Polluting Industries and Agricultural Productivity: Evidence from Ghana*

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Abstract

This paper examines the effect of polluting industries on agricultural productivity. The focus is on large-scale gold mining in Ghana that, similar to other fuel intensive activities, releases environmental pollutants with the potential to have cumulative negative effects on crops' health and key agricultural inputs. Guided by a consumer-producer household framework, we estimate an agricultural production that incorporates the effects of pollution. We find that, between 1997 and 2005, farmers near mines experienced a reduction on total factor productivity of almost 40%. We also document higher concentrations of air pollutants near mines and an increase in rural poverty. The effects are not driven by mines' competition for agricultural inputs, selective migration, or changes in perceived risk of expropriation. Our results highlight an important externality —i.e., losses in agricultural productivity—through which polluting industries can affect living conditions in rural areas.

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1 Introduction

The investigation of the social costs of environmental pollution mostly focuses on its negative effects on human health.[1] Scholars also find that, through its effect on health, pollution can hinder human capital accumulation (Currie et al., 2009), labor supply (Hanna and Oliva, 2011) and labor productivity (Graff Zivin and Neidell, 2013). However, the economic literature has paid less attention to the externalities of pollution on other economic outcomes, such as agricultural productivity. This is surprising given the existing biological evidence linking pollution to reduction in crops' health and yields (Heck et al., 1982; Miller, 1988; Marshall et al., 1997) and degradation of key agricultural inputs, such as water and soil (Menz and Seip, 2004; U.S. Environmental Protection Agency, 2012).

This paper fills this gap in the economic literature by examining how polluting industries affect agricultural productivity in a context where traditional farming is the main source of livelihood. Quantifying this externality is important to inform the debate on environmental policies, and to assess the net benefits of (potentially) polluting activities, such as urban growth and extractive industries, that may occur in the vicinity of agricultural areas.

We study gold mining in Ghana. This context has three useful features from the point of view of identifying and quantifying a pollution externality on agricultural productivity. First, most gold production is done in large-scale, modern, mines. These mines are heavily mechanized and release air pollutants similar to other fuel-intensive activities, such as power plants and urban traffic. These pollutants can be carried over long distances and, in high concentrations, can stock up in the environment (in the form of acid depositions) and have cumulative effects.[2] Second, large gold mines have little interaction with local economies: they hire few local workers, buy few local products, and almost none of its profits are locally distributed (Aryeetey et al., 2007). This shuts down a number of channels through which mining activity can affect agricultural activities. Finally, gold mines are located in the vicinity of fertile agricultural lands with important cash crops, such as cocoa.

We use micro-data from household surveys with agricultural information for years 1997 and 2005, and detailed data on location of gold mines and households. To study the effect of pollution

[1] See Graff Zivin and Neidell (2013) and Currie et al. (2013) for a comprehensive review of this literature.

[2] Gold mining also has other industry-specific stock pollutants, such as cyanide spills and acidic discharges. These pollutants are mostly carried by water or localized in the close vicinity of mine sites.

on agricultural productivity, we estimate an agricultural production function, augmented with pollution effects. This allow us to examine how total factor productivity, i.e, residual output conditional on observable inputs, is affected by exposure to mining-related pollution. As a measure of the *stock* of these pollutants, we use cumulative gold production.

A main empirical challenge is that agricultural productivity may be systematically different in mining and non-mining areas. To overcome this concern, we use a difference-in-difference approach exploiting two sources of variation: distance to a mine, and changes in mining production. The main identification assumption is that the change in agricultural productivity in areas far and close to a mine would be similar in the absence of mining.

