Pollution in Ugandan Cities: Do Managers Avoid it or Adapt in Place?*

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July 14, 2021

Abstract

Developing countries suffer from rising urban pollution levels, with associated negative effects on health and worker productivity. We study how managers in developing country cities cope with the polluted environment. We collect high resolution pollution measurements within Ugandan cities and match these with a novel firm survey. We find that firms locate in close proximity to major polluted roads, which bundle a bad (exposure to pollution) with a good (market demand). Higher ability managers do not avoid polluted areas, but better adapt to the pollution by protecting their workers through both provision of equipment and flexibility in work schedules.

*We gratefully acknowledge financial support from CEGA, IGC, PEDL, and USC. We also acknowledge support from the Pollution Management and Environmental Health Program (PMEH) supported under the World Bank's TF0A3415. The PMEH program focuses on providing technical assistance to countries, facilitating pollution management, promoting public awareness, and helping them reduce the negative effects of pollution on health. We thank Bjoern Brey for an insightful discussion. We also thank Simon Franklin, Jonas Hjort, Namrata Kala, Paulina Oliva, Munir Squires, as well as seminar participants at USC, John Hopkins, the European Meeting of the Urban Economics Association, and PacDev for useful feedback. Kasey Chatterji-Len, Jiong Gao, Jung Hyuk Lee and Leire Sarasola provided excellent research assistance. We also thank everyone at BRAC Uganda who made this project possible, in particular Raffaela Muoio and Esau Tugume. This study received ethical approval from the Mildmay Research Ethics Committee of Uganda (MUREC), Reference No. 1106-2018. The findings, interpretations, and conclusions expressed in this paper are entirely those of the authors. They do not necessarily represent the views of the International Bank for Reconstruction and Development/World Bank and its affiliated organizations, or those of the Executive Directors of the World Bank or the governments they represent. All errors are our own.

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1 Introduction

Developing countries are becoming increasingly urbanized and this trend is expected to continue, with half of the population in low-income countries projected to live in cities by 2050 (Glaeser and Henderson 2017, United Nations 2019).

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 increasing pollution generates severe health consequences which may reduce worker productivity. Recent research has established the negative productivity effects of pollution exposure.[2] These effects are likely to be even more severe in developing countries due to poor healthcare systems.

Managers may play a key role in mediating the severity of the health cost of pollution on worker productivity, especially in low income countries where the ability of governments to regulate pollution emissions and work conditions is limited by weak state capacity. As air pollution is not uniformly distributed within the city, the location choice of where to set up the firm determines workers' pollution exposure. Managers can also undertake mitigation investments to limit exposure to pollution conditional on location, such as providing their workers with protective equipment or putting in place organizational strategies to limit exposure, such as flexibility in work schedules to avoid exposure at peak pollution times. Despite an established literature on the role of management for firm productivity in both developed and developing countries (Bloom and Van Reenen 2007, 2011; McKenzie and Woodruff 2017), little is known on the role of managers in mediating exposure to pollution. Answering this question is important as it sheds light on another avenue through which good management may raise both firm productivity and worker welfare.

Our contribution is to fill this evidence gap by collecting a unique dataset that allows us to characterize the role of managers in polluted cities in sub-Saharan Africa. We combine street-level pollution measurements within Ugandan cities with rich information on management practices and investments to protect workers from pollution from a novel representative geocoded survey of manufacturing firms. Guided by a simple model that illustrates the trade-offs faced by a manager in a polluted city, we document three facts. First, we show that the nature of informal production in developing countries generates a location choice trade-off between high profitability areas, and areas with low exposure to pollution, since proximity to large and busy roads bundles a good (product demand) with a bad (pollution exposure). Second, we document

[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.

[2]See Graff Zivin and Neidell (2012), Chang et al. (2016), Adhvaryu et al. (2019) and Fu et al. (2021).

that, facing this trade-off, firms choose not to avoid pollution, but rather to cluster in the most polluted and high-traffic areas of the city. They do so primarily in order to access customers. Third, we find an important role of managerial skills: high ability managers do not avoid polluted areas, but better protect their workers from pollution exposure. Overall, our results bring new evidence on how pollution affects firms and workers, and uncover better adaptation to pollution as a novel channel through which good management raises worker well-being and firm productivity.

We begin by developing a simple model of a manager that maximizes profits in a polluted city to clarify how taking into account pollution exposure affects production choices, and how this relationship may be mediated by managerial ability. We consider three interrelated choices: (i) where to locate the firm; (ii) which type of workers to hire; and (iii) whether to mitigate the effects of pollution by investing in protective equipment or other organizational strategies to limit exposure. Managers wish to reduce pollution exposure to avoid a productivity cost, and to be able to hire high-skilled workers, who may demand more protection, for instance due to higher awareness of pollution and its effects on health. Managers have two means to reduce exposure: (i) by choosing a less polluted location (avoidance), or (ii) through investment in protective equipment or organizational strategies (adaptation). Both avoidance and adaptation are costly: less polluted areas may be less profitable, and protective investments come at a cost. This creates the key trade-offs in the model. Managerial skill is allowed to affect all these choices both through possible complementarities with location-specific profitability and workers' type, as well as through a potentially lower cost of protective investments. The framework offers a series of testable predictions that motivate our data collection and empirical strategy.

To test the model's predictions and offer a descriptive picture of how pollution exposure affects firm production, we collected pollution measurements at high spatial resolution and matched these to a novel firm survey with detailed information on firm location, managerial skills, and managers' investments to protect their workers from pollution exposure.

We gathered 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 novel representative geo-coded survey of 1,000 firms in small-scale manufacturing and their employees that we conducted in the same areas and at the same time as our pollution measurements (Bassi et al. 2021). For each firm, we have available detailed measures of productivity, such as profits per worker, as well as a range of questions about location choice, pollution avoidance behaviors and investments, and awareness of pollution as a problem among employees. Building on the seminal work of Bloom and Van Reenen (2007, 2011) and McKenzie and Woodruff (2017), our survey of small firms also includes a module on eliciting the manager's quality, which we use to generate one summary index of managerial skill. Finally, we have access to the geo-coded universe of Ugandan roads.

Guided by the model, we use this data to present three results on the role of managers in mediating exposure to pollution in urban Uganda. First, we show that road traffic bundles product demand and pollution exposure: areas near major roads are substantially more polluted, but also feature significantly higher profits per worker. As a result, location choice entails a trade-off between pollution exposure and market access. We also verify that the higher pollution is mainly driven by road traffic, and we use our survey data to provide direct evidence that the profitability benefits can be explained primarily by the fact that, as it is typically the case across the developing world, firms are small and do not have any means to market their products, so that they sell locally through face-to-face interactions. Hence, proximity to busy roads is essential to access customers. Having established the presence of bundling, we study how managerial choices determine workers' exposure to pollution within the city.

Our second result is that firms do not actively avoid polluted areas; in fact, they locate along the most trafficked, most highly polluted roads. This is true even within very small geographical units, and we rule out that it is driven by reverse causality by showing that firms themselves are not the source of pollution and the location of roads is pre-determined with respect to firm location. Importantly, managers' quality does *not* predict firm location choice. This rules out one potential type of differential avoidance behavior: even high ability managers have chosen to locate in the midst of pollution to access customers. Seen through the lenses of the model, this result shows that the profitability benefits of locating in busy areas outweigh the productivity costs of higher exposure to traffic pollution for all types of managers.

The fact that firms cluster along polluted roads opens up the possibility that workers may be exposed to substantial pollution. Our readings show that high-polluted areas within Ugandan cities feature similar pollution levels as Chinese cities. In addition, our survey confirms that these small manufacturing firms produce output mostly in the open air near the roadside. As a result, daily production activities are a large source of pollution exposure for workers, as they spend their whole day working essentially in the streets while being exposed to pollution. Documenting whether and how managers adapt to the local pollution exposure is therefore critical to understand the implications of the observed location choices on workers' welfare.

Our third result is that higher ability managers better protect their workers from pollution exposure. In addition to having higher profits per worker and paying higher wages, managers of higher ability are significantly more likely to provide pollution protective equipment (e.g., masks) to their workers, and to allow flexibility in commuting times to their workers to avoid being exposed to pollution at rush hour. In line with this, workers employed by high ability managers are more likely to report that their managers engage in active steps to protect them from pollution exposure, and these workers are also significantly more aware of pollution as a problem. As the model makes clear, these results could be driven either by high ability managers facing a lower marginal cost of adaptation, or by higher ability managers employing more highly skilled workers, who demand more protection. Our evidence is consistent with the first mechanism. That is, we show that our results on adaptation are not just driven by the sorting of better workers to better managers: while higher ability managers do employ higher skilled workers, controlling for a rich set of worker characteristics barely affects the role of managerial quality in explaining these results. The fact that mitigation activities include not only the provision of physical equipment but also changes in organizational strategies further suggests that the lower cost of adaptation for higher ability managers is not just driven by easier access to capital, and may reflect also a higher awareness of the costs of pollution on worker productivity.[3]

Taken together, our results highlight the importance of managerial quality in determining adaptation to environmental conditions and in limiting workers' exposure to pollution. In doing so, we contribute to a classic literature on the role of managers for firm productivity (Bloom and Van Reenen 2007, 2011; Bloom et al. 2013; McKenzie and Woodruff 2017; Bruhn et al. 2018). This literature has established that good management practices lead to a reduction in pollution emissions by firms: Bloom et al. (2010) document that higher quality managers are more energy efficient, and Gosnell et al. (2019) show the importance of management practices in reducing carbon emissions in the airline industry. In addition, recent evidence shows that higher quality managers are better able to respond to shocks to worker productivity caused by exposure to pollution: Adhvaryu et al. (2019) find that more attentive managers in Indian factories reallocate workers across tasks to mitigate the productivity impacts of exposure to pollution. Our contribution is to study the role of managers in *preventing* workers' exposure to pollution, distinguishing between the possible channels of avoidance and adaptation.

We also contribute to a growing literature on access to demand for small firms in developing countries. This literature highlights that information frictions are a critical source of inefficiency for buyers and sellers (Jensen and Miller 2018, Startz 2018) and that lack of managerial or marketing ability creates a sizable barrier to accessing new markets (Anderson et al. 2018, Hjort et al. 2020). As a consequence, small firms tend to sell locally. We contribute by highlighting exposure to traffic pollution as another negative consequence of firms struggling to tap into new markets and having to locate on busy roads to access the local demand. In doing so, we

[3] Our cross-sectional data is appropriate to study avoidance through location choice and adaptation through investment in protective equipment/organizational strategies, as these are likely the result of sustained exposure to pollution. However, our data is not appropriate to study the short-run (nor the long-run, which are inherently harder to pin down) productivity impacts of pollution exposure (or of adopting mitigation strategies), as identification would require high-frequency panel data on both pollution and firm outcomes. Therefore, we do not estimate the productivity impacts of pollution, and instead rely on an extensive literature that is able to do so with appropriate data (see Graff Zivin and Neidell 2012, Chang et al. 2016, Adhvaryu et al. 2019 and Fu et al. 2021).

also provide new insights to an established urban literature on agglomeration (Duranton and Puga 2004; Ellison et al. 2010; Combes and Gobillon 2015) and on the relationship between environmental amenities and location choice within the city (Kahn and Walsh 2015).[4]

Finally, we contribute to the literature studying the role of firms in driving wage inequality among workers (Song et al. 2019, Card et al. 2013). Recent work (Sorkin 2018, Morchio and Moser 2020) highlights that a large share of welfare inequality across firms is not due to differences in wages but rather to differences in non-monetary compensation, or amenities. We contribute by focusing on one specific dis-amenity - exposure to pollution - and showing how this varies as a function of manager characteristics. 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.

The rest of the paper is organized as follows. Section 2 presents background information on the context of our study. Section 3 presents the model. Section 4 describes the sample and data. The empirical strategy is discussed in Section 5 and the results are presented in Section 6. Section 7 concludes. Additional details are in the Appendix.

2 Background

In this section, we provide background information on the context of our study. We discuss trends in urbanization, motorization and pollution emissions in Uganda. Importantly, we highlight key findings from the literature showing that pollution has a negative effect on individuals' health and, consequently, workers' productivity. While our empirical work focuses on urban Uganda, the points we make below generalize to other developing countries.

Pollution levels in Uganda. Uganda features high levels of pollution: average annual concentration of PM2.5 particulate matter was 50.5 micrograms per cubic meter in 2017.[5] In Appendix Figure A10 we compare the evolution of average pollution levels in Uganda to the US, China and India. The figure shows that pollution levels in Uganda are similar to Chinese levels, and far higher than US levels. Pollution in Uganda is also far above the recommendations by the US Environmental Protection Agency (EPA), set in 2012 and confirmed recently

[4]Heblich et al. (2021) document the persistent effects of industrial pollution on neighborhood sorting within English cities. By focusing on location choices within as opposed to across cities, we also relate to a growing literature on how environmental conditions such as pollution or natural resource availability determine the sorting of firms and households across space and migration decisions (Gollin et al. 2021; Liu and Sekhri, 2021; Khanna et al. 2021; Chen et al. 2017).

[5]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 inhalable particles pose the greatest risk to health. For additional details see https://www.epa.gov/pm-pollution/particulate-matter-pm-basics.

in 2020, which suggest an annual standard of 12 micrograms per cubic meters, and a daily corresponding standard of 35 micrograms per cubic meters. Further, a 2016 WHO study (WHO, 2016) emphasizes that fine particle pollution disproportionally affects urban areas in Uganda with PM2.5 concentration 40 percent higher than in rural areas. This estimated urban-rural gap in pollution exposure is wider in Uganda than in India, China and the US.[6] Importantly, as shown in Appendix Figure A10, while both Chinese and Indian PM2.5 pollution levels have been declining since 2010 by 24 percent and 5 percent respectively, pollution in Uganda has been *increasing* from 44.8 to 50.5 micrograms per cubic meter, or an increase of 13 percent from 2010 to 2017.

Productivity and health effects of pollution. Such high and growing pollution levels are a serious concern as the impacts of air pollution on health and productivity are well established. Pope and Dockery (2006) argue that PM2.5 has been shown to be the deadliest component of air pollution. Early work provides evidence on how plausible exogenous changes in pollution affect health as measured by 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 concentration (10 percent of the mean) leads to 0.69 more deaths per million elderly over the following three days (0.18 percent increase relative to the average mortality rate). Anderson (2020) identifies a causal link between long-term exposure to air pollution from road traffic and adult mortality.

Air pollution, including fine particle pollution such as PM2.5, also has adverse effects on workers' labor supply and productivity. At the extensive margin, pollution 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. 2019 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 growth and increasing incomes that have been shown to speed up 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

[6]The corresponding median pollution concentrations (micrograms per cubic meters) reported by the same WHO study for Uganda, China, India and the US are: 57 (overall) and 80 (urban only) for Uganda; 54 (overall) and 59 (urban only) for China; 62 (overall) and 66 (urban only) for India; and 8 (overall) and 8 (urban only) for the US.

recent decades. The population of Kampala, the capital city, more than doubled since 1990 and has now reached over 1.5 million (UBOS 2016). Some estimates suggest that Kampala could have ten million inhabitants by 2040 (Hobson and Kathage 2017). Urbanization in Uganda has been accompanied by a rapid increase in motorization. The road network in Kampala was built in 1960 for about 100,000 vehicles per day. Today, about 400,000 vehicles per day use these roads (KCCA 2014)[7]. The growth of a second-hand vehicle fleet (see Appendix Figure A11), 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]

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 A12. 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 Conceptual Framework

We introduce a simple framework to clarify the key trade-offs that we study empirically in the next sections. Our goal in this paper is to study the role of managers in mediating the pollution exposure of workers. Therefore, we consider the problem of a manager that operates within a polluted city and maximizes profits. We focus on three decisions that are plausibly directly affected by pollution considerations: (i) the choice of the production location l; (ii) the choice of the ability of workers h, as high ability workers may be less willing to work in a polluted environment;[9] (iii) the amount of investment in equipment or organizational strategies to limit pollution exposure, e. We abstract from all other choices made by managers, such as firm size and capital intensity, which we assume are not directly affected by pollution exposure. We also abstract from any equilibrium consideration as our goal is not to characterize the equilibrium allocation of production, but rather to describe how firms are managed in polluted cities.

A manager i, with productivity (or ability) z_i, chooses a location l, workers' type h, and investments e to maximize profits, solving

[7]Cross-country research estimates an income elasticity of vehicle ownership of 1.1 (Dargay et al. 2007, Ingram and Liu 1999).

