line with the discussion in the previous sub-section. Seen through the lenses of the model, these results imply that the amenity cost of locating in more polluted areas is outweighed by the profitability benefits of access to higher demand similarly for high and low ability managers.

Managers reveal to choose locations to access customers. Our survey corroborates the idea that firms locate in the more polluted areas of town to access customers. We asked all firms that relocated or considered relocating in the previous year the reasons for their location choice, among a list of 18 possible reasons. Panel C of Table 4 shows the share reporting each potential reason among their top three 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. The table shows that: (i) access to customers is the most important reason driving location choice; (ii) 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 (the relevance of exposure to water and solid pollution is even lower). This provides direct evidence that firms locate on busy (and polluted) roads to access customers.[42] In line with this, Appendix Figure A19 shows that lack of demand is the main perceived constraint to growth in our survey. This again highlights that small firms struggle to access demand in this context, which then justifies why access to demand considerations are the main reasons driving their location choice.

[42]Figure A20 reports the distribution of all 18 possible reasons for location choice. Access to customers is clearly the primary reason.

Location choice exposes workers to pollution. As firms locate primarily near polluted roads, this opens up the possibility that workers may be exposed to substantial pollution. Our data shows that, as a result of firms sorting to polluted areas, the median employee works in a neighborhood with about 56 $\mu g/m^3$ of PM2.5, that is substantially higher than the 24-hour fine particle standard recommended by the EPA (35 $\mu g/m^3$). In Section 7, we will show that this pollution exposure could be substantially reduced if firms were to relocate, even within the same sub-county. In addition, 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 D of Table 4 reveals that 64% of firms produce only outside or mostly outside, and only 16% of firms produce entirely inside.

6.3 Heterogeneity: High-Ability Owners Better Adapt to Pollution

Ultimately, the negative health impact of pollution depends on the *actual* levels of pollution that workers are exposed to on the job. Even if firms sort to the most polluted areas, they could still limit the health impact through different margins of adaptation. We next use our survey data to study the amount of adaptation that takes place, and whether this differs for high- and low-ability owners. We estimate firm- and worker-level regressions analogous to equation 5 but with various measures of adaptation from our survey as outcomes. As shown in Table 5 and discussed more in detail in Appendix A.3, we notice again that managerial ability does *not* predict location choices, which justifies looking at the role of managerial ability conditional on location choice.

The dependent variable in column 1 of Table 6 is a dummy equal to one if firm owners report providing any pollution protective equipment to their workers, such as masks. The mean of the dependent variable reported at the bottom of the table 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.[43] Consistent with the results in column 1, column 2 shows that employees working for higher ability owners take more protective measures themselves.

[43] Appendix Figure A21 reports the breakdown of workers' answers. Almost half of the workers report taking some protective measures. Dominant strategies are wearing a scarf/tissue and wearing a mask. Notably, very few workers report staying inside the firm premises when air quality is bad, which is consistent with work being predominantly outdoor. Figure A21 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.

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.[44] Our coefficient of interest is remarkably stable when employee-level controls are excluded (not shown), which confirms that the results are more consistent with higher ability owners treating their workers differently. In Appendix A.4, 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.[45]

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.

Linking back to the model, the fact that high ability owners are better able to adapt to the pollution implies that they would have a stronger incentive to move to larger and more polluted roads. However, as shown in the previous sub-section, we do not find differential sorting by managerial ability onto large roads. This is plausibly due to the fact that the net benefits of locating in busier and more polluted areas are positive for all types of managers and the marginal effect of higher adaptation on net profits is minor, which would also be consistent with the documented overall low level of adaptation. The model also highlights at least three potential channels why firm owners of higher ability might adapt more: (i) they might be better aware of pollution levels; (ii) they might be better aware of the direct productivity effects of pollution; (iii) they might face a higher disamenity cost from pollution. We explore these potential channels in the next section, using our survey data on perceptions.

[44] 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.

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

Finally, we note that our measures of road size are always positive throughout Table 6, although they are largely insignificant. These results are again consistent with the fact that the level of adaptation is not a relevant aspect in the firm location choice.

7 Implications

The results so far have established that the way manufacturing production is organized in urban Uganda and the resulting firm location choice expose workers to high levels of air pollution. This observation leads to several related questions, which we tackle in this section: Is the magnitude of the trade-off meaningful from an economic and healthcare perspective and who bears its cost and benefits? To which extent are firm owners aware of the distribution of pollution and the trade-off? And finally, can policy limit the documented health costs and if so, how?

7.1 Magnitudes: the Profitability-Pollution Trade-off is Meaningful

The extent to which the documented trade-off has quantitatively meaningful implications depends on the variation in pollution and profitability within sub-counties and on the strength of the sorting of firms towards the most polluted areas. We next use back of the envelope calculations to show that the trade-off is indeed quantitatively meaningful.

Using the elasticity of pollution to road size from Table 2, column 1, and the elasticity of profits and worker salary to road size from Table 3, columns 2 and 6, we predict pollution, profits and salary from road traffic in each grid cell in our sample. 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.[46] More details on how we predict profits, salary and pollution can be found in Appendix A.5.

Using this data, we start by investigating what the observed spatial distribution of roads can potentially imply for the trade-off between life expectancy and value added per worker, defined as the average of owner's profits and workers' salary. This is a preliminary step to document that, at least in theory, the spatial distribution of firms could have meaningful consequences. To transform 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 5 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.[47] We see that there is substantial heterogeneity in the pollution and profitability of available

[46]We restrict observations to grid cells containing at least one road to address concerns of data quality.

[47]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 magnitudes.

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.

Next, we quantify the impact of the *actual* distribution of firms by comparing the predicted firm-level value added per worker and health costs from firms' actual location versus those if firms were randomly located within their sub-county. To do so, we first recover the average predicted pollution across all grid cells in a sub-county, which corresponds to the pollution that the average firm would be exposed to if firms were randomly located across cells within sub-counties. We then compare such level of pollution to the average exposure from the observed location of all the firms in our census, which we compute by weighting the grid-cell average pollution by the number of firms actually located in each cell. We repeat the same procedure for value added per worker. Results are presented in the first column of Table 7. 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 have also meant lower access to customers, hence lower firm profitability and ultimately value added. Following the same approach, we find that random location would result in a loss in annual value added per worker of \$42.

One way to quantify the relative magnitudes of the impact of the random allocation on life-expectancy and profitability is to consider the return in terms of life-expectancy of a policy to relocate individuals. We can then compare those benefits with the WHO guidelines in terms of cost-effectiveness. Specifically, we consider a policy that relocates individuals to replicate the random firm allocation within sub-counties described above, and compensates them for the present value of earning losses from such move (discounted at either a 5% or 10% interest rate). This policy would cost about \$758 (or \$453 at the 10% discount rate) per individual, but would increase life-expectancy by 1.89 months. The WHO guidelines (Iino et al. 2022) indicate that a policy investment should cost no more than 3 times GDP per capita for one year of life saved, thus suggesting that this policy would not be cost-effective: given that per capita GDP in Uganda is \$720, for the increase in life expectancy of 1.89 months to be cost-effective, the policy should have cost at most \$340. Thus, the policy would imply a net negative surplus of about \$-418 per capita (\$-112 for 10% discount rate) (Panel C). In other words, given the low level of development of Uganda, and the high cost (in terms of forgone value added) of locating away from where demand is, it would be hard to justify relocating firms to less polluted areas. It is crucial, however, to keep in mind that these back of the envelope calculations assume that the distribution of demand within cities is unaffected by the location of firms. Therefore, they are a useful benchmark to quantify the choices of individual firms, but do not offer proper policy counterfactuals.[48]

As a final benchmark exercise, we show the potential from pollution avoidance in our setting by comparing the predicted value added and health costs of firms' actual location versus those if firms were to actively *avoid* polluted and busy roads. We find that moving all firms to grid-cells at the 10^{th} percentile of the distribution of pollution (and profitability) 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 $138.8 (Panel B).