A second challenge is the endogeneity of input use. This problem has long been recognized in the empirical literature on production functions (Blundell and Bond, 2000; Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg et al., 2006). We are, however, unable to implement the standard solutions due to data limitations. Instead, we use the analytical framework of consumer-producer households (Benjamin, 1992; Bardhan and Udry, 1999) to derive an empirical strategy. We show that, in the presence of imperfect input markets, endowments are a good predictor of input use. Consequently, we use farmers' input endowments, such as land holdings and household size, as instruments. This instrumental variables strategy exactly identifies our parameters if the instruments are uncorrelated with unobserved productivity shifters. We also investigate the case where there is some correlation between instruments and unobserved shifters, using the partial identification strategy of Nevo and Rosen (2012). We find that our major results are robust to small correlations of this type.

We find evidence of a significant reduction in agricultural output and total factor productivity. Our estimates suggest that an increase of one standard deviation in gold cumulative production is associated with a 10 percent decline in productivity in areas within 20 km of a mine.. Given the increase in mining activity between 1997 and 2005, this implies that the average agricultural productivity in mining areas decreased 40 percent relative to areas farther away. Similar results are obtained using partial measures of productivity, such as crop yields.

The results are robust to alternative estimation methods and model specifications, and are driven by proximity to operating mines. A placebo test, for instance, shows no changes on productivity of farmers close to new mining projects that were not operating in the period of analysis. We also check that our results are not driven by (observable) changes in the composition of farmers. These may occur, for example, if there is selective migration, or switching towards non-agricultural activities. Similarly, we find no evidence that the results are driven by a weakening of property rights that may affect agricultural investments (such as cocoa trees) as in Besley (1995). There is, however, some evidence of changes in agricultural practices, such as increase in crop concentration. This finding might be indicative of adjustments to ameliorate the negative effect of pollution.[3]

We interpret these results as evidence that pollution from mining activities is the most plausible channel to explain the reduction in agricultural output and productivity. The first piece of evidence supporting this interpretation comes from the finding that mining has not affected agricultural input prices. This is contrary of what we could expect if the effects were driven by reallocation of local inputs to non-agricultural activities. The second piece of evidence is the finding of higher levels of air pollutants in mining areas. Using satellite imagery, we obtain local measures of nitrogen dioxide (NO_2), a key indicator of air pollution. We find that concentrations of NO_2 are higher in mining areas and decline with distance, in a way that parallels the reduction of agricultural productivity.

An important question is: how would pollution affect total factor productivity? The biological and economic literature suggest at least three main channels: reduction of labor productivity, that would occur, for instance, if workers' health deteriorate (Graff Zivin and Neidell, 2012); degradation of other agricultural inputs (such as soil and water), or deterioration of crops' health and yields. We cannot directly examine the importance of these channels.[4] But, we can provide suggestive evidence that the effect is not entirely driven by reduction in labor productivity. For example, a back-of-the envelope calculation using the structural estimates, suggests that the reduction of labor productivity would need to be very large (around 80%) to fully account for the observed drop in total factor productivity.[5] Similarly, we examine the effect of urban workers near mining areas under the presumption that their wage or non-wage income might reflect changes in their productivity. However, we do not find evidence that this is the case.

[3]This behavioral response has the flavor of the avoidance behavior documented in the environmental literature (Neidell, 2009; Moretti and Neidell, 2011; Graff Zivin et al., 2011).

[4]To do so, we would need data on crop's health and quality of soil, which are unavailable in the case we study.

[5]To put this figure in context, in the U.S. case, Graff Zivin and Neidell (2012) find that a decrease on ozone of 10 parts per billion (ppb) increases worker's productivity by 5.5%. In their study, the average ambient ozone is under 50 ppb with a standard deviation of 13 ppb.