[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 driving up PM2.5 concentrations in Kampala and Jinja, two Ugandan cities: residential sites with unpaved roads had very high PM2.5 concentrations of 152.6 micrograms per cubic meter vs 120.5 micrograms per cubic meter on average in residential sites.

[9]Khanna et al. (2021) show that high-skilled individuals in China are more likely to migrate in response to pollution.

$$\max_{l,h,e} \underbrace{f(z,h)}_{\text{Output}} - \underbrace{\chi(p)}_{\text{Direct Cost of Pollution}} - \underbrace{w(h)}_{\text{Wage}} - \underbrace{c(e,z_i)}_{\text{Cost of Pollution Mitigation}} - \underbrace{R_l}_{\text{Rental Cost of Location } l}$$

$$\begin{aligned} &\text{s.t.} \\ z =& \quad g(z_l, z_i) \quad \text{(Productivity)} \\ p =& \quad p_l - e \quad \text{(Adaptation)} \\ w(h) \geq& \quad \Omega(h,p) \quad \text{(Compensating Differentials).} \end{aligned}$$

The first constraint shows that the firm productivity z is an increasing function of both the location-specific productivity z_l and managers' productivity z_i, as we assume that g is increasing in both arguments, with possible complementarities. The second constraint shows that the overall pollution exposure p depends on the location-specific pollution p_l but is abated by protective investment e. The third constraint shows that in order to hire workers of type h, a manager may need to offer them an environment with sufficiently low pollution – i.e., the wage must be higher than an exogenous function Ω that is increasing in both arguments with possible complementarities. We treat the wage, from the manager perspective, as an exogenous increasing schedule. This schedule should be interpreted as the reduced-form outcome of an equilibrium matching model which we do not model explicitly. Since managers do not directly choose the wage, if the compensating differential constraint is binding they must either choose a lower worker type h or offer more pollution abatement through higher investment e.[10]

We highlight two key assumptions embedded in this framework. First, we assume that pollution exposure has a direct negative effect on output by lowering worker productivity. As discussed in Section 2, a number of papers identify the negative short-run effects of pollution exposure on worker productivity. Second, we assume that workers are paid below their marginal product, so that there are rents to be shared between managers and workers, and the pollution exposure of workers potentially reduces managers' profits. This is justified by the literature on labor market frictions in developing countries, which finds evidence in line with substantial search frictions, driven primarily by lack of information on the skills of workers at recruitment.[11] Bassi et al. (2021) show direct evidence of labor market frictions in our same context.

Next, we characterize the solution of this problem and highlight how it may vary across managers of different ability z_i. The main goal of the characterization is to provide guidance and interpretation to the empirical results that we show below. While all choices are jointly

[10]In practice, allowing managers to offer a monetary compensation to workers to satisfy the third constraint would not change the analysis. Rather, it would simply attenuate the role of adaptation and workers' choice as managers would have an alternative additional instrument (wage compensation) to maximize profits.

[11]See Abebe et al. (2020), Alfonsi et al. (2020), Bassi and Nansamba (2021) and Carranza et al. (2020).

determined, we work through the problem backwards, solving first the choice of protective investments e, then the one for the workers' type h, and last the location choice l.

Adaptation: choice of investment e. Taking the first order conditions with respect to e, we obtain

$$\underbrace{\chi_p\left(p_l-e\right)}_{\text{MB of Pollution Reduction}} \quad + \quad \underbrace{\mu\Omega_p\left(h,p_l-e\right)}_{\text{MB due to Lower Compensating Diff.}} \quad = \quad \underbrace{c_e\left(e,z_i\right)}_{\text{MC of Mitigation}}$$

where μ is the Lagrangian multiplier on the compensating differential constraint, which is equal to 0 if the constraint is not binding.[12] This equation shows that investments to adapt to a polluted environment are driven by two motives: (i) mitigation of the direct cost of pollution, captured by the first term χ_p; (ii) reduction in the distortions, in terms of workers' types, generated by the compensating differential if it was binding, captured by the second term $\mu\Omega_p\left(h,p_l-e\right)$.

We also notice that high ability managers could choose higher investment in mitigation due to two economic forces. First, they may have a lower cost of mitigation – i.e., $c_z<0$. This may capture easier access to credit to purchase protective equipment or higher ability to make organizational changes to reduce exposure, but also higher awareness of pollution and its productivity costs. Second, due to complementarities between managerial ability and worker skill, high ability managers may prefer to hire high skilled workers, who may demand lower pollution exposure. As long as $\Omega_{hp}>0$ – i.e., if high skilled workers need to be compensated more for pollution exposure – and assuming that there is sorting between high ability managers and high skilled workers (discussed below), then high ability managers might have to invest more in mitigation to satisfy the compensating differential constraint.

Sorting: choice of worker type h. Taking the first order condition with respect to h, we obtain

$$\underbrace{f_h\left(z,h\right)}_{\text{MB of Workers' Skills}} \quad = \quad \underbrace{w_h\left(h\right)}_{\text{MC due to Higher Wage}} \quad + \quad \underbrace{\mu\left(w_h\left(h\right)-\Omega_h\left(h,p\right)\right)}_{\text{MC due to Change in Compensating Diff.}}$$

Firm output increases in worker skill, as long as $f_h>0$. The cost of employing high skilled workers is a higher wage, $w_h>0$, and possibly more investment in reducing pollution exposure to satisfy the compensating differential constraint if high skilled workers have a relatively higher distaste for pollution. As a result, we may observe sorting between high ability managers and high skilled workers due to either complementarity in productivity, as long as $f_{hz}>0$, or complementarity due to pollution exposure. This second complementarity is novel to our

[12]Notation: we use $g_p\left(h,p\right)$ for the derivative of $g\left(h,p\right)$ with respect to p.

framework: if high ability managers choose lower pollution exposure – i.e., lower p – then they may be able to hire high skilled workers while still satisfying the compensating differential constraint. In contrast, this constraint may be costly to satisfy for low ability managers that have higher cost of mitigation, as long as $c_z < 0$.

Avoidance: choice of location l. Last, we consider the location choice. To do so, we need to define the set of available locations within the city. We let each location l be defined by a pair $\{z_l, p_l\}$ of productivity and pollution. Firm location may affect productivity through several channels. 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, too high firm congestion could hinder productivity, either due to business stealing, or diseconomies of density such as road traffic making it harder to access suppliers. Of course, locations may also differ in their rental price R_l, which could itself be a function of local pollution p_l and productivity z_l.

We assume that there are only two levels of productivity and pollution: $z_l \in \{\underline{z}, \overline{z}\}$ and $p_l \in \{\underline{p}, \overline{p}\}$, thus implying a maximum of four possible location choices. Of course, any location with high pollution and low productivity would never be chosen. Similarly, if a location with low pollution and high productivity existed, all managers would pick that one. In practice, however, not all pollution-productivity pairs may exist within a city. Our starting hypothesis, which we will verify in the data, is that pollution and demand are positively correlated due to road traffic. Areas with higher traffic, hence higher pollution, are more visible and more reachable, thus increasing the local demand and profitability. In fact, we posit that road traffic bundles a good (market demand) with a bad (pollution exposure). In our model, that implies that managers can only choose between two locations: $\{\overline{z}, \overline{p}\}$ and $\{\underline{z}, \underline{p}\}$.

A manager, according to our framework, would choose the high pollution location if and only if

$$\underbrace{f\left(g\left(\overline{z}, z_i\right), h^*\left(\overline{z}, \overline{p}\right)\right) - f\left(g\left(\underline{z}, z_i\right), h^*\left(\underline{z}, \underline{p}\right)\right)}_{\text{Productivity Premium + Change in Workers' Type}} -$$
$$\underbrace{R\left(\overline{z}, \overline{p}\right) - R\left(\underline{z}, \underline{p}\right)}_{\text{Difference in Rental Costs}} \geq \underbrace{w\left(h^*\left(\overline{z}, \overline{p}\right)\right) - w\left(h^*\left(\underline{z}, \underline{p}\right)\right)}_{\text{Wage Premium due to Change in Workers' Type}} +$$
$$\underbrace{\chi\left(\overline{p} - e^*\left(\overline{z}, \overline{p}\right)\right) - \chi\left(\underline{p} - e^*\left(\underline{z}, \underline{p}\right)\right)}_{\text{Cost of Higher Pollution Exposure}} +$$
$$\underbrace{c\left(e^*\left(\overline{z}, \overline{p}\right), z_i\right) - c\left(e^*\left(\underline{z}, \underline{p}\right), z_i\right)}_{\text{Cost of Higher Mitigation}}.$$

Hence a manager will choose the high pollution location if the productivity premium from producing in the more profitable location, taking into account the optimal choice of worker types and net of the difference in rental costs, is larger than the sum of: (i) the wage premium for the workers; (ii) the direct productivity cost of being exposed to higher pollution (net of protective investments); and (iii) the cost of higher mitigation expenditures.[13]

Ex-ante, it is not clear whether we should observe managers sorting to high or low pollution locations. This depends on the empirical strength of the negative correlation between productivity and pollution, and the relative perceived costs of pollution relative to the profitability benefits. Similarly, higher ability managers could be either more or less likely to sort towards more polluted areas. The pattern of sorting depends on the relative costs and benefits, which are themselves mediated by the choice of workers' type.

4 Sampling Strategy, Data and Descriptives

In Section 2 we have shown that the urban environment in Uganda is becoming increasingly polluted due to rapid motorization and the resulting traffic emissions, thus plausibly inflicting severe health costs on workers and productivity losses to firms. The simple framework of Section 3 describes how managers' actions can mediate these negative effects through avoidance of pollution (through location choice) or adaptation (through investment in protective equipment or organizational strategies). In order to study how firms in urban Uganda respond to the challenge created by increasing levels of urban pollution, we need the following types of data. First, we need data on pollution within and across cities to document variation in pollution exposure 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 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 any adaptation strategies, as well as manager's characteristics. To the best of our knowledge, such highly granular data did not exist. Hence, a core contribution of our study was to build this data. In the following section we describe the sampling design and data collection strategy.

4.1 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. Crucially for the purpose of this study, the pollution measurements and the

[13]Producing in the more profitable location affects the choice of workers' type and wages through the compensating differential constraint: workers demand higher wages in the more polluted location, and this may be especially true for higher skilled workers. As a result, the optimal choice of workers' types may be different in the low and high profitability location.

firm survey are both geo-located and were collected in the same geographical areas and at the same time, which then allows us to combine them together for the analysis.

More specifically, our sampling units are sub-counties. For a sense of scale, the average sub-county spans about 64 square miles and consists of about 5,000 households. A sample of 52 sub-counties was randomly extracted for our study, stratifying by population and by whether the sub-county is in the broader Kampala area (the capital city).[14] Notably, our sample includes several sub-counties within Kampala and within other major cities (such as Jinja, Iganga, Mbale and Fortportal) over these three regions. Our pollution measurement and survey activities took place within these sub-counties and are described in the next sub-sections.

4.2 Pollution Measurements

We create a unique database of pollution measures with geo-coordinates and time stamps that we collected in Uganda in partnership with AirQo and the World Bank.[15]

Stationary and mobile measurements. Pollution measurements come from two distinct types of monitors, subsequently referred 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.[16] Additional details on the technical details of monitors and processes used for data collection are summarized in Okure et al. (2021).

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. Within a district, stationary monitor locations were determined to reflect local pollution exposure.[17] Monitoring devices were installed between 2.5 and 4 meter high to ensure that captured pollution levels are reflective of population exposure. The stationary monitors were active 24 hours a day. 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

[14] Appendix Figure A13 shows the final sample of sub-counties.

[15] AirQo was founded in 2015 at Makerere University and works to improve air quality data in Uganda using AI. AirQo develops and deploys low-cost air quality monitors across urban areas in Uganda. In 2019, it received a $1.3m grant from Google as one of the 20 winners of the Google AI Impact Challenge.

[16] Appendix Figure A14 reports pictures of a stationary and mobile monitor.

[17] Most major emission sources being close to the ground, they predominantly have localized effects on PM2.5 concentration. Stationary monitors were thus deployed within a maximum of 1-2 km from identified activities likely to affect local air quality.

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.[18]

By moving across space, the mobile monitors allow us to measure the spatial variation in pollution at a highly 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. We present two descriptives about our pollution data. First, in Appendix Figure A15, we show 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). This positive correlation reassures us about the internal validity of our measurements.[19] Second, in Figure 1, we report average and median 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 meters, which lines up well with the average of 50 micrograms per cubic meter 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, as expected, 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.

4.3 Firm Survey

The second data source is a novel survey of manufacturing firms 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 of firms and survey design, and then focus on those aspects that are particularly relevant for this paper.

[18]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 less than 7 km from a stationary monitor.

[19]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.

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 and (ii) are not dominated by microenterprises with no paid employees. The first criterion implies that we target sectors that are important for policy, whereas the second criterion allows us to focus on labor relationships and human resource management 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 on the universe of firms in our sampled sub-counties and sectors.[20]

We then randomly selected about 1,000 firms from our listing to be included in the survey, oversampling firms with five or more employees. In firms selected for the survey, we interviewed the owner[21] and all the employees working on the main product.[22] As described in Bassi et al. (2021): (i) compliance with the survey was high at over 90%; (ii) all the results from our survey are appropriately weighted to reflect our sampling strategy.

Survey design. Our 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 and profits per worker 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 also detailed information on how firms access customers (e.g., whether orders are placed in person or by phone, whether the firm relies on shipping etc.). We also collected information about the size of the business premises and their rental value. 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

[20] Appendix Figure A16 plots the firms in the listing in one of the study sub-counties.

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

[22] More precisely, as discussed in Bassi et al. (2021), for each of the three sectors we pre-specified one "core product" that is commonly produced by firms in that sector. For instance, in carpentry, this is doors. If a firm produced the pre-specified core product, we interviewed all employees working on that product. If a firm did not produce the pre-specified core product, we interviewed all employees working on the main product of the firm. See Bassi et al. (2021) for more details, where we verify also that most firms produce the core product that we asked about in the survey, and that this makes up a large share of revenues for the average firm.

pollution as a problem.

To measure managerial quality, we follow de Mel et al. (2008) and 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 manager quality 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 quality. 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. In addition to managerial quality, we also collected detailed information on other owner and worker characteristics (e.g. education, age, experience etc.) including measures of workers' time use at the firm.

Descriptives. Table 1 reports descriptive statistics for the 1,027 firms in our survey sample. The average firm has about five employees. Average monthly revenues and profits are $1,481 and $244, respectively. To put these numbers into perspective, per capita GDP in Uganda was $60 per month in 2018. Thus, the average firm is profitable, and operates beyond subsistence level. Besides, these are established and regular activities: the average firm has been in business for 10 years. The average owner works 9 hours per day for the firm, so this is the primary job for the majority of them. The average employee has 3.5 years of tenure, works 9.9 hours per day for the firm, and makes about $71 per month. Taken together, the evidence shows that our sample is composed of established and profitable firms that employ workers who hold stable, regular, and well-paying jobs by Ugandan standards.

4.4 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.[23] The WFP shape-file distinguishes between 5 distinct road types in Uganda: *track/trail*, *tertiary roads*, *secondary roads*, *primary roads*, and *highways*, by converting Open Street Map (OSM)'s highway tag.[24] The geo-referenced nature of the dataset allows us to match roads with both the pollution and the firm survey data. We create an ordinal measure of road size. To do so, we rank road types by size such that *track/trail* are assigned the number 1, and *highways* are assigned the number 5. We use these values when

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

[24]The WFP classification is a mapping of the 18 OSM's highway tag into 7 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.

calculating summary statistics within a geographical area. For example, the median road size of a geographical area containing one *track/trail* (1), one *secondary road* (3) and one *primary road* (4), will be 3.[25]

Appendix Table A1 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 2,786 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 geographical area.

5 Empirical Strategy

Our analysis is guided by the conceptual framework of Section 3, which posits several empirical relationships that we are going to test with our data. Specifically, we proceed in three steps. First, we study the relationship between local profitability and pollution, to establish that they are positively related, hence that the trade-off we hypothesized between exposure to pollution and market demand, created by locating near major roads, is present. Second, we study the location choice of managers, to show that they choose to expose themselves to pollution in order to get the benefits from market access on major roads. Third, we study heterogeneity by managerial ability in location choice and adaptation behavior to show that high-skilled managers do not avoid pollution, but better adapt to it.