Unequal impact between workers and owners: similar cost, different benefits. Pollution exposure has a similar negative impact on the health of all individuals in the firm. The benefits from the increased profitability of locating in polluted areas are, however, not split equally. In columns (2) and (3) of Table 7, we show that most of the benefits accrue to the firm owners since, as we discussed in Table 3, locating in polluted areas has a much larger effect on firm profit than on workers' wages. In fact, the random allocation would translate into a loss in annual salary of only $10.9 for the average worker, as firm owners capture most of the surplus from higher revenues in busy and polluted areas with an increase in profits of $195 (Panel B).[49] In Panel C, we notice that this implies that the relocation policy discussed above would be highly cost-effective for workers, but definitely not for firm owners.[50]

7.2 Awareness of Pollution Levels and of the Costs of Pollution

The results in the previous section have shown that firm owners have large benefits, in terms of profits, from locating in polluted areas. While this result suggests that firm owner might rationally sort towards polluted areas to maximize their profits, the very low level of mitigation and the high health cost still opens up the possibility that firm owners are imperfectly informed. If firm owners underestimate either (i) the costs of pollution or (ii) the levels of pollution, this could alter the (perceived) cost-benefit calculation, potentially leading to over-sorting into

[48] We investigate the sensitivity of these results in Panel C of Table 7, which shows that the lack of cost effectiveness of the policy 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 of Oster (2019) and described in Appendix A.3 for firm owners. Only under a 0.90 discount rate and measured rather than predicted pollution would the policy be cost effective for the average worker in the firm (but not for owners).

[49] These back of the envelope calculations also give an upper bound on the (dis)amenity value of pollution exposure for firm owners, who mostly work at the premises of the firm themselves. This includes both the long term health effects, proxied by the loss of life expectancy, and the short term health and non-health effects (e.g., difficulties breathing, smell etc.). In a static framework, the annual, total disamenity value of pollution exposure must be lower than $195, the gain in profits.

[50] In all these calculations we assume no in-place adaptation given the limited overall levels of adaptation documented in Table 6. While column 2 of Table 6 shows that about half of the workers report engaging in some protective strategy, we notice that the main reported strategy is wearing a scarf/tissue (Appendix Figure A21) which likely has a very small impact on protection.

polluted areas and underinvestment in protective strategies. In Appendix A.6, we study firm owners awareness of pollution and show that while they 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.[51]

A simple information experiment. Motivated by this evidence, we investigate whether information campaigns could correct firm owners' underestimation of pollution by randomly exposing the owners in our sample to an information experiment. The experiment 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. To calculate the actual relative pollution and access to customers of each grid cell we use the data collected at baseline.[52] Thus, there are two separate information experiments, each with its own treatment and control group. Firms with available information on both relative pollution and profitability can be part of both experiments. The two treatments are independent.[53]

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 the firm owner the opportunity to buy them for a *medium* price (UGX $2,000$). If at least one map is still not purchased at this price, we make one last offer to sell them at a *low* price (UGX $1,000$). The elicitation

[51]In Appendix A.6 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 Table 6.

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

[53]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 1) we did not feel confident in the precision of our estimates of (predicted) local profitability for grain milling. Appendix Table A13 shows the sample sizes and balance checks for the two experiments.

of willingness to pay for the maps is incentivized and the stakes are relevant for our sample. We create two sets of outcome variables: a dummy if the owner is willing to pay the high price for the pollution/profitability map, and a variable that takes 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 8. Columns 1 and 2 show treatment effects on demand for air pollution maps. Column 1 shows that providing information on local pollution increases the probability that the firm owner is willing to pay the high price 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 the pollution 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. Interestingly, we find that higher ability owners demand more information, which is consistent with them being more aware of pollution as a problem but not of relative pollution levels, something that in Appendix A.6 we show holds for our non-experimental data. Comparing column 2 with column 3, we notice that the treatment leads to an increase in willingness to pay comparable to a 2σ increase in managerial ability. That is, the treatment effect is roughly equivalent to turning low ability managers into high ability ones, in terms of their demand for information.[54] 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.

These results are notable in that they uncover the presence of information frictions on relative pollution within the city, and highlight how simple information interventions could plausibly increase awareness and trigger demand for more information. While such information campaigns may be a promising way to change attitudes and increase adaptation investments, it is unlikely that they may be sufficient to affect location choices by themselves, due to the strength of the trade-off between profitability and pollution documented in Section 7.1. Therefore, we conclude this section with a discussion of the potential role of "bigger push" structural policies, which policy-makers might want to consider in addition to information interventions.

[54] We do not find a significant correlation between being located on larger roads and demand for information.

7.3 Policy Implications

The back of the envelope analysis in Section 7.1 tells us that a firm owner would need to assign a very high value to her life to be willing to locate in less profitable and less polluted areas. However, as we noticed, this is a partial equilibrium exercise relevant for the decision of a marginal firm: if all firms were to relocate, the bundling of pollution and profits may change as customers readjust their commuting in the city. Firms may thus be currently stuck in a bad equilibrium, from which any single firm owner is not willing to deviate, but which could be altered by "big push" policies. Two mechanisms could lead to optimal firms' relocation to less polluted areas of the city: policies fostering firm growth, or urban policies creating industrial districts.

Growth policies and lessons from other sectors. First, policies fostering firm growth could enable firms to grow larger, separate production and retail activities, and invest in marketing. This might allow them to break the bundling problem and locate production in less polluted areas of the city.

To better grasp the potential of such un-bundling, we use the latest Census of Business Establishments for Uganda from 2010 to study how the sorting pattern that we have documented in manufacturing differs by firm size and sector, as not all sectors face the same organization of production. To do so, 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 4 but using the firm census and clustering standard errors at the sub-county level. The results are reported in Table 9. 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 5, restricting to firms in carpentry and metal fabrication. The sorting regression for manufacturing using the Uganda census is in column 2: the coefficient is 0.125. This is remarkably similar to our survey, which is reassuring. In column 3, we restrict the firm density in manufacturing in the Uganda census to firms with at least 10 employees, to study the role of firm size. 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 roads. This speaks to the relevance of policies fostering firm growth in protecting workers from pollution through firm relocation away from congested an polluted areas.

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 likely more expensive along large roads; (ii) in retail the sorting on large roads is almost twice as strong as in manufacturing, which is also expected, as retail firms face a strong incentive to locate where customers are; (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 closer to high-skilled services, the pollution exposure would decrease.

Urban policies. Second, more structural urban policies like industrial parks might help even small firms in breaking the bundling problem, by allowing a critical mass of small firms to relocate away from congested areas while still retaining visibility to customers through the scale of the park. As shown in Figure 5, there is significant heterogeneity in pollution within urban areas, so the gains from such relocation could be substantial.[55]

8 Conclusion

Air pollution is rising in developing country cities due to the lack of environmental regulations to reduce emissions (Grossman and Krueger 1995, Selden and Daqing 1995). This is becoming a critical health challenge in much of sub-Saharan Africa, where life expectancy may already be over two years lower due to air pollution (Air Quality Life Index). This raises the important question of who is most exposed and which policies can help limit exposure. Our contribution is to collect new micro data combining high-resolution pollution measurements with a rich firm-level survey. We show that in their search for customer access, small manufacturing firms in African cities end up locating in the most congested and polluted parts of the city, with large profitability gains but plausibly dire health consequences. For owners, the profitability benefits plausibly outweigh the costs in terms of loss of life expectancy. Workers instead bear most of the costs of such exposure, as the benefits in terms of wages from locating on large roads are much smaller for them.

These results have implications for the study of productivity in the developing world (Bloom et al., 2010a): even though it has been shown that air pollution has a negative effect on workers' productivity, our study highlights that locating in more polluted areas may lead to profit advantages for firms since pollution is correlated with access to customers through road traffic. This shows the importance of collecting data on environmental conditions and the output market to understand productivity differences across firms.

The results of an information experiment show that firm owners are imperfectly informed

[55] More generally, infrastructure investments and improvements in land use and transport policies can help mitigate the negative effects of pollution on worker productivity and welfare.

about pollution levels within the city, pointing to the importance of information campaigns and training interventions as effective means to change attitudes and increase investments in protective strategies. However, given the strength of the bundling between pollution and profitability created by large roads, bigger push policies - such as creating industrial parks away from city centers - are likely to be needed to induce firms to relocate and reduce exposure. Recent papers have started to evaluate the impact of policies aimed at relocating firms away from cities, finding that this leads to a reduction in pollution emissions in the city but to a reduction in firm outcomes and economic activity (Gechter and Kala 2022). Shedding light on which types of urban planning policies can best induce firms to relocate while minimizing any negative effects on productivity remains a promising avenue for future research.