Finally, we look at the effects on local living standards. This is a natural extension given the importance of agriculture in the local economy. We find that rural poverty in mining areas shows a relative increase of almost 18 percent. The effects are present not only among agricultural producers, but extend to other residents in rural areas. There is, however, no effect on urban poverty.[6]

1.1 Related literature

This paper relates to a literature in environmental economics studying the impacts of pollution and, more broadly, environmental disasters. As previously mentioned, this literature has focused mostly on the impact of pollution on human health and human capital.[7] Recently, scholars have started to examine other possible health-related effects, such as reduction on labor supply and labor productivity (Hanna and Oliva, 2011; Graff Zivin and Neidell, 2012), as well as the long-term effects of environmental disasters, such as soil erosion and climate change (Hornbeck, 2012; Dell et al., 2008; Guiteras, 2009). Our main contribution is to highlight the importance of another, understudied, pollution externality: reduction in agricultural productivity.

This paper is closely related to Graff Zivin and Neidell (2012). Using the case of piece-rate farm workers in California's central valley, they find a negative effect of air pollution on labor productivity. Our results complement their findings in two ways. First, we estimate the reductions on total factor productivity, not only on labor productivity. Thus we take into account reductions in productivity that may occur, for instance, if land becomes less productive or if crop yields decline. This distinction is relevant from a policy perspective since it provides a better overview of the total costs imposed by pollution externalities. Second, we explore how pollution ultimately affects measures of living standards, such as consumption and poverty.

This paper also contributes to a literature in development economics studying the impact of natural resources. Using country level data, some studies find that resource abundance may hinder economic performance, specially in the presence of bad institutions (Sachs and

[6]This result contrasts with Aragon and Rud (2013) who find a positive effect of mining activities on household income. This maybe due to the scant backward linkages in the Ghanaian case. Note, however, that the increase in poverty implies that any existing positive effect has not been large enough to offset the loss of agricultural productivity.

[7]For example, there is evidence of the negative effect of pollution on infant mortality (Chay and Greenstone, 2003; Currie and Neidell, 2005; Jayachandran, 2009), children hospitalizations (Lleras-Muney, 2010), birth weight (Currie and Walker, 2011) and incidence of cancer (Ebenstein, 2012). Studies also find that pollution can affect school and cognitive outcomes (Almond et al., 2009; Lavy et al., 2012), and increase school absenteeism (Ransom and Pope III, 1992; Currie et al., 2009).

Warner, 1995; Sachs and Warner, 2001; Mehlum et al., 2006). Departing from these cross-country comparisons, a growing literature is exploiting within-country variation to study other complementary channels that may be more relevant at local level.[8] Our contribution is to highlight the potential costs, in terms of agricultural productivity and rural income, associated to extractive industries. So far, this dimension is absent in the policy debate. Instead, both environmental regulators and opponents of the industry have focused mostly on other aspects, such as risk of environmental degradation, health hazards, and social change. This omission may overestimate the contribution of extractive industries to local economies and lead to insufficient compensation and mitigation policies.

2 Background

2.1 Mining and pollution

Modern mining —akin to other industrial processes, power plants and motor vehicles— have the potential to pollute the environment. First, mining can generate significant amounts of air pollutants such as nitrogen oxide (NO_x), sulphur dioxide (SO_2), ozone and particulate matter. The main sources of these air pollutants are petrol engines of heavy machinery, fumes from smelters and refineries, and blasting operations. These air pollutants can be carried away over larger distances. At low concentrations, air pollutants are short lived: they are dissipated or absorbed by the environment. However, if emissions are relatively large, they can deposit on the ground as acid rain.[9] Acid rain contributes to soil degradation and can have cumulative negative effects (Menz and Seip, 2004).

Second, mines can also generate industry-specific pollutants, such as cyanide, heavy metals, or acid mine drainage (Salomons, 1995; Dudka and Adriano, 1997). Cyanide is used by large gold mines, and though it is re-processed, there is the risk of leakages during transportation or seeping from dumping tailings. In contrast, artisanal mining uses mercury which is usually vaporized during the refining process or released into surface water. Acid mine drainage occurs when sulphide minerals are exposed. Combined with air and water, they form a very acidic

[8] See, for example, Caselli and Michaels (2013), Brollo et al. (2010) and Vicente (2010) for (negative) political economy channels, and Aragon and Rud (2013) for more positive market channels or Kotsadam and Tolonen (2013) for a gender-specific reallocation of labor.