Before showing the regression specifications for each of these three steps, we describe how we residualize our pollution measurements to net out time effects, and how we create measures of pollution, road size, and firm density at the neighborhood level. Residualizing pollution is essential because we are interested in variation in pollution across space within the city (rather than across time). Creating neighborhood or "grid cell" measures of firm density, pollution, and road size allows us to study the location choice of firms.

5.1 Recovering Residual Spatial Variation in PM2.5

As described in Section 4, we collected measures of PM2.5 concentration from both stationary and mobile monitors. Our goal is to construct measures of spatial variation in pollution at a highly granular level within the city. To do this, we exploit our mobile monitors that continuously recorded pollution and GPS coordinates while moving within Ugandan cities.

[25] 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 A17.

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.[26]

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

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

where $ln(PM2.5_{k,h,d})$ is the log of the PM2.5 reading from monitor k recorded on calendar date d and hour h. We include static 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 $\hat{e_{m,h,d}}$ as the log of the raw measurements from our mobile monitors at GPS coordinates m at time h of date d, net of the hour and calendar date fixed effects estimated from the stationary monitors:

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

$\hat{e_{m,h,d}}$ captures residual pollution variation across locations conditional on a particular hour of the day and a particular calendar date. As such, this allows us to document 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. (2017), we split parishes in our sample into grid cells of $500m \times 500m$, drawing grid cells on all selected parishes.[27] Each road, pollution measure and firm are attributed to a cell using their geo-coordinates.[28]

[26] 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.

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

[28] 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

We then compute the following variables for each grid cell: (i) the average residual pollution $\hat{e_{m,h,d}}$, 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 4.4; (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 (rather than just the firms selected for the survey).[29]

Figures 2, 3, and 4, illustrate how our sampled parishes are split into grid cells, and provide suggestive visual evidence 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).

5.3 Regression Specifications and Identifying Assumptions

Equipped with the residualized pollution observations and the grid-cell level variables, we next describe our regression specifications.

Relationship between road size, pollution and productivity. Our first objective is to test whether road traffic bundles a bad (pollution) with a good (access to demand). To do so, we study: (i) whether areas near major roads are more polluted and (ii) whether firms near major roads are more profitable, conditional on observables. To provide evidence on the first point, we run the following regression at the grid cell level, for grid cell j in sub-county s in region r:

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

where $ResidPollution_{j,s,r}$ is the average residual (log) pollution in the grid cell. $MedianRoad_j$ 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* urban areas. 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.[30] To account for spatial correlation, we use Spatial Heteroskedastic and Autocor-

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.

[29] 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 A18. 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).

[30] 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.

relation Consistent (SHAC) standard errors a la Conley (1999) using the routine developed by Hsiang (2010).[31] We also run a version of this regression at the individual pollution measurement level. To do that, we replace the median road size in the cell with a variable capturing the size of the road closest to the pollution measurement.

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. As discussed in Section 2, the core of the road infrastructure in Uganda was built in the 1960s. This alleviates potential concerns related to the endogenous placement of roads based on the current layout of local economic activity. The second identifying assumption is that the firms in our sample are not the sources of PM2.5 pollution themselves. We note that this is unlikely, given that our sample includes small firms in carpentry, metal fabrication and grain milling, and so the nature of their production process is such that they do not produce substantial emissions of PM2.5. In addition, as discussed above, Figure 1 shows that pollution peaks at rush hour rather than when firms are open, which is consistent with pollution coming from traffic rather than the firms themselves.[32]

To study whether firms next to major roads are more profitable, we estimate the following regression for firm i in grid cell j in sub-county s and region r:

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

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

Our main coefficient of interest is β_1. A positive estimate would indicate that firms located near major roads are more profitable. Similarly to equation 3, our identifying assumptions are 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. Therefore, concerns about the validity of this assumption are not first order. A second identifying assumption is that, conditional on sub-county and sector fixed effects and on our

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

[32] Note 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 – firms choose to locate in areas with high pollution since road traffic bundles pollution and firm demand – would be unaffected. The counterfactuals, however, would vary, as changing the firms' location choice would also change the geographical distribution of traffic and demand.

index of managerial ability, there is no selection of more productive firms in the proximity of larger roads. While this assumption may sound strong, our data supports it: in the next section, we show that there is no selection of higher ability managers into areas with larger roads. We are also interested in β_2, as that captures the correlation between managerial skills and firm profitability. Based on the literature on returns to managerial skills in developing countries (McKenzie and Woodruff 2017) we expect a positive and significant estimate.[33]

We also run a specification like equation 4 but with log rental value of the premises as dependent variable, and a version of this equation at the employee level where the dependent variable is log wages. These additional regressions are informative of the costs for firms of locating into areas with larger roads.

Avoidance of pollution and managerial quality. Our next objective is to study whether firms avoid more polluted areas, and whether this varies by managerial ability. We run a grid-level regression similar to equation 3 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.

To study heterogeneity in avoidance behavior by managerial ability, we adopt two strategies. First, we augment the firm density regression at the grid cell level to add a measure of average managerial skills in the grid cell on the right hand side. This specification will test whether managerial skills are a predictor of firm density. Second, we run a regression similar to equation 4, but with $ManScore_i$ on the left hand side, to test directly whether managers of higher ability are more likely to sort in areas with larger roads.

Adaptation to pollution and managerial quality. Our final objective is to study how adaptation to pollution varies by managerial quality. To do so, we estimate versions of equation 4 but with various measures of adaptation on the left hand side, such as whether the manager provides protective equipment to workers. We also run versions of this regression at the worker level whenever the outcome is at the worker level (e.g., workers' perceptions about manager's efforts to protect them from pollution exposure). Our main coefficient of interest in these regressions is again that on the index of managerial quality. As we will show that managerial quality does not predict location choice, this will reassure us that selection effects do not confound the interpretation of the coefficient on managerial ability in these regressions.[34]

[33] Of course, our index of managerial ability could be correlated with other managers' characteristics, such as education or age. Our aim is to document heterogeneity in productivity, pollution avoidance and adaptation along this basic summary measure of managerial quality that is standard in the literature.

[34] We note that avoidance through location choice and adaptation through protective investments/strategies are both outcomes that are unlikely to respond to short-term fluctuations in pollution, and are instead the

6 Results

We now follow our empirical strategy to document, in three sets of empirical results, how pollution exposure shapes production activity in urban Uganda, and how high and low ability managers deal with this challenge.

6.1 Road Traffic Bundles Pollution Exposure with Market Access

We first study the characteristics of available locations within the city to establish that road traffic bundles a good (market access) with a bad (pollution exposure). This result implies that managers face a trade-off in their location choice, in whether to avoid pollution or maximize firm revenues and profits.

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. Third, we show that firms located near larger roads have higher revenues and profits per worker, conditional on a rich set of controls. Finally, we explore the mechanism linking pollution to profitability using our rich survey data and argue that is primarily due to access to market demand.

Larger roads are more polluted. We follow the empirical specification in equation 3 to show that pollution is higher in grid cells with larger roads. 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 magnitude of the coefficient is barely affected by the introduction of sub-county fixed effects, thus showing 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 single pollution measurement rather than the grid cell, by running the same equation 3 using variation across all the observed GPS coordinates m, rather than aggregating at the grid-level.[35] Reassuringly, the results are remarkably similar.

One example to illustrate the empirical variation in our data is shown in Figures 3 and 4, which show pollution measurements and road size in one of our sample sub-counties. It is clear that pollution is higher on the larger roads.

result of sustained exposure. Therefore, the empirical strategies adopted by related papers studying the impact of pollution on labor supply and productivity, which typically rely on high-frequency temporal variation in pollution exposure, would not be appropriate to answer the research questions we are after.

[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.

Pollution is due to road traffic. Next, we bring evidence to argue that the geographic variation in pollution is mainly due to road traffic rather than the firms themselves. First, we study the cyclicality of pollution across hours of the day: if we find that pollution peaks at rush hour rather than when most firms are open for business, then this indicates that the main source of pollution emissions is road traffic. Figure 5 uses data from our stationary monitors and information on time use within the firm from our survey to suggest that the main source of pollution in these urban areas is road traffic rather than the firms themselves. The top panel shows that pollution peaks between 6-9am and 7-9pm. These times correspond to rush hour in Uganda. On the bottom panel, we plot the share of workers that report being at the firm premises working by hour of the day. The figure shows that production activity peaks between 10am to 3pm, that is, when pollution is *lowest*.

We conduct one further test in Figure 6: 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 Figure shows that the cyclicality across the two sets of monitors is almost identical. This provides one more piece of evidence in favor of the interpretation that pollution originates from traffic and is exogenous to firms. Appendix Figure A19 displays the cyclicality of pollution during the day when restricting to grid cells containing roads and is almost identical to Figure 6.

Firms benefit from locating near larger roads. We next study whether locating near larger roads provides profitability benefits to firms. While we do not observe firms moving across locations, we can study, following the specification shown in equation 4, the cross-sectional relationship between proximity to large roads and measures of profitability, conditioning on a rich set of controls. The results are shown in Table 3.

Columns 1-4 show that there are clear benefits from being located on large roads, as shown by an increase in total revenues and profits, as well as per worker. Importantly, note that we control for manager quality, which 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). Therefore, our results do not just capture the fact that more productive managers locate in areas with larger roads (and that are more polluted). In fact, as we show in column 8, high skilled managers are *not* more likely to locate near larger roads. This attenuates the concerns that the documented relationship between profits per worker and road size is driven by omitted variables, as long as sorting on unobservables and observables are related. Rather, these results are in line with there being actual productivity benefits from locating near roads with high traffic (and high pollution).

Columns 5 and 6 show that these productivity benefits pass through to workers in the form of higher salary. The result is still present once we add a rich set of worker controls. Note that a positive effect on salary is not surprising, as in addition to rent sharing motivations, any compensating differentials from the higher exposure to pollution should also be reflected into higher wages.

Finally, in column 7 we study whether the productivity benefits from being located on a large road, hence in a high pollution area, come at the expenses of higher land prices. Note that 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.[36] The result in column 7 shows a precisely estimated and large positive coefficient. Prime locations, that give access to customers, are more expensive. It is relevant to notice that, despite the higher rental cost, the overall effect on profits (shown in columns 3 and 4) is positive. This result is expected, given the magnitude of the effect on revenues and rents and the fact that rents are only a small share of the overall firm costs.

Finally, it is worthwhile to highlight 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 Table A2, we show that we reach similar conclusions if we replace Median Road in the grid cell, with average residual pollution in the cell. This confirms that there are tangible benefits of being located in more polluted areas.[37]

Road traffic provides access to customers. Our final step is to provide support for interpreting the positive effect of being located in polluted areas as being generated by better access to customers, hence higher demand. To shed light on this, we leverage our firm survey, where we collected detailed information on how firms access customers. Panel A of Table 4 shows that marketing activities are extremely limited: 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, and 22% report engaging in no strategies at all to market their products. In addition, sales are

[36]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.

[37]The number of observations is lower in Table A2 than Table 3 because, as described in Section 4.2, information on pollution is available in 32 of our 52 sampled sub-counties, while road size is available in all sub-counties.

conducted 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, firms may gain visibility to potential customers driving down the road. 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 Managers Sort to More Polluted (Higher Demand) Locations

Having established that managers face a trade-off, we study where they locate within the city. We use a version of equation 3 to show that managers sort to more polluted and higher demand locations,. The results are shown in Table 5.[38]

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. We regress this on the median road size in the cell (column 1) and the average residual pollution in the cell (column 2). The results show that cells with larger roads and more polluted grid cells 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, and regress this again on the median road size in the cell and on the average residual pollution in the cell. Both columns show positive and significant estimates. Column 3 shows that an increase in median road size of one unit is associated with an increase in firm density of 13 percent. 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. Note 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 within the city, firms sort into the more polluted areas with better road access. This pattern can be appreciated visually in Figures 2 and 4, which plot grid cells, roads and firms for one of our sampled sub-counties. The figures clearly show that firms cluster along the major roads, and that these areas are more polluted.

Managers reveal to choose locations to access customers. Our survey provides direct evidence that firms choose to locate in the more polluted areas of town as these provide better

[38]Through the lenses of the model, the previous section established that there exists a trade-off between choosing a location with lower pollution or higher productivity. This section shows that managers, both high- and low-skilled, tend to sort to locations with relatively higher pollution. Of course, in practice, there is variation in the location that managers choose, as some managers pick the low pollution location due to factors outside our model, such as proximity to their home. This variation allows us to estimate the empirical regressions.

access to customers. We designed our survey to study the location choice of managers, and thus we asked all firms that relocated or considered relocating in the previous year a question on the reasons for their location choice. Managers were given a list of 18 possible reasons and were asked to select up to 3 main reasons for their location choice[39]. Panel B of Table 4 shows the share of managers reporting each potential reason among their top reasons. To limit the number of rows in the table, we report the three most common options selected by managers, 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, with more than one in two firms selecting it among their top choices; (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 choice (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.[40]

Finally, Figure 7 lists the main constraints to growth reported by firms in our survey, and we see that lack of demand is the main constraint. This 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. On the other hand, Table 4 makes clear that firms do not take pollution exposure into account in their location choice, hence they do not try to avoid it.

Interpreted through the lenses of the model, these results confirm that the productivity benefits of locating in more polluted areas outweigh the potential costs resulting from higher pollution exposure, potentially higher wages due to compensating differentials, and higher rents. This is consistent with the result from Table 3 that firm profits are higher near larger roads.

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. As discussed in Section 2, pollution levels in urban Uganda are high. Our data shows that 83% of employees in our sample work in areas of the city (i.e., grid cells) with average levels of PM2.5 above the 24-hour fine particle standard recommended by the EPA (35 $\mu g/m^3$). In addition, exposure can be exacerbated by the fact that workers in this context operate mostly in the open air and in the immediate vicinity of the road side. Our survey shows direct evidence of this: Panel C of Table 4 reveals that 64% of firms produce only outside or mostly outside, and only 16% of firms produce entirely inside. This underscores the importance of understanding the role of managerial quality in protecting workers from pollution exposure through either avoidance or adaptation. We turn to this next.

[39] This information is available for 138 firms (13% of the sample).

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

6.3 High-Quality Managers Do Not Avoid Pollution, but Better Adapt to it

Finally, we study whether high- and low-ability managers react differently to the challenge of setting up and running a firm in a polluted urban environment.

High-quality managers do not avoid polluted areas. We fail to find any significant heterogeneity in location choice by managerial quality. We show this in two ways. First, in Table 3, we already showed that firms in cells with larger roads have similar managerial quality (column 8). We probe this result further in columns 5 and 6 of Table 5, where we add the average managerial quality in the cell to the grid-cell level regressions for firm density. The coefficient on the average managerial quality is small in magnitude and not significant in both specifications, indicating that the average managerial quality is unrelated to firm density. This confirms that high ability managers do not differ in their location choices. Seen through the light of the model, these results imply that the benefits of locating in more polluted (and productive) areas outweigh the costs of doing so even for high ability managers.

High-quality managers better protect their workers from pollution. Next, we study whether higher ability managers better adapt to pollution by protecting their workers. The model makes clear two potential channels leading to this effect: (i) high ability managers may have a lower marginal cost of adaptation (due to lower credit constraints or higher awareness); (ii) high ability managers may wish to hire more highly skilled workers due to complementarity in production, who may demand more protection. We explore both these channels.

We begin by studying whether higher quality managers engage in more physical or organizational investments to protect their workers from pollution. To do so, we estimate firm and worker level regressions following equation 4, where the standardized index of manager quality is our key independent variable of interest. As shown in Tables 3 and 5, we notice again that manager quality does not predict location choices, which justifies looking at the role of manager quality conditional on location choice.

The dependent variable in column 1 of Table 6 is a dummy equal to one if managers report providing any protective equipment to their workers, such as masks, to limit exposure to pollution. As shown by the mean of the dependent variable reported at the bottom of the table, only 5% of managers engage in such investments. The estimates show that a one standard deviation increase in managerial quality is associated with an increase of 1.9 percentage points in the probability that the manager provides such equipment to their workers, a result significant at the 1% level. That is, the probability of providing protective equipment to workers increases by 40% relative to the mean.

In columns 4 to 7 we focus on organizational strategies to limit pollution exposure. Specifically, 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 (columns 4 and 5), and if managers allow them flexibility in working hours to avoid being exposed to such pollution (columns 6 and 7). The means of these dependent variables are low: only around 6-13% of workers are allowed such flexibility by managers. The coefficients on our measures of manager quality are positive and significant in both cases. For instance, column 6 shows that a one standard deviation increase in managerial quality leads to an increase in the probability that workers report being granted flexibility in commuting by 5.6 percentage points, or 42% relative to the mean.