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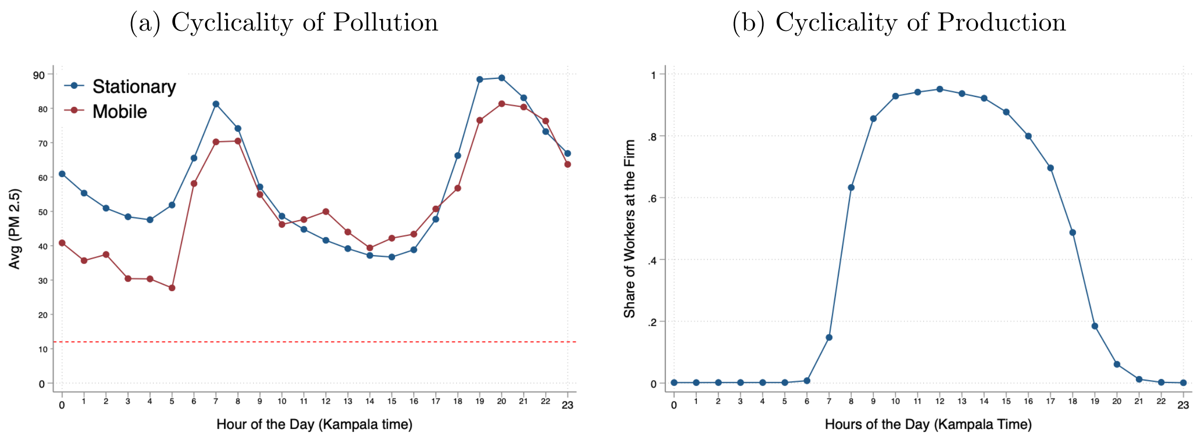
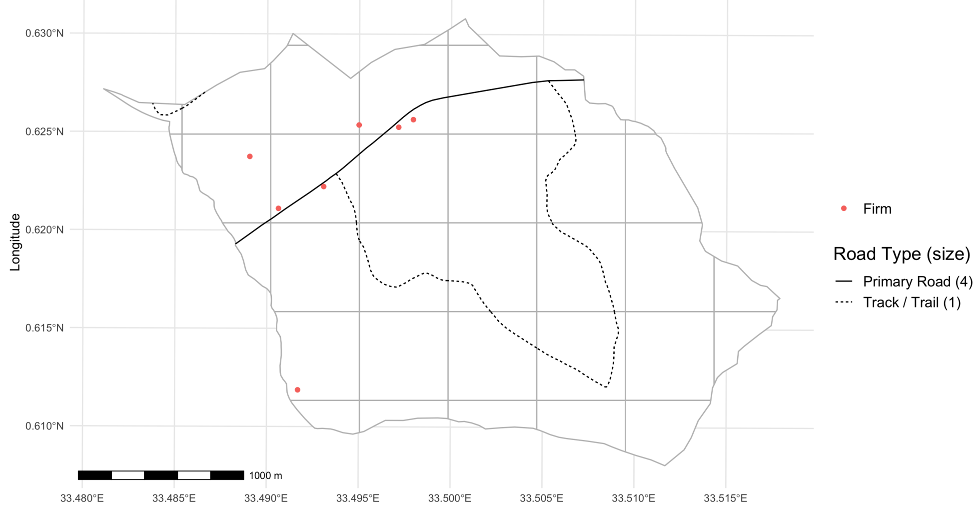
Figure 1: Cyclicality of Pollution and Production Within the Day



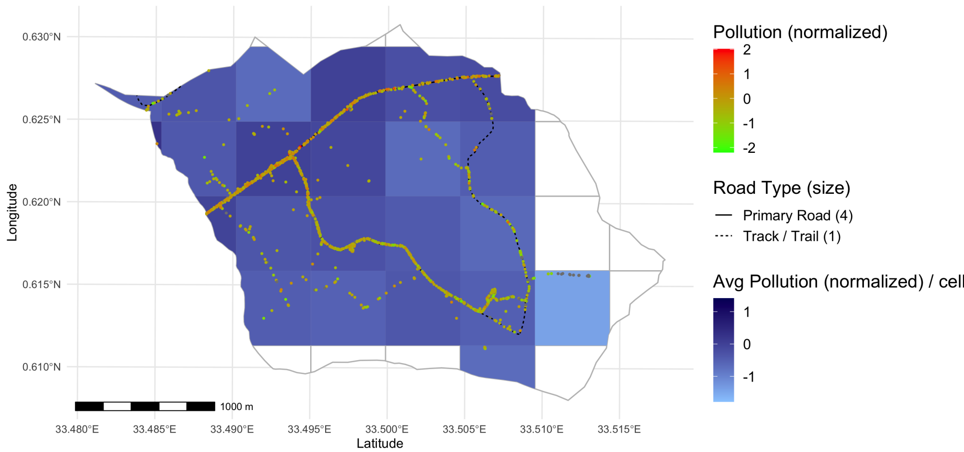
Notes: The left panel shows pollution cyclicality during the day, as measured by our stationary and mobile monitors. The red dotted line corresponds to the 2021 EPA guideline for average annual PM2.5 exposure. The right panel shows the share of employees who report working by hour of the day. In our 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: Firm Location and Road Size in a Sampled Sub-county



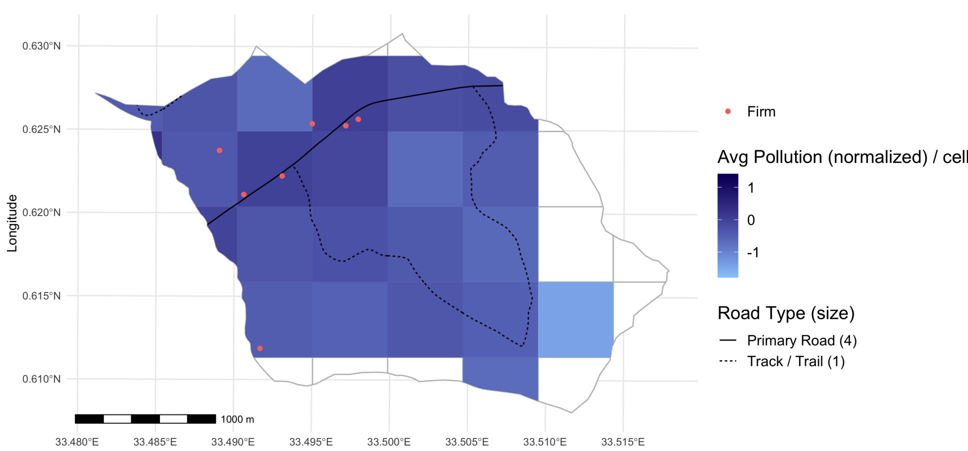
Notes: Location of firms in our survey and roads for the sampled parish in Nakalama sub-county (Iganga District). Road sizes are defined in Section 3.4. Grid cell dimensions are 500m x 500m.

Figure 3: Residual Pollution and Road Size in a Sampled Sub-county



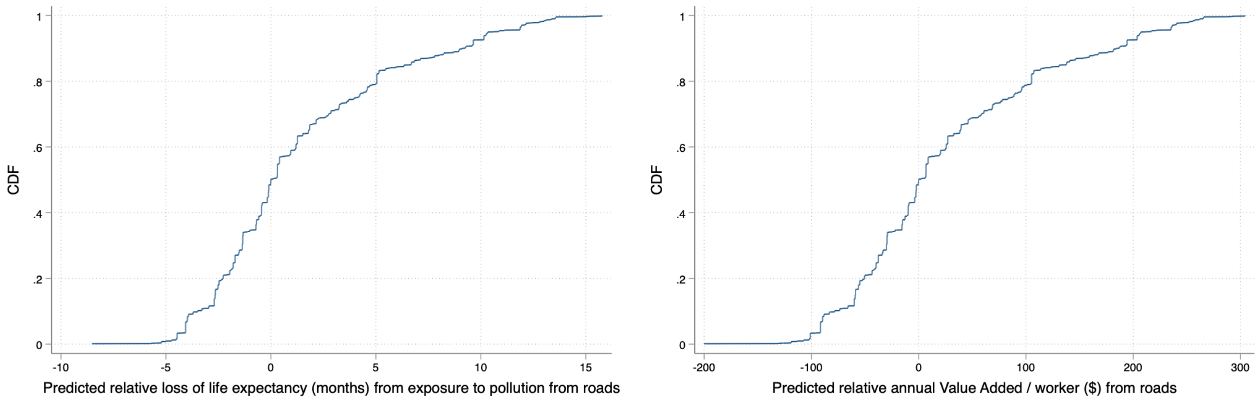
Notes: Location of roads, location of pollution measurements from mobile monitors and average pollution residual per grid cell for the sampled parish in Nakalama sub-county (Iganga District). Road sizes are defined in Section 3.4 and the computation of pollution residuals is described in Section 5.1. Grid cell dimensions are 500m x 500m.