[9] Acid rain is a rain or any other precipitation that is unusually acidic. It is formed when emissions of NO_x or SO_2 react with water in the atmosphere to produce acids.

effluent that can have severe impacts on surrounding water bodies. In modern mines, these pollutants tend to be more closely monitored and prompt mitigation actions. These pollutants are similar to acid rain: they degrade quality of soil and water, and have long-term cumulative effects. Importantly for our analysis, they are mostly carried by surface water. This may limit its impact on agriculture in the Ghanaian case, where most crops are rainfed. For this reason, in the rest of the paper we focus on air pollutants. In Section 4.2, however, we also explore the role of pollutants carried by surface waters.

2.2 Pollution and agricultural productivity

Air pollution can affect agricultural productivity in, at least, three ways. First, it can reduce crops' yields and health. This effect has been well documented in biological sciences (Heck et al., 1982; Miller, 1988; Marshall et al., 1997). The available evidence suggests that air pollutants, such as ozone, NO_x and SO_2, have a negative effect on plants' growth and health. The magnitude of the effect is significant. For example, Emberson et al. (2001), Maggs et al. (1995), and Marshall et al. (1997) find drastic reductions of around 20 to 60 percent in yields of main crops -e.g. rice, wheat, and beans- due to the exposure to polluted air from urban centers located as far as 15 km.[10] This evidence comes from controlled laboratory studies which allow the estimation of crop-specific dose-response functions to pollution.[11] They have two main limitations. First, they do no do not take into account changes in input use or in agricultural practices that may occur as a response to the drop in productivity. Second, they focus on the short-term effect and do not consider possible cumulative effects of pollution, for instance, through soil degradation.

Second, pollution can deteriorate quality of soils. Air pollutants can deposit in the ground in the form of acid rain. Acid rain increase soil acidity and reduces its quality. The increased acidity leaches nutrients from the soil, reduce plants' ability to absorb remaining nutrients, and releases toxic metals, like aluminum. In turn, this weakens vegetation and can cause slower growth, injury or death. The effect of acid rain on soil's quality and vegetation is cumulative, and long lived.[12] These negative effects could be, however, ameliorated by the use of fertilizers,

[10] Most of the available evidence comes from developed countries. The above mentioned studies, however, document the effect of pollution in developing countries such as India, Pakistan and Mexico.

[11] To the best of our knowledge, there are not estimates of dose-response functions to pollution for crops in the Ghanaian context.

[12] For a summary of this evidence see websites of the U.S. and Canada

to replace lost nutrients, or crushed limestone, to reduce soil acidity.

Finally, air pollution can reduce labor productivity. There is a large literature documenting the effect of air pollution on human health. These health shocks can affect human capital and productivity in the short and long-run (Graff Zivin and Neidell, 2013). Recent studies explore this link and find evidence of the negative effects of air pollution on labor supply and labor productivity (Graff Zivin and Neidell, 2012; Hanna and Oliva, 2011).

2.3 Mining in Ghana

Our empirical analysis uses the case of gold mining in Ghana. Most of the gold (around 97%) is produced by modern, large-scale, mines located in three regions: Western, Ashanti and Central.[13] These mines, similar to other modern mines in the world, are capital intensive, highly mechanized operations. They are located in rural areas, amidst fertile agricultural land, and have little interaction with local economies: they hire few local workers, buy few local products, their profits are not distributed among local residents, and only a small fraction of the fiscal revenue is allocated to local authorities (Aryeetey et al., 2007).

Due to data availability, we focus on two years: 1997 and 2005. As shown in Figure 1, before 1997, gold production was increasing from low levels of production. This was mostly driven by the expansion of one mine, Obuasi.[14] After 1997, gold production flattens at a higher level, and reaches a greater number of locations. Many of these mines were new or experienced a significant expansion (e.g. Tarkwa, Bibiani and Damang).