While in columns 4 and 6 we do not control for worker characteristics, in columns 5 and 7 we add a host of employee controls to disentangle whether this effect is driven by differential sorting of workers to higher quality managers or by higher quality managers actually treating their workers differently.[41] Our coefficient of interest is remarkably stable when employee-level controls are added, which confirms that the results are more consistent with higher quality managers treating their workers differently. At the end of this section, we perform additional checks to show that the role of sorting in explaining our results is limited. This reinforces the conclusion that the differential investments of high quality managers in protecting their workers are a direct result of their ability as managers.

In columns 8 and 9 we create a dummy equal to one if the worker reported that their manager is careful in trying to avoid exposing them to pollution. Again, we find a positive and significant coefficient on our index of managerial quality in these regressions, which is very stable when employee level controls are included.

Taken together, these results show that while investments by managers in protecting workers are overall low, higher quality managers are better able to protect their workers from pollution exposure.[42] Interestingly, this is not just the consequence of higher quality managers having more financial resources to purchase protective equipment; rather, it also reflects the adoption of different organizational strategies to time production and employee commute such that peaks in road traffic and hence pollution levels, are avoided. This is consistent with higher quality managers being better aware of the negative consequences of pollution on worker productivity.

Finally, it is worth noting that columns 4-9 of the table 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 managers. Therefore, our results cannot be contaminated by any reporting bias correlated with managerial ability. Emphasizing the overall result again,

[41]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).

[42]The low overall level of investment in protecting workers from pollution is consistent with the findings of the literature on management practices, which shows that managerial quality is substantially lower in developing countries (Bloom et al. 2013).

workers that are managed by higher ability manager report to be receiving better protection from pollution exposure through several means.

Workers employed by better managers take more protective measures. 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. If the answer was positive, workers were invited to give up to three examples of such protective measures. Appendix Figure A21 gives the detail of workers' answers. Almost half of the workers report taking protective measures when facing air pollution. Dominant strategies are wearing a scarf or tissue (more than 25%) and wearing a mask (about 20%). Notably, very few workers report staying inside the firm premises when air quality is bad, which is consistent with work being predominantly open air.[43] We create a dummy equal to one if the worker reports taking any protection measure. Columns 2 and 3 of Table 6 show that employees working for higher ability managers take more protective measures when facing air pollution. Our coefficient of interest is virtually unaffected by the addition of employee-level controls, which again confirms that these effects are not driven by sorting.

Finally, we note that our measures of road size are largely insignificant predictors of adaptation throughout Table 6, although the coefficients are always positive. This indicates a lack of significant spatial variation in adaptation within the urban areas in our sample. This is not surprising because as shown in Figure 1 pollution is high overall throughout these urban areas (even the 25th percentile of pollution has hourly peaks above 40 micrograms per cubic meter (not shown), that is above recommended U.S. standards) so that even though actual pollution levels do vary within these urban areas, the perceived pollution levels deriving for instance from smell and dust might not vary sufficiently from street to street to result in significant spatial differences in adaptation.

Employees of higher quality managers are more aware of pollution as a problem. In Table 7, we study employees' perceptions of pollution as a problem, and how this varies by manager quality. The specifications mirror those in Table 6, with odd columns excluding worker controls and even columns including them.

First, workers were asked how concerned they are with the effects of pollution on the planet and on their own health. Both questions were asked using a 0-5 likert scale, where higher values indicate higher concerns about pollution. Columns 1-4 show that employees working for higher ability managers are significantly more concerned about the effects of pollution on the planet and on their own health. In columns 5-6 we use as dependent variables the answers to a question

[43] Appendix Figure A21 also shows that the availability of larger (and more expensive) technologies such as air cleaners or air conditioners is extremely limited. As the firms in our sample operate at small scale and mostly open air, 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.

about whether the worker thought the government should do more on pollution (using a 1-5 scale). We again see positive and significant coefficients on managerial quality. 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 variables in columns 7 and 8. We find that workers employed by higher quality managers are substantially more likely to indicate exposure to pollution among the characteristics of their ideal job. Interestingly again, the inclusion of employee controls in columns 2, 4, 6 and 8 barely alters the coefficients on our index of manager quality. This once again suggests that the effects are driven by higher quality managers being 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 quality.

In columns 1 and 2 of Appendix Table A3 we construct a standardized index of all the outcome variables in Table 7 and use this as dependent variable. We again find a precisely estimated positive correlation between managerial quality and this index of employee awareness of pollution. Notably, we fail to find a significant correlation between median road size and this index of employee awareness, although again the coefficients are positive. This suggests again that spatial variation in awareness within the city is limited, while the effect of managerial quality is significant.

Limited role of worker sorting in explaining the results. As discussed above, the inclusion of worker-level controls in the regressions in Tables 6 and 7 barely affects the coefficient on the managerial quality dummy. 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 role of sorting. First, we look for direct evidence of sorting. We do so in Appendix Table A3, 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.[44] 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.[45] The lack of sorting on our pre-determined measure of employee pollution awareness limits concerns that the specifications in Tables 6 and 7 with employee controls might capture sorting. Nevertheless, in

[44] 18% of workers report that pollution was an important consideration in their location decision.

[45] Appendix Table A4 shows that employee age and education do predict awareness as pollution as a problem.

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 all the outcome variables in Table 7 (odd columns). This further reassures us that the results on manager's adaptation are not primarily driven by sorting.

7 Conclusion

In developing nations, pollution tends to rise with economic development due to the lack of environmental regulations to reduce emissions (Grossman and Krueger 1995, Selden and Daqing 1995). During a time when pollution is rising in many growing developing country cities, it is important to explore who bears the economic incidence of these costs and who can affect it. Our contribution is to collect new micro data combining high-resolution pollution measurements with a rich firm-level survey and show that managers can play an important role in mediating the severity of the health cost of pollution on worker productivity.

Studying the location choice of managers within polluted cities, we show that they face a trade-off in whether to avoid pollution or maximize profits. Since road traffic bundles product demand and pollution exposure, we show that managers choose to locate on high-traffic and polluted roads to maximize access to customers. At the same time, firms are not passive victims in the face of the threat of pollution exposure, and the extent to which they are able to adapt depends on the ability of the manager: high ability managers better protect their workers from pollution, through both equipment and organizational strategies to minimize their exposure. This result highlights an important, yet overlooked, dimension of welfare inequality across workers in low income countries: employees who work at the best firms earn higher wages but also benefit from lower pollution exposure. In addition, this finding has implications for our understanding of the effects of pollution on aggregate productivity: as those managers who are better able to adapt are also the most productive ones, this may limit the negative effects of pollution on industry productivity (Graff Zivin and Kahn 2016).

Our results have several implications for city leaders. First, they highlight one additional potential benefit of policy interventions aimed at fostering firm growth: as firms grow larger and become able to separate production and retail activities and to invest in marketing, this might allow them to break the bundling problem and locate production in less congested and less polluted areas of the city. Second, 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. Our data shows that such firm relocation could lead to significant reduction in pollution exposure as there is substantial variation in pollution within developing country cities. For instance, the average employee in our sample works in an area of Kampala where average pollution is about twice as high as the 24-hour particle standard recommended by the US Environmental Protection Agency (EPA). If workers could move to an area of Kampala at the 10^{th} percentile of the distribution of pollution, their exposure would drop by two-thirds to levels below the EPA standard. 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.

Finally, our results suggest that information campaigns that increase managers' awareness of the negative effects of pollution may prove cost-effective at increasing adaptation. While there is a vast literature on business training programs in the developing world, evidence on the impact of interventions to help managers adapt to a polluted environment is missing (McKenzie and Woodruff 2014). Our results suggest this is a promising avenue for future research. Given the speed at which pollution is growing in low income countries, evaluating these types of programs should become a priority in both the academic and policy agendas.

References

Abebe, Girum, A Stefano Caria, Marcel Fafchamps, Paolo Falco, Simon Franklin, and Simon Quinn, "Anonymity or Distance? Job Search and Labour Market Exclusion in a Growing African City," *The Review of Economic Studies*, 2020, *88* (3), 1279–1310.

Adhvaryu, Achyuta, Namrata Kala, and Anant Nyshadham, "Management and Shocks to Worker Productivity," *NBER Working Paper w25865*, May 2019.

Ahlfeldt, Gabriel M., Stephen J. Redding, Daniel M. Sturm, and Nikolaus Wolf, "The Economics of Density: Evidence From the Berlin Wall," *Econometrica*, 2015, *83*, 2127–2189.

Akbar, Prottoy A, Victor Couture, Gilles Duranton, and Adam Storeygard, "Mobility and Congestion in Urban India," *NBER Working Paper w25218*, 2018, p. 77.

Alfonsi, Livia, Oriana Bandiera, Vittorio Bassi, Robin Burgess, Imran Rasul, Munshi Sulaiman, and Anna Vitali, "Tackling Youth Unemployment: Evidence From a Labor Market Experiment in Uganda," *Econometrica*, 2020, *88* (6), 2369–2414.

Anderson, Michael L, "As the Wind Blows: The Effects of Long-Term Exposure to Air Pollution on Mortality," *Journal of the European Economic Association*, August 2020, *18* (4), 1886–1927.

Anderson, Stephen J., Rajesh Chandy, and Bilal Zia, "Pathways to Profits: The Impact of Marketing vs. Finance Skills on Business Performance," *Management Science*, 2018, *64* (12), 5559–5583.

Aragon, Fernando M., Juan Jose Miranda, and Paulina Oliva, "Particulate matter and labor supply: The role of caregiving and non-linearities," *Journal of Environmental Economics and Management*, 2017, *86* (C), 295–309.

Arzaghi, Mohammad and J. Vernon Henderson, "Networking off Madison Avenue," *The Review of Economic Studies*, October 2008, *75* (4), 1011–1038.

Bassi, Vittorio and Aisha Nansamba, "Screening and Signaling Non-Cognitive Skills: Experimental Evidence from Uganda," *SSRN Working Paper 3268523*, 2021.

_ , Raffaela Muoio, Tommaso Porzio, Ritwika Sen, and Esau Tugume, "Achieving Scale Collectively," *NBER Working Paper w28928*, 2021.

Bloom, Nicholas and John Van Reenen, "Measuring and Explaining Management Practices across Firms and Countries," *The Quarterly Journal of Economics*, 2007, *122* (4), 1351–1408.

_ and _ , "Human Resource Management and Productivity," Handbook of Labor Economics, Elsevier 2011.

_ , Benn Eifert, Aprajit Mahajan, David McKenzie, and John Roberts, "Does Management Matter? Evidence from India," *The Quarterly Journal of Economics*, February 2013, *128* (1), 1–51.

_ , Christos Genakos, Ralf Martin, and Raffaella Sadun, "Modern Management: Good for the Environment or Just Hot Air?," *The Economic Journal*, 2010, *120* (544), 551–572.

Bruhn, Miriam, Dean Karlan, and Antoinette Schoar, "The Impact of Consulting Services on Small and Medium Enterprises: Evidence from a Randomized Trial in Mexico," *Journal of Political Economy*, April 2018, *126* (2), 635–687.

Card, David, Jorg Heining, and Patrick Kline, "Workplace Heterogeneity and the Rise of West German Wage Inequality," *The Quarterly Journal of Economics*, August 2013, *128* (3), 967–1015.

Carozzi, Felipe and Sefi Roth, "Dirty Density: Air Quality and the Density of American Cities," *SSRN Working Paper 3590889*, May 2020.

Carranza, Eliana, Robert Garlick, Kate Orkin, and Neil Rankin, "Job Search and Hiring with Two-sided Limited Information about Workseekers' Skills," *Working Paper*, 2020.

Chang, Tom, Joshua Graff Zivin, Tal Gross, and Matthew Neidell, "Particulate Pollution and the Productivity of Pear Packers," *American Economic Journal: Economic Policy*, August 2016, *8* (3), 141–169.

Chay, Kenneth Y. and Michael Greenstone, "The Impact of Air Pollution on Infant Mortality: Evidence from Geographic Variation in Pollution Shocks Induced by a Recession," *The Quarterly Journal of Economics*, 2003, *118* (3), 1121–1167.

Chen, Shuai, Paulina Oliva, and Peng Zhang, "The Effect of Air Pollution on Migration: Evidence from China," *NBER Working Paper w24036*, 2017, p. 69.

Collier, Paul, "African urbanization: an analytic policy guide," *Oxford Review of Economic Policy*, 2017, *33* (3), 405–437.

Combes, Pierre-Philippe and Laurent Gobillon, "Chapter 5 - The Empirics of Agglomeration Economies," in Gilles Duranton, J. Vernon Henderson, and William C. Strange, eds., *Handbook of Regional and Urban Economics*, Vol. 5 of *Handbook of Regional and Urban Economics*, Elsevier, 2015, pp. 247–348.

Conley, T. G., "GMM estimation with cross sectional dependence," *Journal of Econometrics*, September 1999, *92* (1), 1–45.

Dargay, Joyce, Dermot Gately, and Martin Sommer, "Vehicle Ownership and Income Growth, Worldwide: 1960-2030," *The Energy Journal*, 2007, *28* (4), 143–170.

de Mel, Suresh, David McKenzie, and Christopher Woodruff, "Returns to Capital in Microenterprises: Evidence from a Field Experiment," *The Quarterly Journal of Economics*, November 2008, *123* (4), 1329–1372.

_ , _ , and _ , "Labor Drops: Experimental Evidence on the Return to Additional Labor in Microenterprises," *American Economic Journal: Applied Economics*, January 2019, *11* (1), 202–35.

Deryugina, Tatyana, Garth Heutel, Nolan H. Miller, David Molitor, and Julian Reif, "The Mortality and Medical Costs of Air Pollution: Evidence from Changes in Wind Direction," *American Economic Review*, December 2019, *109* (12), 4178–4219.

Duranton, Gilles and Diego Puga, "Chapter 48 - Micro-Foundations of Urban Agglomeration Economies," in J. Vernon Henderson and Jacques-Francois Thisse, eds., *Cities and Geography*, Vol. 4 of *Handbook of Regional and Urban Economics*, Elsevier, 2004, pp. 2063–2117.

Ebenstein, Avraham, Maoyong Fan, Michael Greenstone, Guojun He, Peng Yin, and Maigeng Zhou, "Growth, Pollution, and Life Expectancy: China from 1991-2012," *American Economic Review*, May 2015, *105* (5), 226–231.

Ellison, Glenn, Edward L Glaeser, and William R Kerr, "What Causes Industry Agglomeration? Evidence from Coagglomeration Patterns," *American Economic Review*, June 2010, *100* (3), 1195–1213.

Fu, Shihe, V Brian Viard, and Peng Zhang, "Air Pollution and Manufacturing Firm Productivity: Nationwide Estimates for China," *The Economic Journal*, 2021.

Glaeser, Edward and J. Vernon Henderson, "Urban economics for the developing World: An introduction," *Journal of Urban Economics*, March 2017, *98*, 1–5.

Glaeser, Edward L., Jed Kolko, and Albert Saiz, "Consumer city," *Journal of Economic Geography*, 2001, *1* (1), 27–50.

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

Gosnell, Greer K., John A. List, and Robert D. Metcalfe, "The Impact of Management Practices on Employee Productivity: A Field Experiment with Airline Captains," *Journal of Political Economy*, July 2019, *128* (4), 1195–1233.

Graff Zivin, Joshua and Matthew E. Kahn, "Industrial Productivity in a Hotter World: The Aggregate Implications of Heterogeneous Firm Investment in Air Conditioning," *NBER Working Paper w22962*, December 2016.

_ **and Matthew Neidell**, "The Impact of Pollution on Worker Productivity," *American Economic Review*, December 2012, *102* (7), 3652–3673.

Grossman, Gene M. and Alan B. Krueger, "Economic Growth and the Environment," *The Quarterly Journal of Economics*, 1995, *110* (2), 353–377.

Hanna, Rema and Paulina Oliva, "The effect of pollution on labor supply: Evidence from a natural experiment in Mexico City," *Journal of Public Economics*, 2015, *122* (C), 68–79.

Harari, Mariaflavia, "Cities in Bad Shape: Urban Geometry in India," *American Economic Review*, August 2020, *110* (8), 2377–2421.