Figure 4: 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 5.1. Grid cell dimensions are 500m x 500m.

Figure 5: 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 1: 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 2: 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 5.1.

Table 3: Benefits of Locating on Large (and Polluted) Roads

	(1) log(Profit)	(2) log(Profit)	(3) log(Profit/Worker)	(4) Nb Customers	(5) log(Rev)	(6) log(Salary)	(7) log(Salary)	(8) log(Rent)
Median Road Size/Cell	0.155	0.145	0.0800	0.250	0.132	0.0294	0.0250	0.106
	(0.0314)	(0.0325)	(0.0327)	(0.0975)	(0.0316)	(0.0157)	(0.0152)	(0.0288)
Man. Score		0.237	0.131	0.413	0.292	0.0878	0.0842	0.0747
		(0.0310)	(0.0278)	(0.106)	(0.0296)	(0.0193)	(0.0192)	(0.0296)
log(Size Premises)								0.0499
								(0.0213)
N	967	967	967	792	976	2272	2272	655
R2	0.506	0.537	0.483	0.374	0.449	0.316	0.392	0.476
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	Employee	Employee	Firm
SE clustering	Grid Cell	Grid Cell	Grid Cell	Grid Cell	Grid Cell	Grid Cell	Grid Cell	Grid Cell
Employee Controls						No	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 are trimmed. Road size goes from 1 (Trail/Track) to 5 (Highway).

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: 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 D: 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 Panel B and 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, C and D comes from the baseline survey. The questions in Panel C were only asked to firms that had relocated (or considered to relocate) their premises in the previous year (138 firms). For Panel C, firms were asked to indicate their top 3 out of a list of 18 potential reasons for their location choice. Panel C 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 C report the most common reasons; the three bottom rows report the environmental-related reasons.

Table 5: 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 5.1.

Table 6: 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.

Table 7: 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 ($)	720	720	720
WHO cost-effectiveness guidelines - 1 year LE	2,160	2,160	2,160
Estimated Elasticities and Quantities from Our Data			
Elasticity of Pollution to Road Size	0.0767	0.0767	0.0767
Elasticity of Earnings to Road Size		0.145	0.0294
Average Annual Earnings ($)	1,203.1	2,923.2	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	-3,516.2	-196
NPV Δ Lifelong Earnings ($\beta = 0.90$; Over 40 years) ($)	-453	-2,099.4	-117
Move to 10^{th} Pct. Exposure Within the Same Sub-county			
Δ PM2.5 Exposure ($\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) ($)	-2,500.9	-11,590.1	-645.9
NPV Δ Lifelong Earnings ($\beta = 0.90$; Over 40 years) ($)	-,493.1	-6,919.8	-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	-3,176	145
- $\beta = 0.90$; Over 40 years ($)	-112	-1,759	224
(ii) Sensitivity: Measured Pollution (Rather Than Predicted)			
- $\beta = 0.95$; Over 40 years ($)	-249	-3,006	314
- $\beta = 0.90$; Over 40 years ($)	57	-1,589	393
(iii) Sensitivity: Oster Lower Bound on the Elasticity of Profits to Roads			
- $\beta = 0.95$; Over 40 years ($)		-2,942	
- $\beta = 0.90$; Over 40 years ($)		-1,619	

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 1, 2 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 10^{th} 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 6.

Table 8: 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 7.2 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.

Table 9: Correlation Between Pollution 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 colunm 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).

A Appendix

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.[56] 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,
  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

[56] 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.

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).

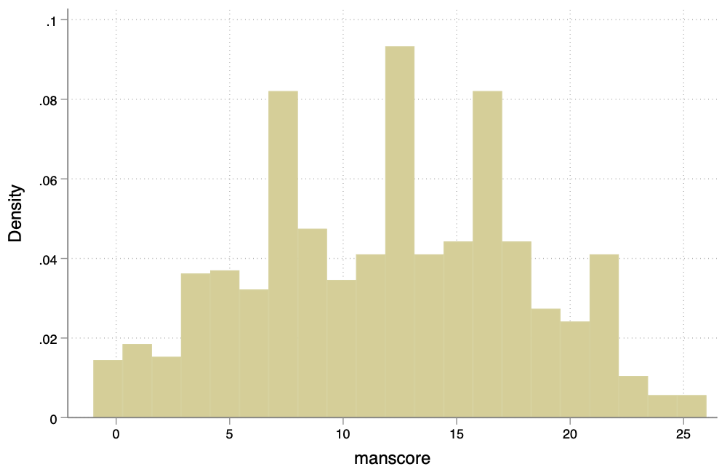
- The *forecasting* score ranges from a minimum score of 0 to a maximum of +5. The score is calculated by adding one point for each of the following activities reported by the firm owner/manager at the time of the survey:

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

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).

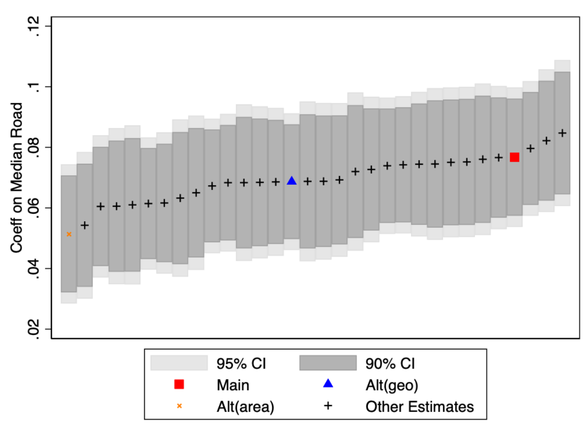
[57]The average ([Q25, Q75]) raw managerial ability score index is 11.6 ([8, 16]) for carpentry, 11.9 ([8, 16]) for metal fabrication and 12.6 ([7, 18]) for grain milling.

A.2 Grid Construction and Robustness Checks

As described in Section 5.2, 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.

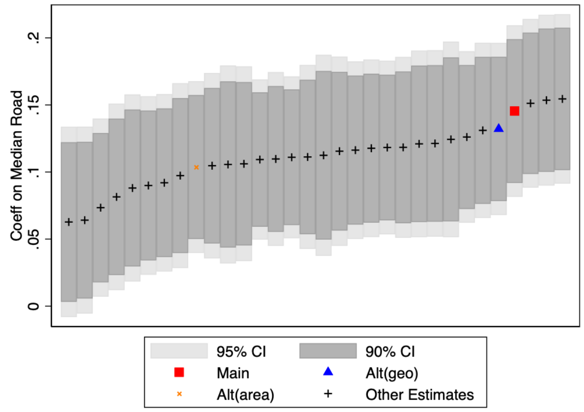
By default in the software used to generate the grids, the bottom-left grid cell matches the bottom-left corner of the smallest rectangle covering these sampled parishes. The grid starting point (i.e., coordinates of the bottom-left corner) may mechanically affect the aggregation of firms, pollution 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 2, col 1)