As a measure of mining activity, we use cumulative gold production. This gives us a measure of the exposure to cumulative pollutants, such as heavy metals and acid rain.[15] Table 1 shows that aggregate cumulative production has almost tripled between the two relevant years (1997 and 2005) and that there is substantial variation across mines[16]. We exploit these differences in gold production by mine in our empirical analysis.

environmental agencies (http://www.epa.gov/acidrain/effects/forests.html and http://www.ec.gc.ca/air/default.asp?lang=En&n=7E5E9F00-1ws0EF0FB73).

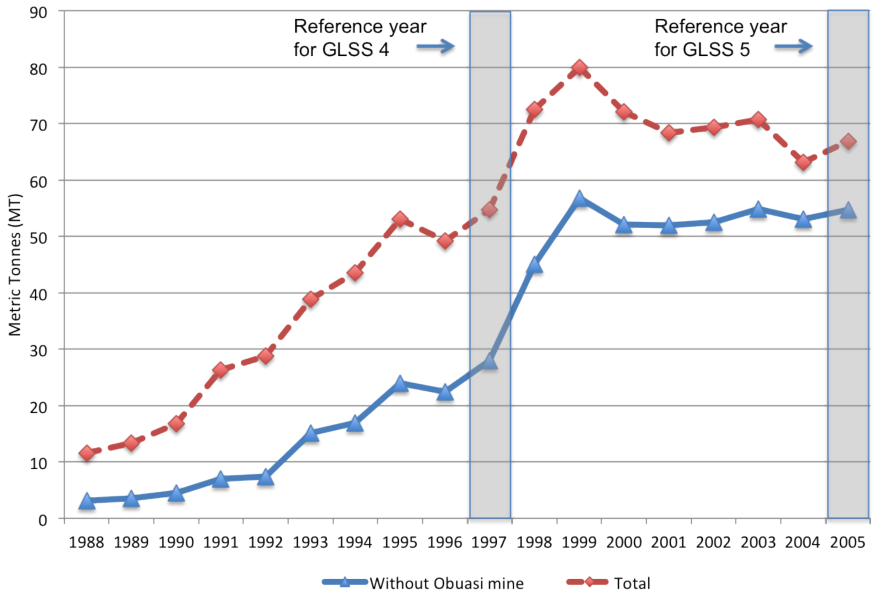
[13]The rest is produced by small artisanal mines, and informal miners called *galamseys*. Both share similar labor-intensive, small-scale technology and are usually owned by locals.

[14]The main results are robust to excluding observations in the vicinity of Obuasi mine (see Table B.5.

[15]The environmental literature distinguishes two types of pollutants: flow, or fund, pollutants and stock pollutants. Flow pollutants are dissipated or absorbed by the environment, while stock pollutants accumulate in the environment over time.

[16]There is little variation across mines in 2004, suggesting that production one year before the measurements cannot explain results across different mining areas.

Figure 1: Total gold production (in MT), by year



Source: U.S. Geological Service, *The Mineral Industry of Ghana* 1994-2004, Infomine, and Aryeetey et al. (2007).

Table 1: Cumulative gold production by mine, in Metric Tonnes (MT)

Mine name	Type	Cumulative production Up to 1997	Up to 2005	Diff.
Bibiani	open pit	0.0	51.2	51.2
Bogoso/Prestea	open pit, underground and and tailings	23.9	55.9	32.0
Central Ashanti	open pit	5.4	9.7	4.3
Damang	open pit	0.0	73.6	73.6
Dunkwa placer	placer	1.2	1.2	0.0
Essase placer	placer	2.8	12.4	9.6
Iduapriem/Teberebie	open pit	19.6	61.2	41.6
Konong/Obenamasi	open pit	1.5	1.5	0.0
Obotan	open pit	2.2	19.4	17.3
Obuasi	open pit and underground	204.3	346.3	142.0
Tarkwa	open pit and underground	9.4	121.0	111.6
Wassa	open pit	0.0	10.3	10.3
TOTAL		270.3	763.7	493.4

Source: U.S. Geological Service, *The Mineral Industry of Ghana* 1991-2004, Infomine, and Aryeetey et al. (2007).