Hausman, Jerry A., Bart D. Ostro, and David A. Wise, "Air Pollution and Lost Work," *NBER Working Paper w1263*, January 1984.

Heblich, Stephan, Alex Trew, and Yanos Zylberberg, "East-Side Story: Historical Pollution and Persistent Neighborhood Sorting," *Journal of Political Economy*, May 2021, *129* (5), 1508–1552.

Hjort, Jonas, Vinayak Iyer, and Golvine de Rochambeau, "Informational Barriers to Market Access: Experimental Evidence from Liberian Firms," *NBER Working Paper w27662*, August 2020.

Hobson, E. and Angus Morgan Kathage, "Uganda - From regulators to enablers : role of city governments in economic development of greater Kampala," *Working Paper*, 2017.

Hsiang, Solomon M., "Temperatures and cyclones strongly associated with economic production in the Caribbean and Central America," *Proceedings of the National Academy of Sciences*, August 2010, *107* (35), 15367–15372.

Ingram, G. and Z. Liu, "Determinants of Motorization and Road Provision," *World Bank: Infrastructure (Topic)*, 1999.

Jensen, Robert and Nolan H. Miller, "Market Integration, Demand, and the Growth of Firms: Evidence from a Natural Experiment in India," *American Economic Review*, December 2018, *108*

(12), 3583–3625.

Kahn, Matthew E. and Randall Walsh, "Cities and the Environment," in "Handbook of Regional and Urban Economics," Vol. 5, Elsevier, 2015, pp. 405–465.

KCCA, (Kampala Capital City Authority), "Strategic Plan 2014/15-2018/19, Laying the Boundation for Kampala City Transformation," Technical Report 2014.

Khanna, Gaurav, Wenquan Liang, A. Mushfiq Mobarak, and Ran Song, "The Productivity Consequences of Pollution-Induced Migration in China," *Discussion Papers. 1083.*, 2021.

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

Kreindler, Gabriel E, "The Welfare Effect of Road Congestion Pricing: Experimental Evidence and Equilibrium Implications," 2018, *Working Paper*, 73.

Liu, Jiahua and Sheetal Sekhri, "Groundwater Accessibility and Firm Behavior," *Working Paper*, 2021, p. 68.

McKenzie, David and Christopher Woodruff, "What Are We Learning from Business Training and Entrepreneurship Evaluations around the Developing World?," *The World Bank Research Observer*, February 2014, *29* (1), 48–82.

_ and _ , "Business Practices in Small Firms in Developing Countries," *Management Science*, 2017, *63* (9), 2967–2981.

Michaels, Guy, Dzhamilya Nigmatulina, Ferdinand Rauch, Tanner Regan, Neeraj Baruah, and Amanda Dahlstrand-Rudin, "Planning Ahead for Better Neighborhoods: Long Run Evidence from Tanzania," *CESifo Working Paper 6680*, 2017.

Morchio, Iacopo and Christian Moser, "The Gender Pay Gap: Micro Sources and Macro Consequences," *SSRN Working Paper 3176868*, July 2020.

Okure, Deo, Engineer Bainomugisha, Nancy Lozano-Gracia, and Maria Edisa Soppelsa, "Characterization of Ambient Air Quality in Selected Urban Areas in Uganda: A Low-Cost Approach," *Working Paper*, 2021.

Ostro, Bart D., "The effects of air pollution on work loss and morbidity," *Journal of Environmental Economics and Management*, 1983, *10* (4), 371–382.

Pope, C. Arden and Douglas W. Dockery, "Health Effects of Fine Particulate Air Pollution: Lines that Connect," *Journal of the Air & Waste Management Association*, June 2006, *56* (6), 709–742.

Selden, Thomas and Song Daqing, "Neoclassical Growth, the J Curve for Abatement, and the Inverted U Curve for Pollution," *Journal of Environmental Economics and Management*, 1995, *29* (2), 162–168.

Song, Jae, David Price, Fatih Guvenen, Nicholas Bloom, and Till von Wachter, "Firming Up Inequality," *The Quarterly Journal of Economics*, 2019, *134* (1), 1–50.

Sorkin, Isaac, “Ranking Firms Using Revealed Preference,” *The Quarterly Journal of Economics*, 2018, *133* (3), 1331–1393.

Startz, Meredith, “The value of face-to-face: Search and contracting problems in Nigerian trade,” *Working Paper*, 2018.

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

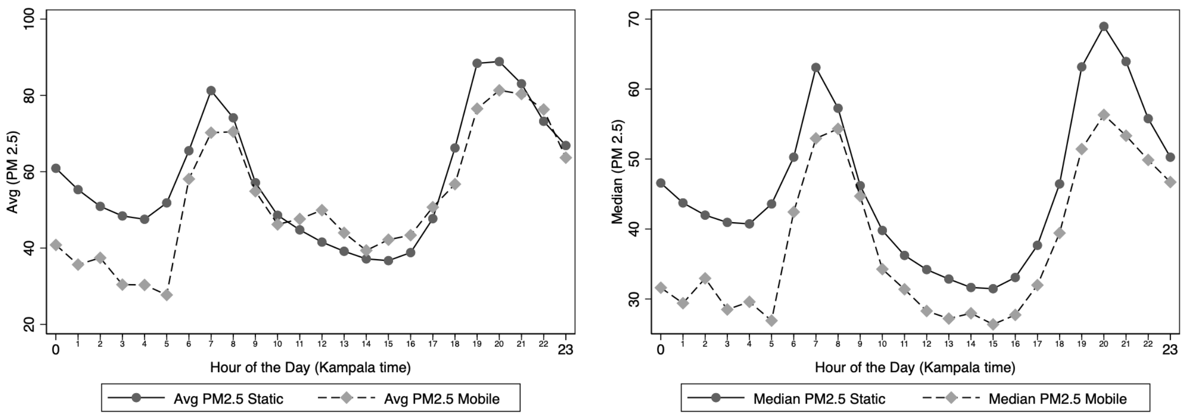
Sun, Cong, Matthew E. Kahn, and Siqi Zheng, “Self-protection investment exacerbates air pollution exposure inequality in urban China,” *Ecological Economics*, 2017, *131* (C), 468–474.

UBOS, “The National Population and Housing Census 2014 - Main Report, Kampala, Uganda,” Technical Report 2016.

United Nations, Population Division, Department of Economic and Social Affairs, “World Urbanization Prospects: The 2018 Revision,” Technical Report (ST/ESA/SER.A/420). New York: United Nations. 2019.

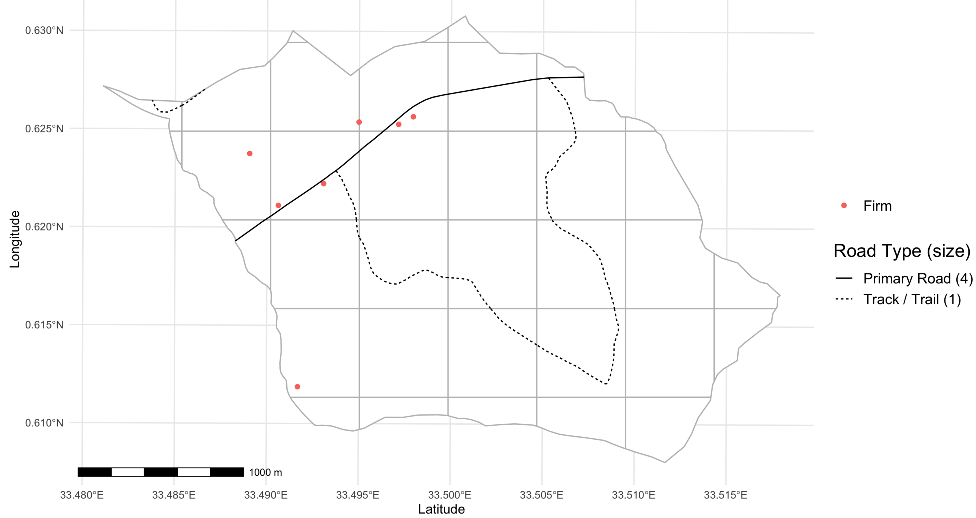
WHO, (World Health Organization), “Ambient Air Pollution: A Global Assessment of Exposure and Burden of Disease,” Technical Report 2016.

Figure 1: Hourly Fluctuation in Pollution Within the Day



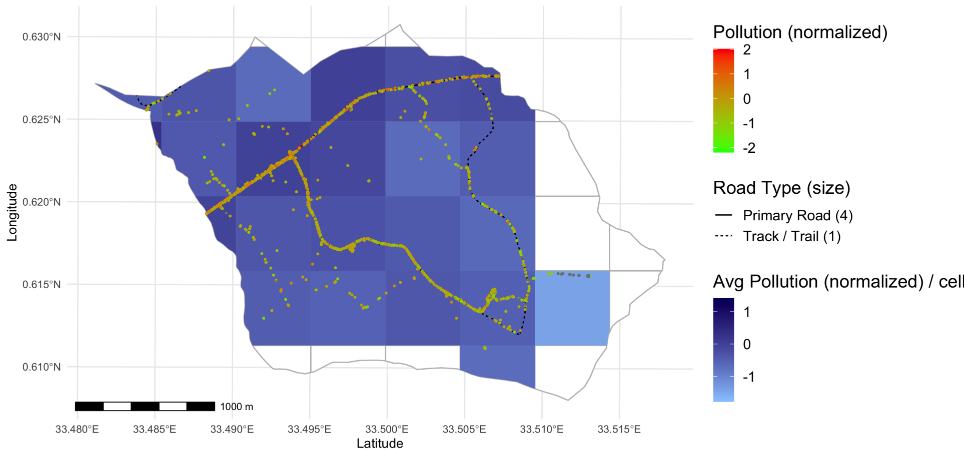
Notes: Averages (left panel) and medians (right panel) of PM2.5 measurements from our stationary and mobile monitors are plotted for each hour in Kampala time (GMT +3).

Figure 2: Firm Location and Road Size in a Sampled Sub-County



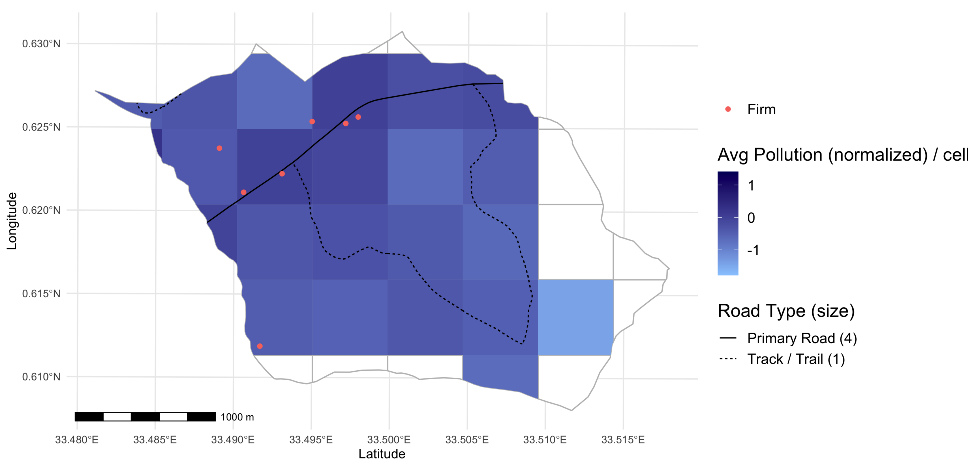
Notes: Location of firms in our survey and roads for the sampled parish in Nakalama Sub-county (Iganga District). Road sizes are defined in section 4.4. Grid cell dimensions are 500m x 500m. Sources: Own survey, OSM Road data.

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 4.4 and the computation of pollution residuals is described in section 5.1. Grid cell dimensions are 500m x 500m. Sources: Own measurements, OSM Road data.

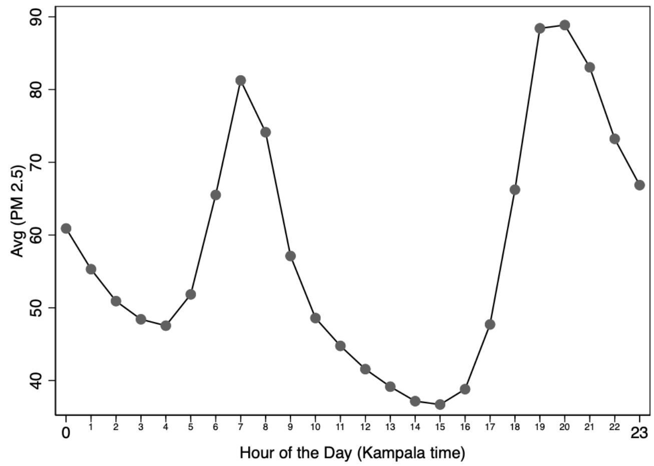
Figure 4: Average Residual Pollution, Firm Location and Road Size in a Sampled Sub-County



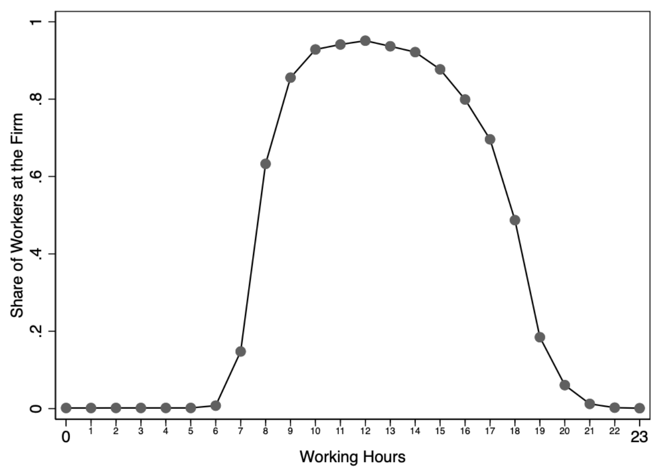
Notes: Location of firms in our survey, roads and average pollution residual per grid cell for the sampled parish in Nakalama Sub-county (Iganga District). Road sizes are defined in section 4.4 and the computation of pollution residuals is described in section 5.1. Grid cell dimensions are 500m x 500m. Sources: Own measurements, OSM Road data.

Figure 5: Cyclicality of Pollution During the Day Does Not Match Firms' Working Hours

(a) Cyclicality of Pollution Levels Throughout the Day

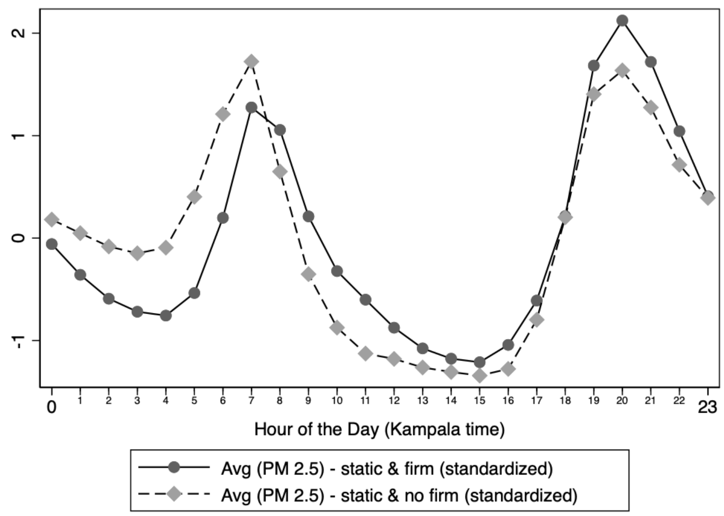


(b) Times of the Day When Production Takes Place



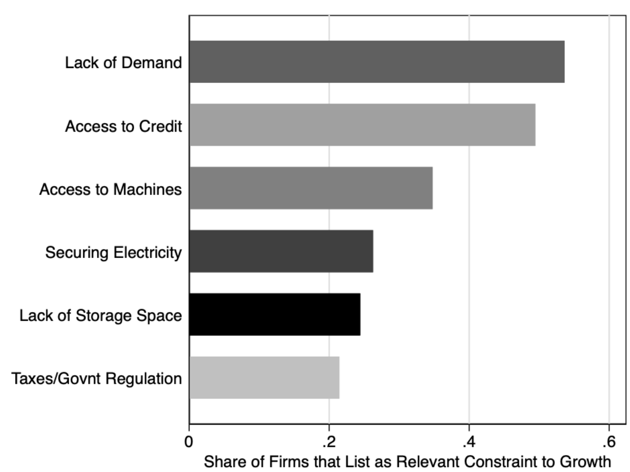
Notes: The top panel shows pollution cyclicality during the day, as measured by our stationary monitors. The bottom panel shows the share of employees who report working by hour of the day. In our survey, both managers and employees are asked at what time they started and finished work at the firm during the last day worked.