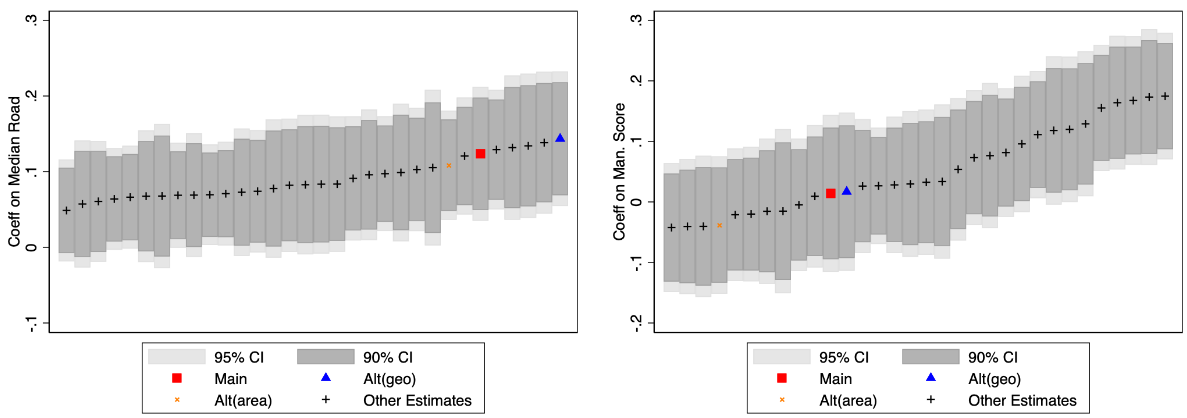
Notes: We run the specification in Table 2, Column 1 for different starting points of the covering grid. The red square is the estimate from our main specification. The blue triangle corresponds to the mirroring specification as described in Appendix A.2. The orange cross corresponds to the randomized 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(profit) on median road size/cell (Table 3, col 1)



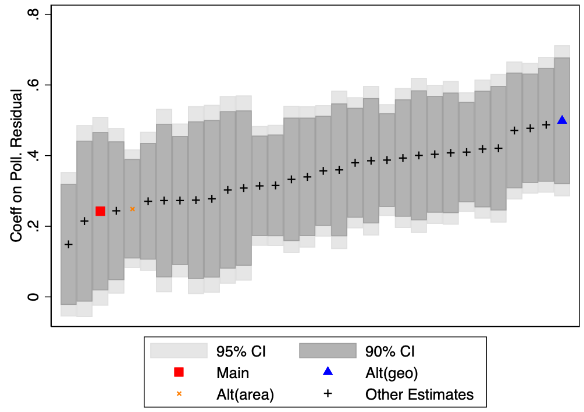
Notes: We run the specification in Table 3, Column 1 for different starting points of the covering grid. The red square is the estimate from our main specification. The blue triangle corresponds to the mirroring specification as described in Appendix A.2. The orange cross corresponds to the randomized 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 A4: Log firm density per grid cell on median road size and average managerial score (Table 5, col 5)



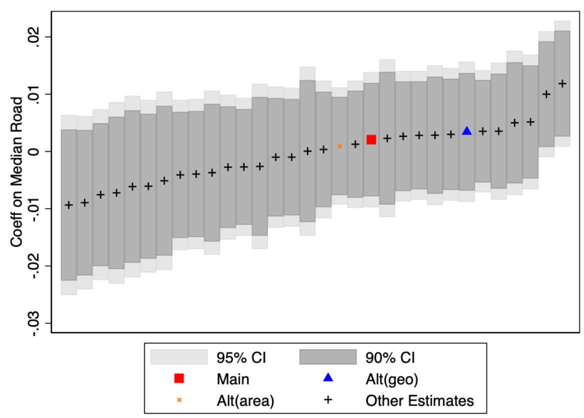
Notes: We run the specification in Table 5, Column 5 for different starting points of the covering grid. The red square is the estimate from our main specification. The blue triangle corresponds to the mirroring specification as described in Appendix A.2. The orange cross corresponds to the randomized 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 A5: Log firm density per grid cell on average log pollution residual (Table 5, col 6)



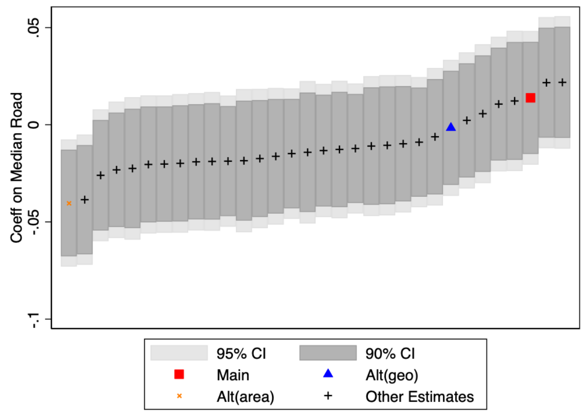
Notes: We run the specification in Table 5, Column 6 for different starting points of the covering grid. The red square is the estimate from our main specification. The blue triangle corresponds to the mirroring specification as described in Appendix A.2. The orange cross corresponds to the randomized 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 A6: Manager's use of protective equipment in the firm on median road size/cell (Table 6, col 1)



Notes: We run the specification in Table 6, 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 6, col 2)



Notes: We run the specification in Table 6, 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 Benefits of 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 5, 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 5, 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 5, but where sub-county and sector fixed effects are netted out before running the regression.[58] We also show robustness to using the more conservative assumption of $R_{max} = 2 \times \tilde{R}$ and even $R_{max} = 3 \times \tilde{R}$,

[58] 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 5 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: Benefits of 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: Benefits of 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.4 Limited Role of Worker Sorting in Explaining the Results

As discussed in section 6.3, the inclusion of worker-level controls in the regressions in Tables 6 and A7 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 A4, 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.[59] 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.[60] The lack of sorting on our pre-determined measure of employee pollution awareness limits concerns that the specifications in Tables 6 and A7 with employee controls might capture sorting. Nevertheless, in Appendix Table A5 we verify that the results in Table 6 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 A7 (odd columns). This further reassures us that the results on owners' adaptation are not primarily driven by sorting.

[59] 18% of workers report that pollution was an important consideration in their location decision.

[60] Appendix Table A6 shows that employee age and education do predict awareness as pollution as a problem.

Table A4: 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 A7 (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 A5: 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 A7 (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 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.5 Counterfactual Exercise: Predicting Pollution and Profits

In Section 7.1, 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 2, column 1, and the elasticity of profit to road size from Table 3, respectively. Here we give more details on the calculations.

Predicting Profits

In Table 3, 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, $\widehat{\log Y_c}$, 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

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

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 6 of Table 3.).

Predicting Pollution

In Table 2, 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 $\hat{b}$

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

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 $\widehat{res_c - \overline{res_c}^s}$ into $\widehat{poll_c - \overline{poll_c}^s}$, or the predicted pollution (in levels) at the grid-cell level, in deviation from the sub-county average, for average FEs, we calculate:

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

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:

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

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 $\hat{\overline{Y}}^s_{actual}, Y \in \{poll, profits, salary\}$, given the total number of firms in subcounty 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 10^{th} 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.6 Perceived Costs of Pollution and Pollution Levels

The perceived costs of pollution depend on managerial ability. In Table A7, 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.[61]

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).[62] 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.4 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 A8, 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

[61] Owners were asked about their perceived costs of pollution during the follow-up phone survey.
[62] Workers were asked about their perceived costs of pollution during the baseline survey.

variable takes values 1 (low), 2 (average) or 3 (high).[63] Analogously, within each sub-county, we categorize grid-cells into low (1^{st} tercile), average (2^{nd} tercile) or high (3^{rd} tercile), based on the actual measurements from our mobile pollution monitors (net of time variation, as described in Section 5.1) . 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.[64] 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.

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 A8. This suggests that the higher levels of adaptation by higher ability owners documented in Table 6 are the result of higher awareness of pollution as a problem for productivity and health (as shown in Table A7), rather than of higher awareness of relative pollution levels per se.

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

[64] 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 A7: 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.

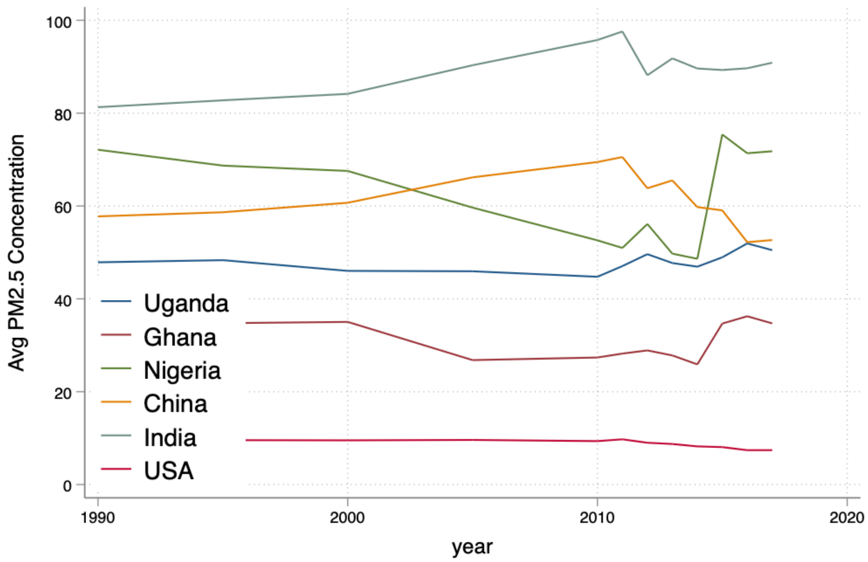
Table A8: Firm Owners Perceive the Positive Correlation Between Pollution, Profitability, and Road Traffic

	(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.

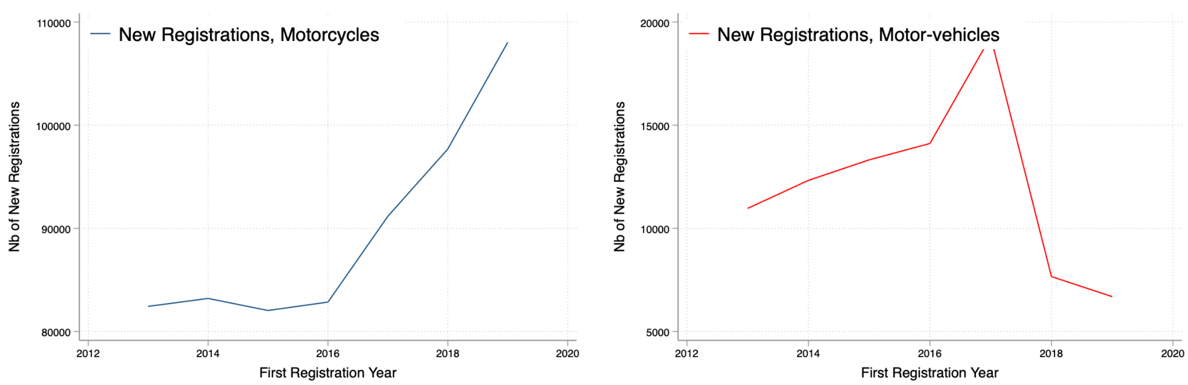
A.7 Additional Tables and Figures

Figure A8: Average Annual Pollution Over Time in Selected Countries



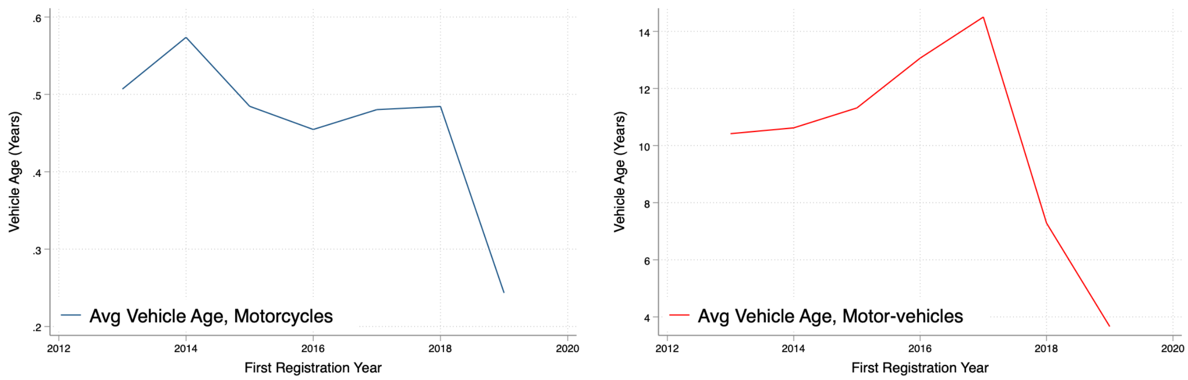
Notes: Average PM2.5 concentration (microgram per cubic meter) in selected countries over time. Source: World Bank.

Figure A9: Vehicle Registrations Over Time in Uganda



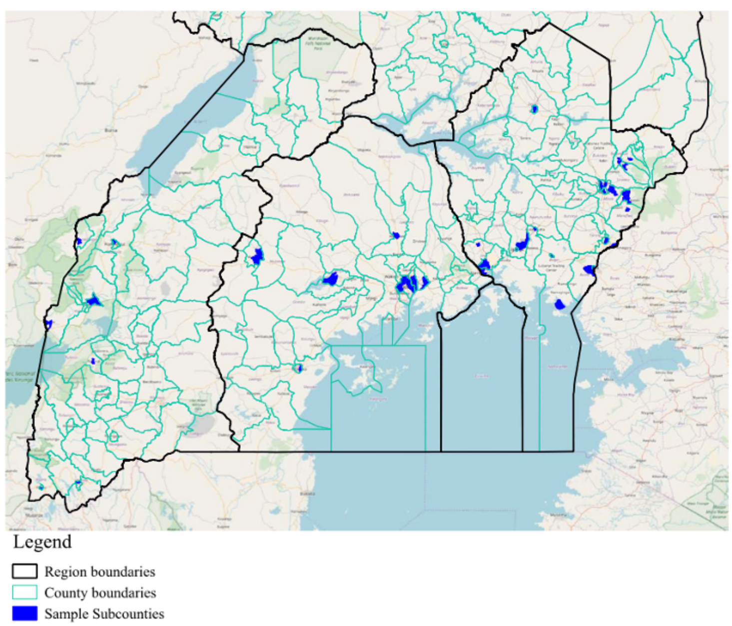
Notes: Annual number of first registrations for motorcycles (left panel) and motor-vehicles (right panel) from 2013 to 2019. The number of new motorcycle registrations has been sharply increasing since 2016. The number of newly registered motor-vehicles peaked in 2017. Source: Uganda Revenue Authority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

Figure A10: 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 A11: Geographical Scope of the Survey

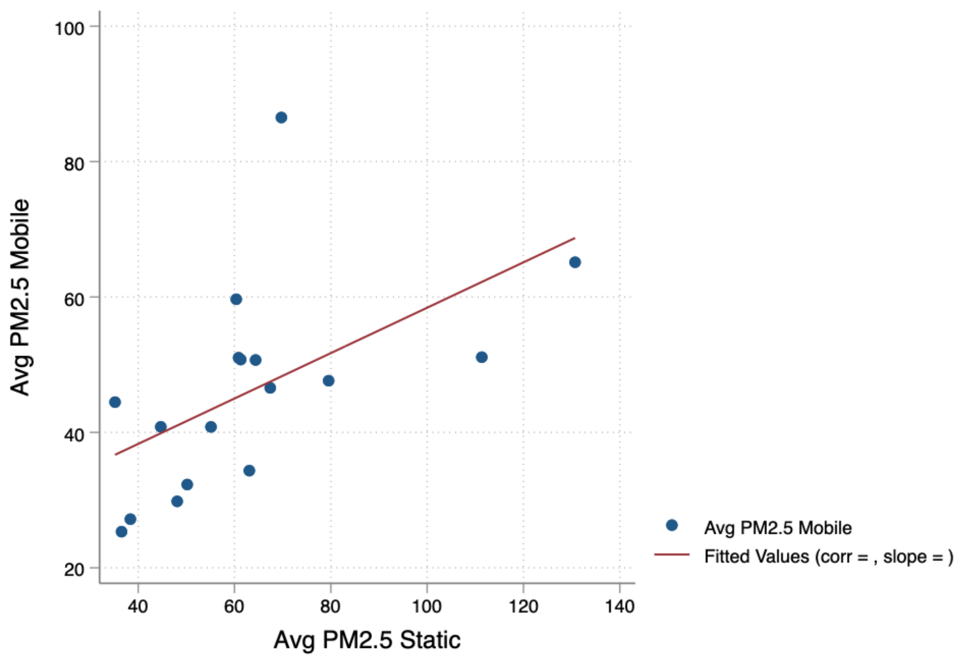


Notes: The figure shows in dark blue the sub-counties in our sample. The figure highlights that our sample region is scattered across three of the four regions of the country (Central, Eastern and Western).