Figure 6: Cyclicality of Pollution Does Not Depend on Firm Density



Notes: Avg (PM2.5) is the standardized mean PM2.5 measurement from stationary monitors (top 1% trimmed) 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.

Figure 7: Lack of Demand is the Main Reported Constraint to Firm Growth



Notes: In our survey, managers / 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.

Table 1: Firm Descriptives

	All Sectors
Number of firms	1027
Carpentry (%)	49.3
Metal fabrication (%)	37
Grain milling (%)	13.7
Panel A: Firm characteristics	
Number of employees	4.9
Monthly revenues (USD)	1481
Monthly profits (USD)	243.6
Firm age (years)	10.1
Panel B: Owner characteristics	
Owner is male (%)	96.1
Owner age (years)	40.3
Owner years of education	10
Owner hours usually worked per day for the firm	9.2
Panel C: Employee characteristics	
Employee is male (%)	98
Employee age (years)	28.5
Employee years of education	9.3
Employee tenure (years)	3.5
Employee hours usually worked per day for the firm	9.9
Employee monthly wage (USD)	71

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.

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	0.0774***	0.0708***		
	(0.0118)	(0.0161)		
Closest Road Size			0.0988***	0.0597*
			(0.0156)	(0.0334)
N	972	972	52965	52965
R2	.3516	.1636	.1591	.0334
Fixed Effects	Subcounty		Subcounty	
Level of Observation	Grid Cell	Grid Cell	Poll. measure	Poll. measure
SE clustering	SHAC	SHAC	Grid Cell	Grid Cell

Notes: Standard errors are displayed in parentheses (* $p < 0.10$, ** $p < 0.5$, *** $p < 0.01$). 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 whether the grid cell contains any road (dummy), 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. The top and bottom one percent of pollution residuals are trimmed. Regressions at the pollution measure level have the same geographical coverage than regressions at the grid cell level and include a dummy for whether observations are 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(Rev/Worker)	(2) log(Rev)	(3) log(Profit/Worker)	(4) log(Profit)	(5) log(Salary)	(6) log(Salary)	(7) log(Rent)	(8) Man. Score
Med. Road Size/Cell	0.0672**	0.136***	0.0815**	0.148***	0.0308*	0.0260*	0.106***	0.0542
	(0.0317)	(0.0316)	(0.0327)	(0.0325)	(0.0158)	(0.0152)	(0.0287)	(0.0375)
Man. Score	0.191***	0.292***	0.132***	0.237***	0.0881***	0.0844***	0.0745**	
	(0.0276)	(0.0296)	(0.0278)	(0.0310)	(0.0191)	(0.0191)	(0.0296)	
log(Size Premises)							0.0499**	
							(0.0212)	
N	977	976	967	967	2272	2272	654	950
R2	0.418	0.450	0.483	0.537	0.316	0.392	0.475	0.187
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	Firm	Firm
SE clustering	Grid Cell	Grid Cell	Grid Cell	Grid Cell	Grid Cell	Grid Cell	Grid Cell	Grid Cell
Employee Controls					No	Yes		

Notes: Standard errors are displayed in parentheses (* $p < 0.10$, ** $p < 0.5$, *** $p < 0.01$). 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 whether the grid cell contains any road. We also control 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 (measured through a Raven matrices test), employee tenure. We control for missing managerial score (dummy) and missing employee controls (dummy). 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
Owner does nothing	21.5
(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: 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 C: 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: Panel A describes the average firm's marketing strategies and business practices, using the full sample of firms in our survey. Firms that had relocated (or considered to relocate) their premises in the previous year (138 firms) were asked the reasons for their location choice. Panel B gives the share selected as top 3 out of 18 potential reasons for location choice asked in the survey. The three top rows correspond to the most common reasons. The three bottom rows correspond to the environmental-related reasons. Panel C gives details on production location, again using the full sample of firms in our survey.

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	0.0391**		0.131***		0.121***		
	(0.0170)		(0.0449)		(0.0451)		
Avg log(Pollution) Residual		0.202***		0.269*		0.243*	
		(0.0536)		(0.143)		(0.136)	
Avg Man. Score					0.0137	0.0111	
					(0.0659)	(0.0676)	
log(Pollution) Residual							0.164***
							(0.0454)
N	972	972	420	420	420	420	57569
R2	.2981	.3048	.4422	.4365	.4877	.4825	.4683
Fixed Effects	Subcounty	Subcounty	Subcounty	Subcounty	Subcounty	Subcounty	Subcounty
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: Standard errors are displayed in parentheses (* $p < 0.10$, ** $p < 0.5$, *** $p < 0.01$). 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 whether the grid cell contains any road, 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 than 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 Manager Quality and Protective Investments

	(1) Poll Equipment	(2) Own Protect	(3) Own Protect	(4) Late Commute	(5) Late Commute	(6) Flex Commute	(7) Flex Commute	(8) Managers Careful	(9) Managers Careful
Median Road Size/Cell	0.00207	0.0125	0.0133	0.0130*	0.0133*	0.0135	0.0139	0.0151	0.0139
	(0.00603)	(0.0146)	(0.0145)	(0.00773)	(0.00748)	(0.0136)	(0.0134)	(0.0118)	(0.0119)
Man. Score	0.0194***	0.0456**	0.0450**	0.0284***	0.0249***	0.0556***	0.0499***	0.0654***	0.0601***
	(0.00687)	(0.0180)	(0.0184)	(0.00890)	(0.00869)	(0.0148)	(0.0142)	(0.0151)	(0.0153)
N	1000	2045	2045	2020	2020	2002	2002	1959	1959
R2	0.105	0.197	0.210	0.0836	0.100	0.173	0.194	0.140	0.148
Fixed Effects (1)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects (2)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Level of Observation	Firm	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	Grid Cell
Employee Controls		No	Yes	No	Yes	No	Yes	No	Yes
Mean(dependent var)	.047	.523	.523	.056	.056	.132	.132	.21	.21
Answer scale	Dummy	Dummy	Dummy	Dummy	Dummy	Dummy	Dummy	Dummy	Dummy

Notes: Standard errors are displayed in parentheses (* $p < 0.10$, ** $p < 0.5$, *** $p < 0.01$). 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 whether the grid cell contains any road. We also control 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, employee tenure and log wage. We control for missing managerial score (dummy) and missing employee controls (dummy). 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 excludable technology or equipment (e.g., masks) is provided at 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: Correlation Between Manager Quality and Employees' Perceptions of Pollution as a Problem

	(1) Concerned Poll Planet	(2) Concerned Poll Planet	(3) Concerned Poll Health	(4) Concerned Poll Health	(5) Gov Address Poll	(6) Gov Address Poll	(7) Ideal Job Low Poll	(8) Ideal Job Low Poll
Median Road Size/Cell	0.0511*	0.0518*	-0.00558	-0.00569	0.00252	0.000615	0.0252*	0.0281**
	(0.0284)	(0.0286)	(0.0376)	(0.0368)	(0.0335)	(0.0334)	(0.0131)	(0.0127)
Man. Score	0.274***	0.254***	0.227***	0.211***	0.0897**	0.0957**	0.0693***	0.0603***
	(0.0327)	(0.0319)	(0.0476)	(0.0462)	(0.0446)	(0.0415)	(0.0151)	(0.0146)
N	2045	2045	2044	2044	2045	2045	2045	2045
R2	0.167	0.188	0.187	0.204	0.123	0.135	0.133	0.161
Fixed Effects (1)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects (2)	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	Yes	No	Yes
Mean(dependent var)	3.964	3.964	3.735	3.735	4.043	4.043	.298	.298
Answer scale	1-5	1-5	0-5	0-5	1-5	1-5	Dummy	Dummy

Notes: Standard errors are displayed in parentheses (* $p < 0.10$, ** $p < 0.5$, *** $p < 0.01$). 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 whether the grid cell contains any road. We also control 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, employee tenure and log wage. We control for missing managerial score (dummy) and missing employee controls (dummy). Road size goes from 1 (Trail/Track) to 5 (Highway). The dependent variables are defined as follows: the employee is asked how concerned she is about the effects of air pollution on the health of the planet (cols 1, 2); to what extent she is concerned about the effects of air pollution on her own health (cols 3, 4); 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 (cols 5, 6); and whether her ideal job features low levels of air pollution (cols 7, 8).

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.[46] 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

[46] 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).

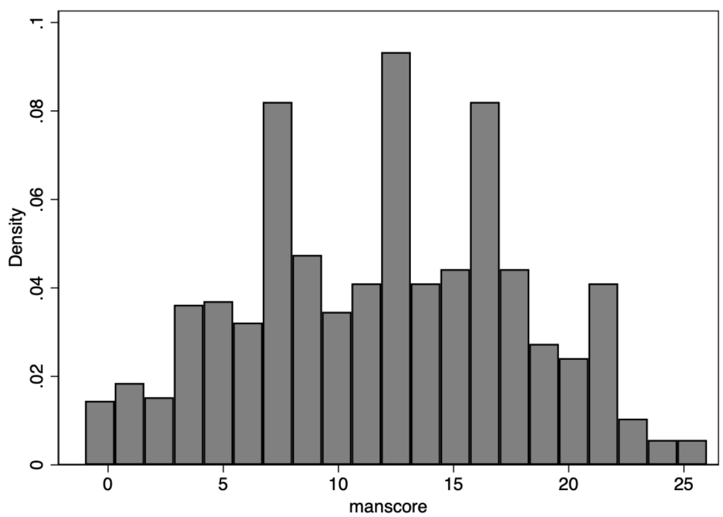
- The *forecasting* score ranges from a minimum score of 0 to a maximum of +5. The score is calculated by adding one point for each of the following activities reported by the firm owner/manager at the time of the survey:

  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.[47] 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).

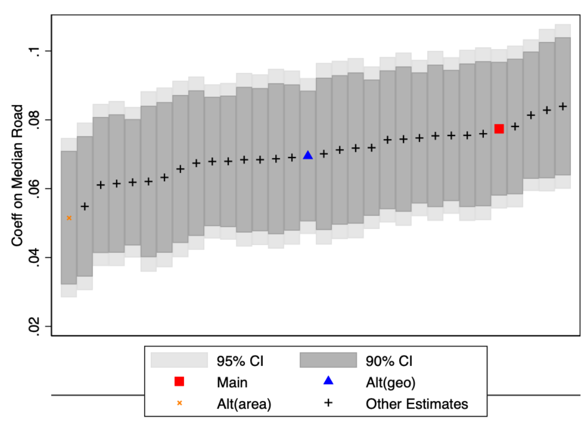
[47]The average ([Q25, Q75]) raw managerial ability score index is 11.6 ([8, 16]) for carpentry, 11.9 ([8, 16]) for metal fabrication and 12.6 ([7, 18]) for grain milling.

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.

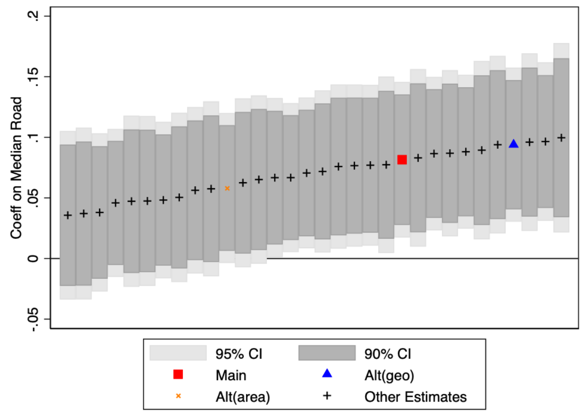
By default in the software used to generate the grids, the bottom-left grid cell matches the bottom-left corner of the smallest rectangle covering these sampled parishes. The grid starting point (i.e., coordinates of the bottom-left corner) may mechanically affect the aggregation of firms, pollution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



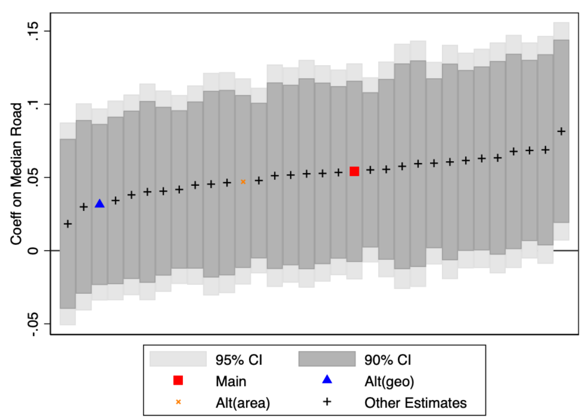
Notes: We run the specification in Table 2, Column 1 for different starting points of the covering grid. The red square is the estimate from our main specification. The blue triangle corresponds to the mirroring specification as described in Appendix A.2. The orange cross corresponds to the randomized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



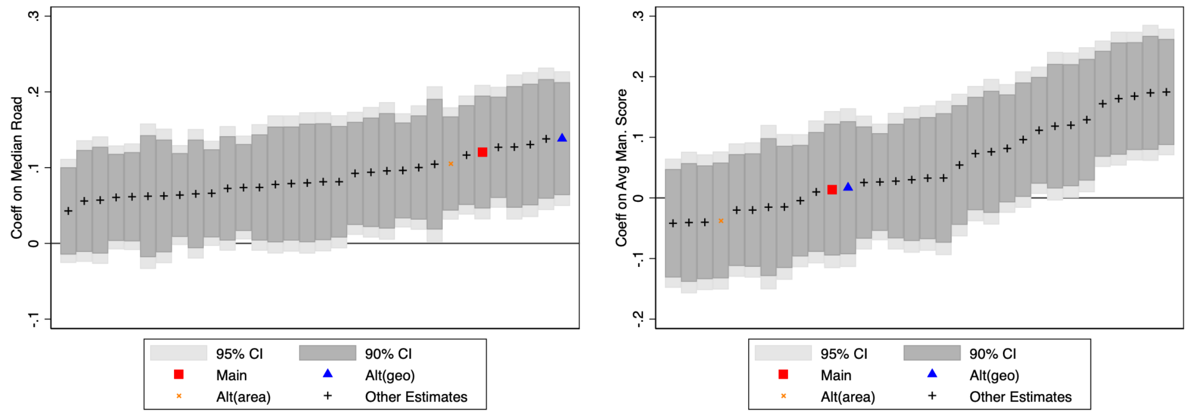
Notes: We run the specification in Table 3, Column 3 for different starting points of the covering grid. The red square is the estimate from our main specification. The blue triangle corresponds to the mirroring specification as described in Appendix A.2. The orange cross corresponds to the randomized 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: Managerial ability index on median road size/cell (Table 3, col 8)



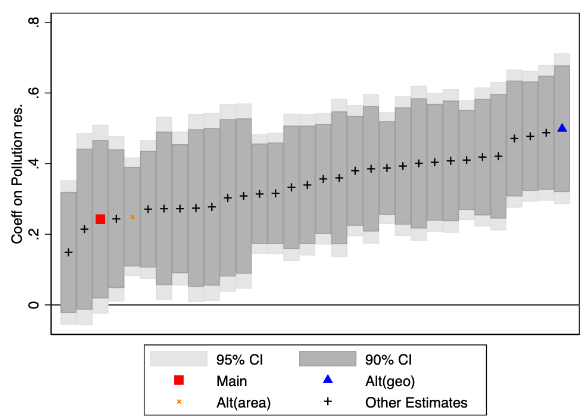
Notes: We run the specification in Table 3, Column 8 for different starting points of the covering grid. The red square is the estimate from our main specification. The blue triangle corresponds to the mirroring specification as described in Appendix A.2. The orange cross corresponds to the randomized 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 median road size and average managerial score (Table 5, col 5)