Figure A12: Stationary and Mobile Monitors

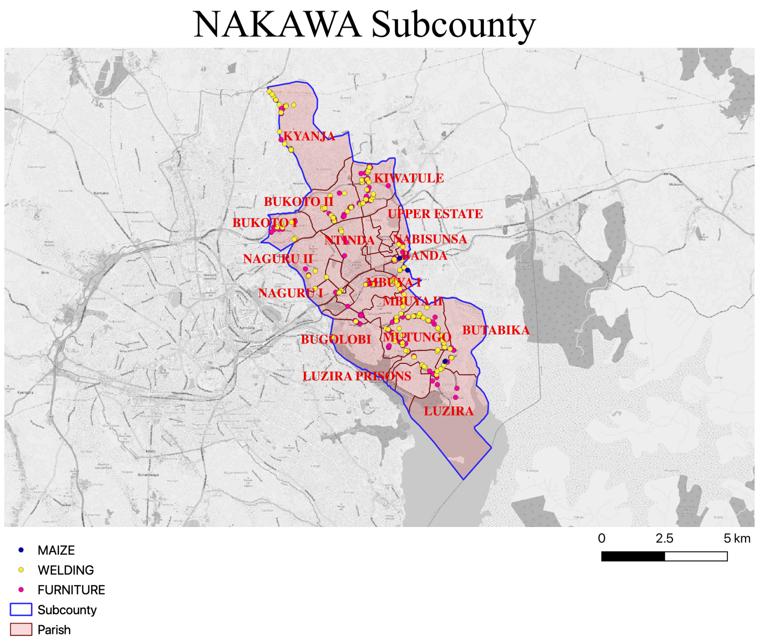
Notes: Photos of AirQo stationary (left panel) and mobile (right panel) pollution monitors.

Figure A13: Correlation Between Average Measurements from Stationary and Mobile Monitors at the Sub-county Level



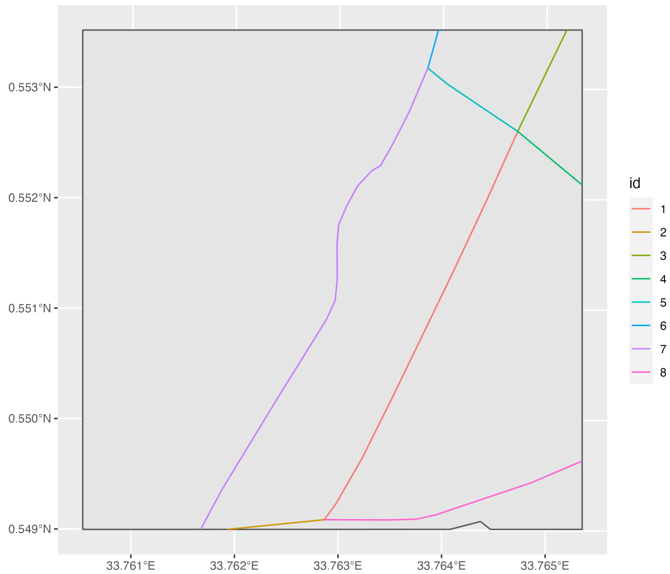
Notes: Data is from the full sample of PM2.5 measurements from the stationary and mobile monitors. We create sub-county level averages of pollution measurements from both types of monitors and plot them against each other. The figure shows that the two are positively correlated.

Figure A14: Example of Listing Exercise in One Sampled Sub-county



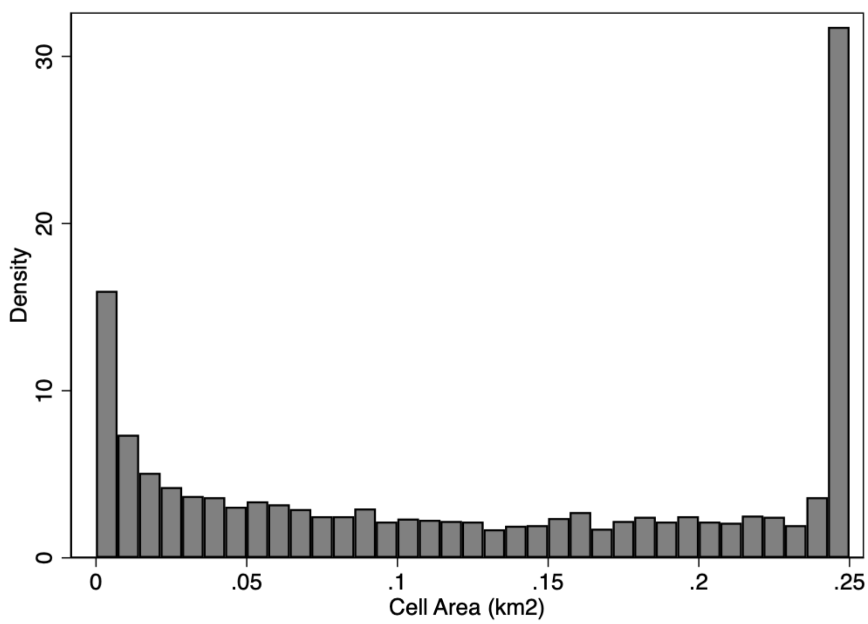
Notes: The figure shows the location of the firms identified in our initial listing in one sampled sub-county.

Figure A15: Illustration of Road Definition



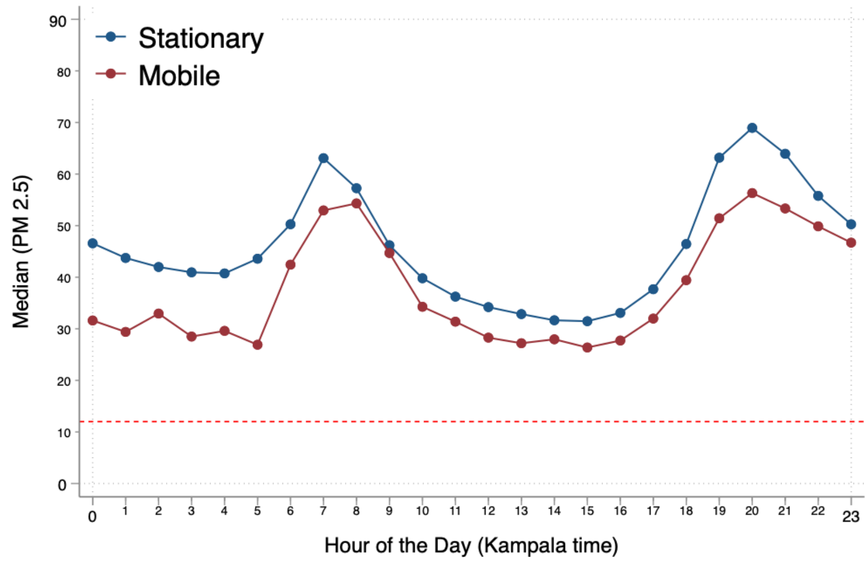
Notes: Each color represents a different road as defined in our dataset by a road segment not intersected by any other road. This grid cell, part of Bugiri Eastern Division, contains eight different roads. The median average grid cell in our sample contains 6 roads (average 11).

Figure A16: 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 A17: Hourly Fluctuation in Pollution Within the Day (Medians)

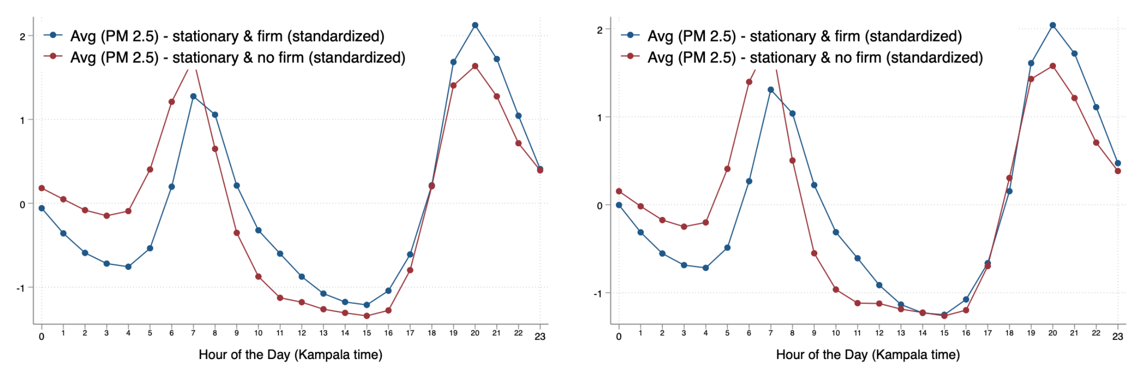


Notes: Medians of PM2.5 measurements from our stationary and mobile monitors are plotted for each hour in Kampala time. The dotted orange line corresponds to the 2021 EPA guideline for average annual PM2.5 values.

Figure A18: Cyclicality of Pollution Does Not Depend on Firm Density

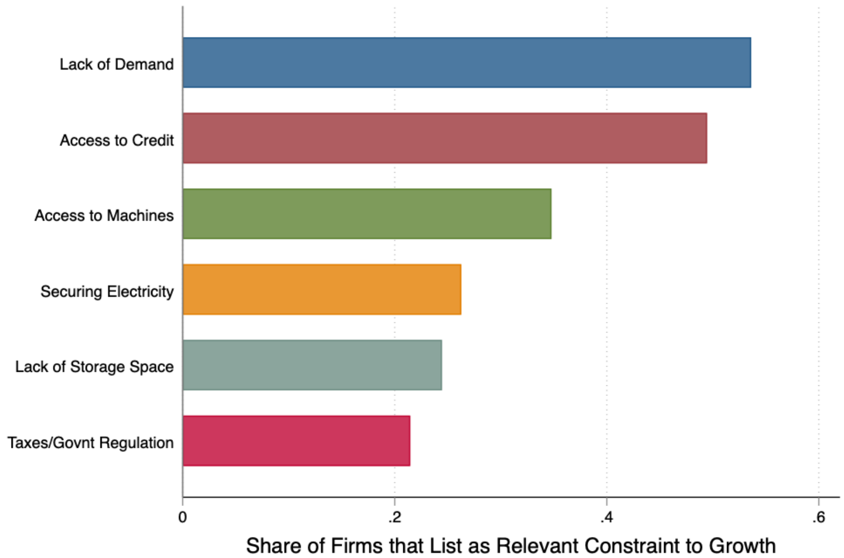
(a) Full Sample

(b) Restricting to Cells Containing at Least One Road



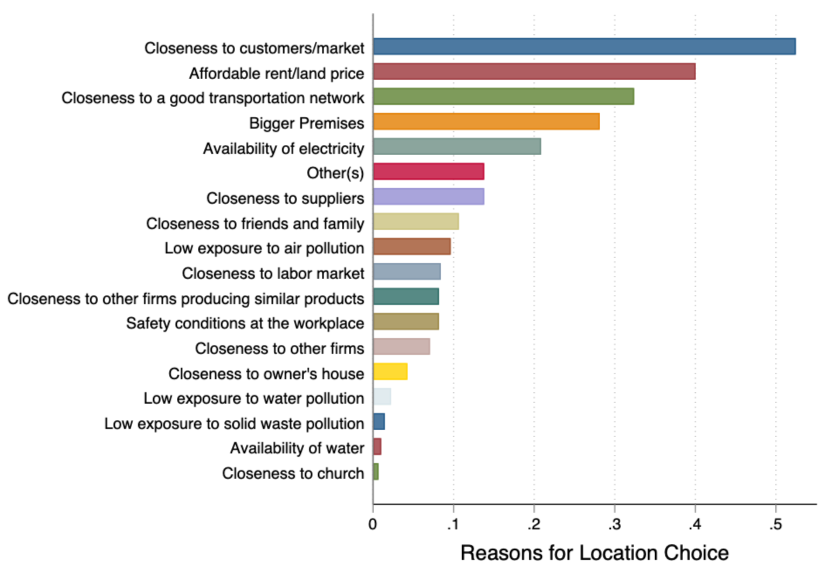
Notes: Avg (PM2.5) is the standardized mean PM2.5 measurement from stationary monitors by grid cell and hour. Grid cells with (without) firm correspond to grid cells containing at least one (no) firm from our initial listing. Normalizing PM2.5 concentrations allows us to focus on pollution cyclicality.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

Figure A19: Lack of Demand is the Main Reported Constraint to Firm Growth



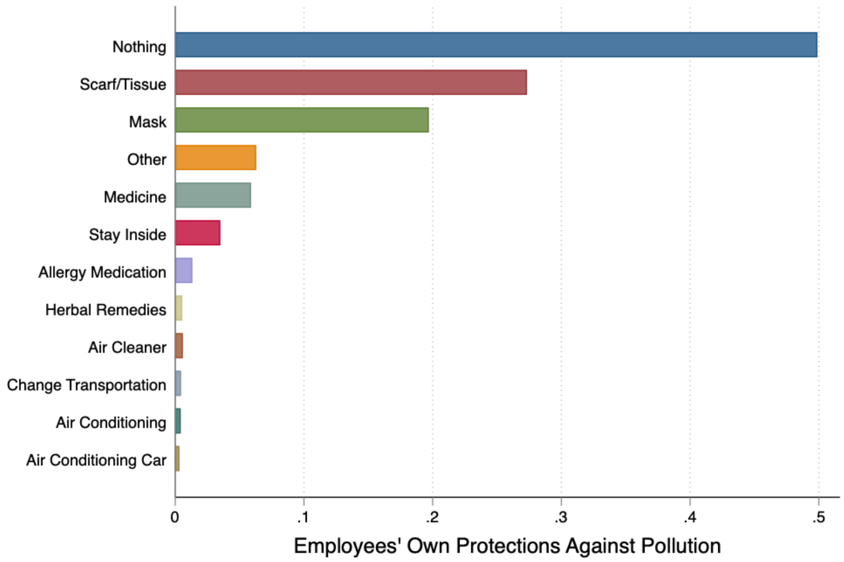
Notes: In the baseline survey, firm owners were asked about the main perceived constraint when thinking about increasing the profitability of their business. Managers could choose among a list of 14 possible constraints, indicating up to three constraints. For each potential constraint, we report the 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 A20: 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 A21: 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.

Table A9: 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 2,754 km 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: Open Street Map (OSM).

Table A10: Benefits of Locating on Polluted Roads

	(1) log(Rev/Worker)	(2) log(Rev)	(3) log(Profit/Worker)	(4) log(Profit)	(5) log(Salary)	(6) log(Salary)	(7) log(Rent)
Avg log(Poll) Resid./Cell	0.229	0.253	0.261	0.250	-0.104	-0.0402	0.00743
	(0.135)	(0.132)	(0.137)	(0.129)	(0.0729)	(0.0649)	(0.124)
Man. Score	0.178	0.260	0.133	0.196	0.0631	0.0563	0.0854
	(0.0347)	(0.0370)	(0.0319)	(0.0378)	(0.0247)	(0.0230)	(0.0422)
log(Size Premises)							0.0369
							(0.0238)
N	595	601	592	591	1359	1359	411
R2	0.357	0.392	0.398	0.441	0.254	0.370	0.405
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	Employee	Employee	Firm
SE clustering	Grid Cell	Grid Cell	Grid Cell	Grid Cell	Grid Cell	Grid Cell	Grid Cell
Employee Controls					No	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 are trimmed. Road size goes from 1 (Trail/Track) to 5 (Highway). The procedure to construct pollution residuals is detailed in section 5.1. The number of observations is lower in Table A10 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 A11: Location Choice - Proximity to Home

	(1)	(2)	(3)	(4)
	Log dist work	<2km from work	<1km from work	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 A12: 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 A8 - col 2, table 6 - col 1 and table 6 - 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 A13: 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.

Table A14: 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 7.2 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.

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