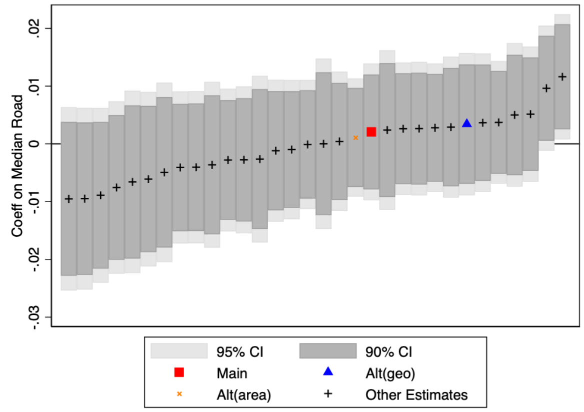
Notes: We run the specification in Table 5, Column 5 for different starting points of the covering grid. The red square is the estimate from our main specification. The blue triangle corresponds to the mirroring specification as described in Appendix A.2. The orange cross corresponds to the randomized 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 A6: Log firm density per grid cell on average log pollution residual (Table 5, col 6)



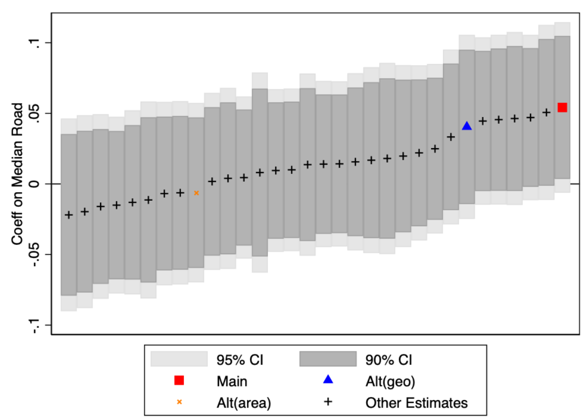
Notes: We run the specification in Table 5, Column 6 for different starting points of the covering grid. The red square is the estimate from our main specification. The blue triangle corresponds to the mirroring specification as described in Appendix A.2. The orange cross corresponds to the randomized 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 A7: Use of protective equipment in the firm on median road size/cell (Table 6, col 1)



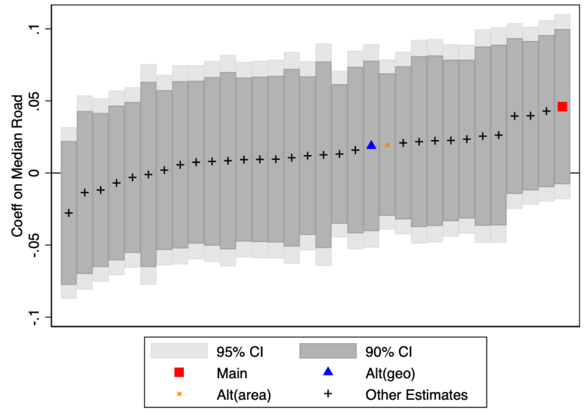
Notes: We run the specification in Table 6, Column 1 for different starting points of the covering grid. The red square is the estimate from our main specification. The blue triangle corresponds to the mirroring specification as described in Appendix A.2. The orange cross corresponds to the randomized 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 A8: Protection of employees from pollution on median road size/cell (Table 6, Index)



Notes: We run the specification in Table 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. The dependent variable is constructed as the average of the dependent variables in Table 6, columns 3, 5, 7 and 9 capturing employees' exposure to air pollution.

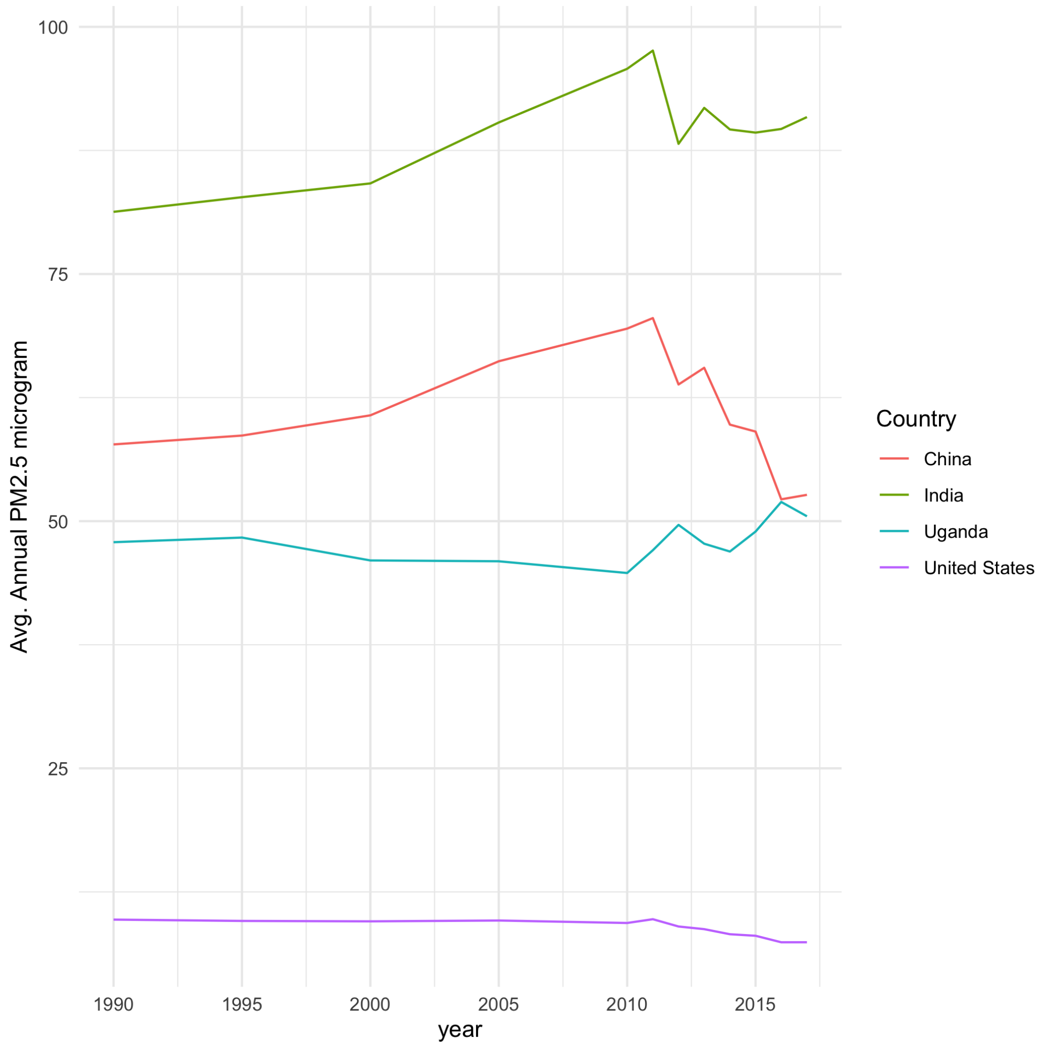
Figure A9: Employee pollution awareness on median road size/cell (Table 7, Index)



Notes: We run the specification in Table 7 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. The dependent variable - Pollution awareness at the firm - is a normalized average of the dependent variables in Table 7 (mean 0, sd 1).

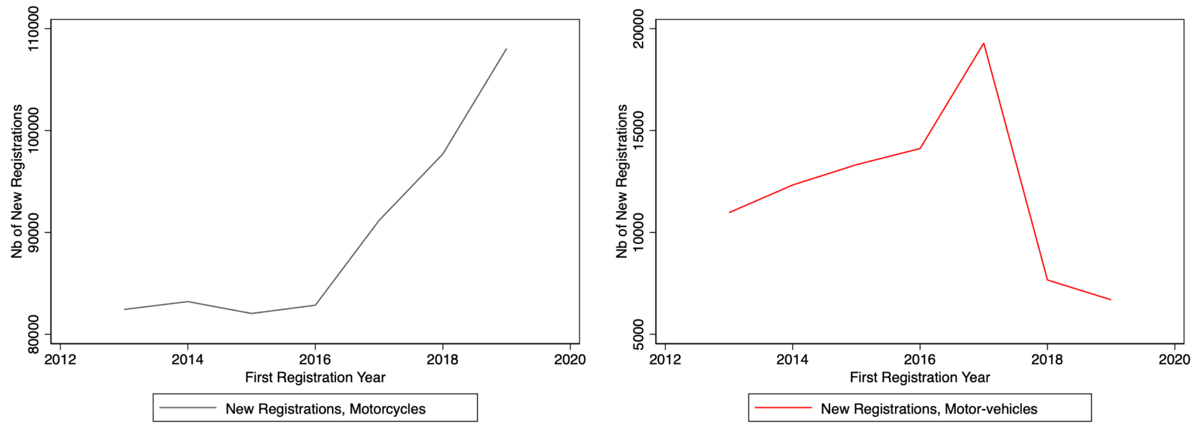
A.3 Additional Tables and Figures

Figure A10: Average Annual Pollution Over Time in Selected Countries



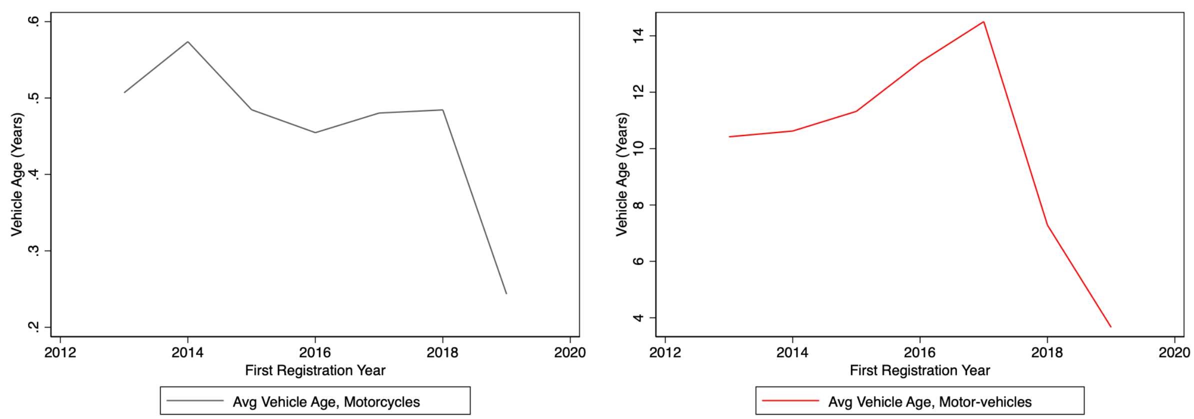
Source: World Bank

Figure A11: Vehicle Registrations Over Time in Uganda



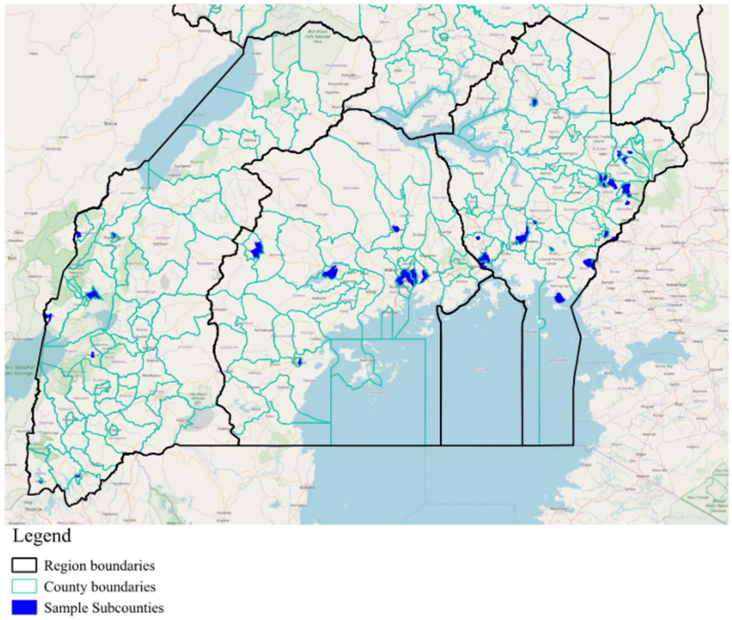
Notes: Annual number of first registrations for motorcycles (left panel) and motor-vehicles (right panel) from 2013 to 2019. The number of new motorcycle registrations has been sharply increasing since 2016. The number of newly registered motor-vehicles peaked in 2017. Source: Uganda Revenue Authority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

Figure A12: 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 A13: Geographical Scope of the Survey

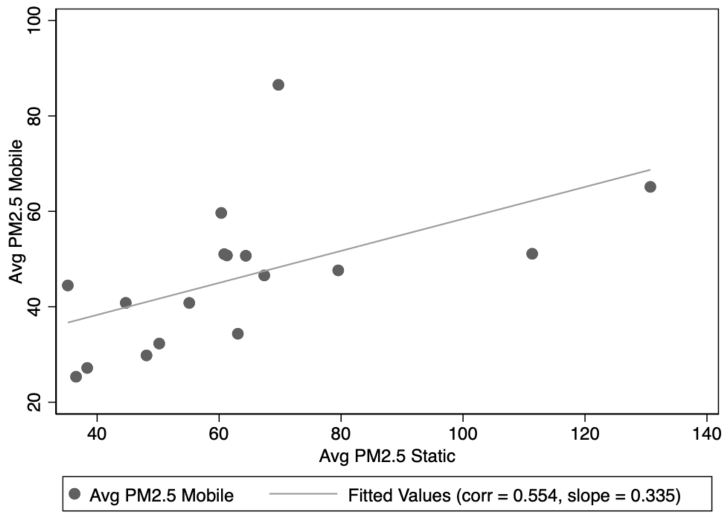


Notes: The figure shows in dark blue the sub-counties in our sample. The figure highlights that our sample region is scattered across three of the four regions of the country (Central, Eastern and Western).

Figure A14: Stationary and Mobile Monitors

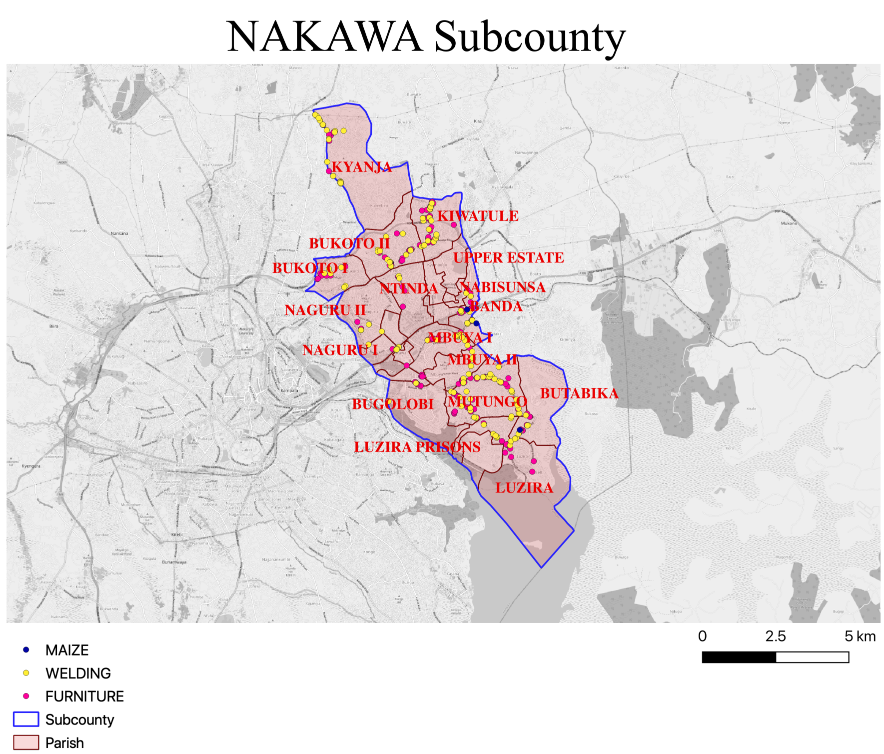
Notes: Photos of AirQo stationary (left panel) and mobile (right panel) pollution monitors.

Figure A15: Correlation Between Average Stationary and Mobile Monitors' Measures at the Sub-county Level



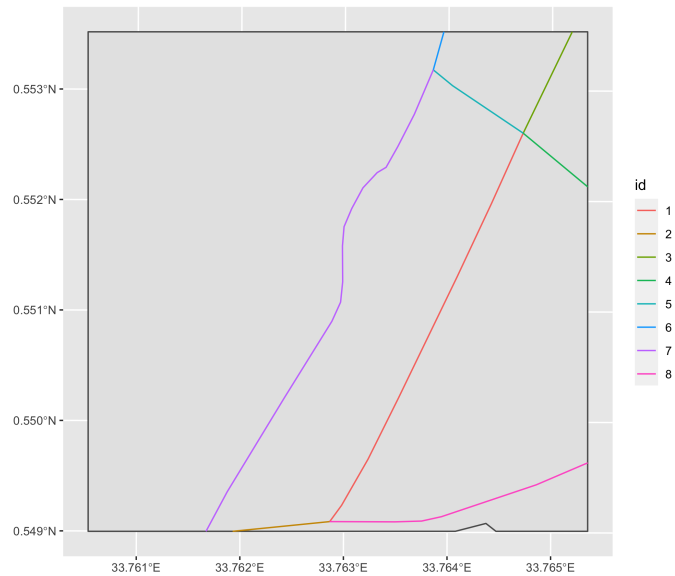
Notes: Sub-county level averages of pollution measurements from mobile and stationary monitors. Source: Own measurements.

Figure A16: Example of Listing Exercise in One Sampled Sub-County



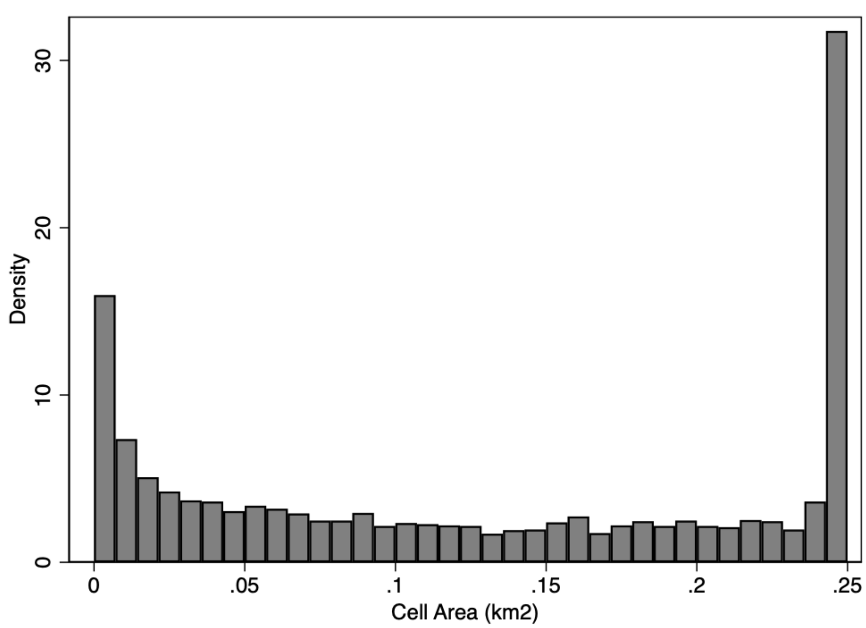
Notes: The figure shows the location of the firms identified in our initial listing in one sampled sub-county.

Figure A17: Illustration of Road Definition



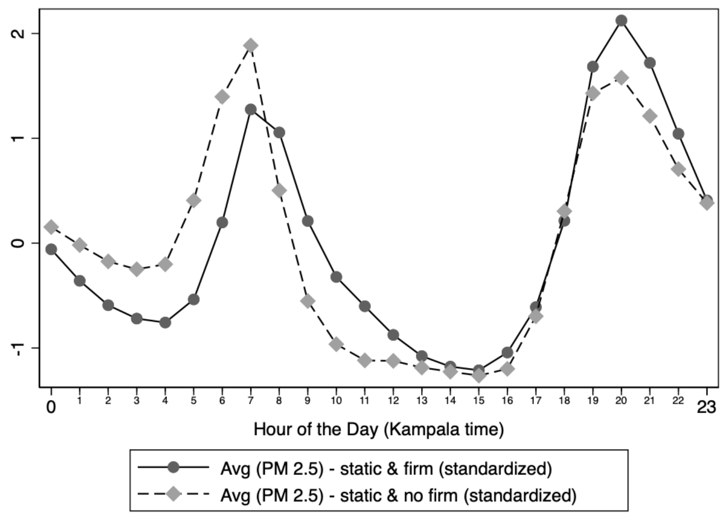
Notes: Each color represents a different road as defined in our dataset by a road segment not intersected by any other road. This grid cell, part of Bugiri Eastern Division, contains eight different roads. The median average grid cell in our sample contains 6 roads (average 11).

Figure A18: Histogram of Grid Cell Areas



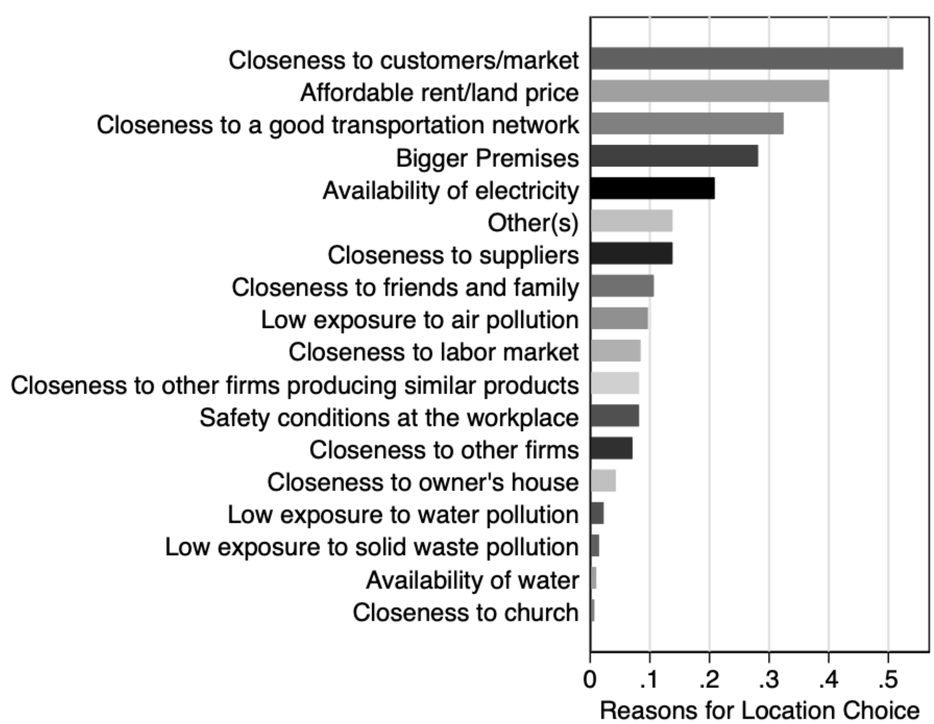
Notes: Distribution of grid cell area in km2 in our data. 3,936 grid cells in total.

Figure A19: Cyclicality of Pollution Does Not Depend on Firm Density (Restricting to Cells Containing at Least One Road)



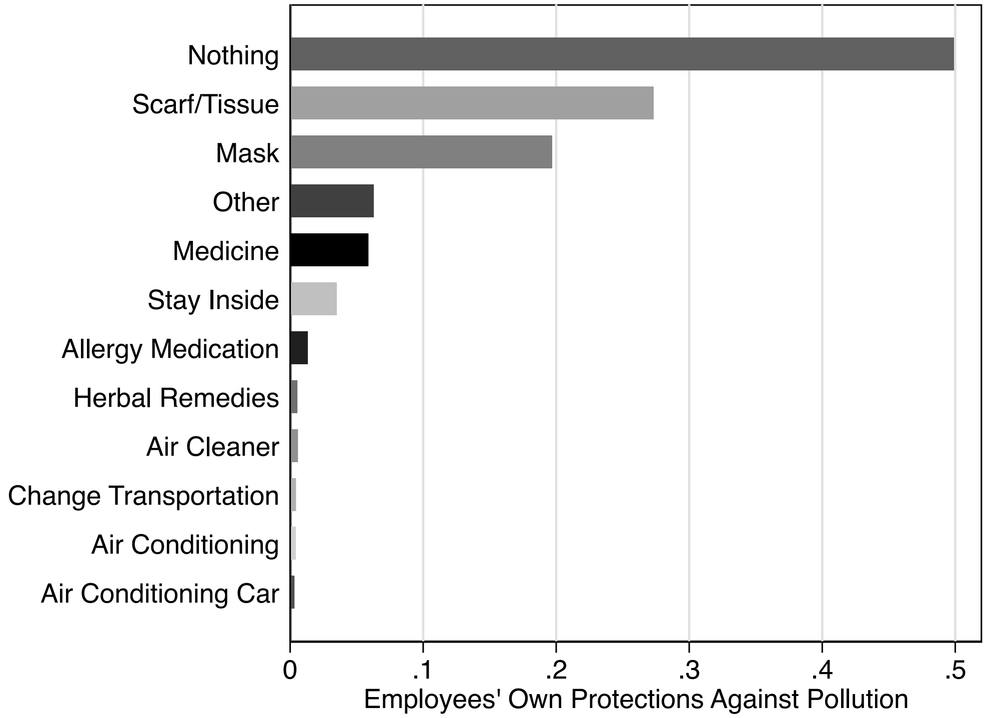
Notes: Avg (PM2.5) is the standardized mean PM2.5 measurement from stationary monitors (top 1% trimmed) by grid cell and hour. Normalizing PM2.5 concentrations allows us to focus on pollution cyclicality. The sample is restricted to grid cells containing at least one road.

Figure A20: Reasons for Location Choice



Notes: 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: 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 A1: Kilometers by Road Size

Road Type	Corresponding Size	Sample (Grid)		Uganda	
		Length (km)	Share	Length (km)	Share
Motorway	5	8	0.003	55	0
Primary Road	4	669	0.24	1288	0.011
Secondary Road	3	502	0.18	3049	0.025
Tertiary Road	2	547	0.196	11786	0.097
Track / Trail	1	1059	0.38	104763	0.866
Total		2786	1	120940	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 2,786 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 28 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 A2: 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)	(8) Man. Score
Avg log(Poll) Resid./Cell	0.228*	0.252*	0.261*	0.250*	-0.104	-0.0400	0.00798	-0.0701
	(0.135)	(0.132)	(0.137)	(0.129)	(0.0731)	(0.0651)	(0.123)	(0.147)
Man. Score	0.179***	0.260***	0.133***	0.196***	0.0639***	0.0569**	0.0850**	
	(0.0346)	(0.0370)	(0.0320)	(0.0378)	(0.0244)	(0.0228)	(0.0422)	
log(Size Premises)							0.0370	
							(0.0238)	
N	595	601	592	591	1359	1359	410	579
R2	0.357	0.393	0.398	0.441	0.253	0.370	0.406	0.183
Fixed Effects (1)	Sector	Sector	Sector	Sector	Sector	Sector	Sector	Sector
Fixed Effects (2)	Subcounty	Subcounty	Subcounty	Subcounty	Subcounty	Subcounty	Subcounty	Subcounty
Level of Observation	Firm	Firm	Firm	Firm	Employee	Employee	Firm	Firm
SE clustering	Grid Cell	Grid Cell	Grid Cell	Grid Cell	Grid Cell	Grid Cell	Grid Cell	Grid Cell
Employee Controls					No	Yes		

Notes: Standard errors are displayed in parentheses (* $p < 0.10$, ** $p < 0.5$, *** $p < 0.01$). 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 whether the grid cell contains any road. We also control 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, employee tenure. We control for missing managerial score (dummy) and missing employee controls (dummy). 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.

Table A3: Correlation Between Manager Quality and Employees' Pollution Awareness

	(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 Employee
Mean Road Size/Cell	0.0438	0.0460	0.00540	0.00526	0.167	-0.114	0.0942	-0.0962
	(0.0331)	(0.0326)	(0.0113)	(0.0114)	(0.206)	(0.0820)	(0.201)	(0.0830)
Man. Score	0.293***	0.273***	0.00616	0.0113	0.127	0.209***		
	(0.0338)	(0.0330)	(0.0165)	(0.0156)	(0.229)	(0.0791)		
Age Manager							0.0872***	
							(0.0195)	
Years School. Man.								0.0657***
								(0.0218)
N	2045	2045	2045	2045	2615	2633	2615	2633
R2	0.165	0.182	0.112	0.123	0.165	0.151	0.174	0.150
Fixed Effects (1)	Sector	Sector	Sector	Sector	Sector	Sector	Sector	Sector
Fixed Effects (2)	Subcounty	Subcounty	Subcounty	Subcounty	Subcounty	Subcounty	Subcounty	Subcounty
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)	0	0	.175	.175	27.59	9.13	27.59	9.13

Notes: Standard errors are displayed in parentheses (* $p < 0.10$, ** $p < 0.5$, *** $p < 0.01$). 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 whether the grid cell contains any road. We also control 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, employee tenure and log wage. We control for missing managerial score (dummy) and missing employee controls (dummy). The top and bottom one percent of pollution residuals are trimmed. 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 Table 7 (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 A4: Correlation Between Employees' Characteristics and Perceptions of Pollution as a Problem

	(1) Concerned Poll Planet	(2) Gov Address Poll	(3) Ideal Job Low Poll	(4) Concerned Poll Health
Years Schooling	0.0298***	-0.000325	0.000942	0.0163
	(0.00834)	(0.0100)	(0.00374)	(0.00990)
Age	0.0120	-0.00816	-0.0133**	0.0163
	(0.0141)	(0.0199)	(0.00591)	(0.0157)
Age^2	-0.0000739	0.000124	0.000215***	-0.000106
	(0.000198)	(0.000288)	(0.0000806)	(0.000217)
Vocational Training (Dummy)	0.113	0.0355	-0.0132	0.194**
	(0.0757)	(0.0951)	(0.0348)	(0.0800)
N	2045	2045	2045	2044
R2	0.112	0.113	0.115	0.167
Fixed Effects (1)	Sector	Sector	Sector	Sector
Fixed Effects (2)	Subcounty	Subcounty	Subcounty	Subcounty
Level of Observation	Employee	Employee	Employee	Employee
SE clustering	Grid Cell	Grid Cell	Grid Cell	Grid Cell
Mean(dependent var)	3.964	4.043	.298	3.735
Answer scale	0-5	1-5	Dummy	0-5

Notes: Standard errors are displayed in parentheses (* $p < 0.10$, ** $p < 0.5$, *** $p < 0.01$). 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 the health of the planet; to what extent she is concerned about the effects of air pollution on her own health; to what extent she agrees that the government should do more to promote and encourage a better air quality even if her taxes have to go up slightly; and whether her ideal job features low levels of air pollution.

Table A5: Correlation Between Manager Quality, Employees' Pollution Awareness and Protective Investments

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Own	Own	Late	Late	Flex	Flex	Managers	Managers
	Protect	Protect	Commute	Late Commute	Commute	Commute	Careful	Careful
Mean Road Size/Cell	0.0106	0.0126	0.0120	0.0133*	0.0116	0.0140	0.0126	0.0138
	(0.0141)	(0.0141)	(0.00735)	(0.00749)	(0.0132)	(0.0134)	(0.0121)	(0.0119)
Man. Score	0.0290	0.0436**	0.0160*	0.0249***	0.0369***	0.0503***	0.0514***	0.0599***
	(0.0189)	(0.0181)	(0.00862)	(0.00866)	(0.0140)	(0.0143)	(0.0155)	(0.0153)
Log Salary	0.00491	0.0113	0.0149*	0.0171*	0.0422***	0.0450***	0.0462**	0.0484***
	(0.0246)	(0.0254)	(0.00867)	(0.00888)	(0.0145)	(0.0146)	(0.0183)	(0.0183)
Poll Awareness - At The Firm	0.0585***		0.0319***		0.0476***		0.0309**	
	(0.0155)		(0.00645)		(0.00956)		(0.0126)	
Poll Awareness - At Home		0.127***		0.00415		-0.0346		0.0161
		(0.0370)		(0.0164)		(0.0247)		(0.0326)
N	2045	2045	2020	2020	2002	2002	1959	1959
R2	0.221	0.218	0.117	0.100	0.211	0.195	0.153	0.149
Fixed Effects (1)	Sector	Sector	Sector	Sector	Sector	Sector	Sector	Sector
Fixed Effects (2)	Subcounty	Subcounty	Subcounty	Subcounty	Subcounty	Subcounty	Subcounty	Subcounty
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	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean(dependent var)	.523	.523	.056	.056	.132	.132	.21	.21
Answer scale	Dummy	Dummy	Dummy	Dummy	Dummy	Dummy	Dummy	Dummy

Notes: Standard errors are displayed in parentheses (* $p < 0.10$, ** $p < 0.5$, *** $p < 0.01$). 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 whether the grid cell contains any road. We also control 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 (dummy). The top and bottom one percent of pollution residuals are trimmed. 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 Table 7 (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.