Note: Cumulative production is calculated adding annual production from year 1988 to 1997, and from 1988 to 2005, respectively.

There are no systematic data on pollutants concentration near mining sites.[17] There is, however, several case studies suggesting that gold mining is associated with high levels of pollution and loss of agricultural livelihoods (Human Rights Clinic, 2010; Akabzaa, 2009; Aryeetey et al., 2007; Hilson and Yakovleva, 2007). For instance, Armah et al. (2010) and Akabzaa and Darimani (2001) document heavy metal pollution in surface and groundwater near Tarkwa. The levels of pollutants decrease with distance to mining sites. The authors also document levels of particulate matter near or above international admissible levels. WACAM (2010) reports high levels of heavy metals, acidity and turbidity in streams and water bodies near Obuasi and Tarkwa. Tetteh et al. (2010) find high levels of mercury and zinc content in the top-soil of towns in Wassa West. The levels of concentration decrease with distance to mining sites probably due to air dispersion.[18]

3 Methods

3.1 A consumer-producer household

In this section we lay down a simple analytical framework based on the standard model of consumer-producer households (Benjamin, 1992; Bardhan and Udry, 1999). This framework has been used to analyze farmers' decisions when consumption and production are interrelated. In our case, it clarifies how mining could affect agricultural output, and guides the empirical analysis.

We assume that households (farmers) are both consumers and producers of an agricultural good with price $p = 1$. Households have an idiosyncratic productivity A and use labor (L) and land (M) to produce the agricultural good $Q = F(A, L, M)$, where F is a well-behaved production function.

Households have endowments of labor and land (E^L, E^M). They can use these endowments as inputs in their farms, sell them in local input markets (L^s, M^s) at prices w and r, or, in the case of labor, also consume it as leisure. As producers, households can buy additional labor and

[17] Only since 2009, Ghana's Environmental Protection Agency (EPA) has started assessing, and reporting, the environmental compliance of mines (see `http://www.epaghanaakoben.org/`). The results are consistent with the academic evidence mentioned in this section. Of the 9 operative gold mines studied, 7 were red-flagged as failing to comply environmental standards. These mines were considered to pose serious risks due to toxic and hazardous waste mismanagements and discharge.

[18] We cannot use this information in our empirical analysis because it is geographically sparse and cover different periods than the available household data..

land (L^b, M^b).

Households maximize utility $U(c,l)$ over consumption c and leisure l, subject to the endowment constraints and agricultural technology. In particular, the household's problem is:

$$\begin{aligned} & \max U(c,l) \text{ subject to} \\ c &= F(A,L,M) - w(L^b - L^s) - r(M^b - M^s) \\ L &= E^L + L^b - L^s - l \\ M &= E^M + M^b - M^s. \end{aligned}$$

We assume households are heterogeneous in their access to markets for inputs. In particular, there are two types of farmers: unconstrained farmers, who operate as in perfectly competitive input markets, and fully-constrained farmers, who cannot buy nor sell inputs.[19] The assumption of imperfect input markets is reasonable in the context of weak property rights of rural Ghana.[20] Besley (1995), for example, documents the co-existence of traditional and modern property right systems in West Ghana. Some farmers have limited rights to transfer property of land, and in many cases require approval from the community while others do not face this constraint. Botchway (1998) also discusses the customary framework that rules the right to trade land in Ghana. Similar arguments can be made about labor markets, due to market incompleteness, farmers' preference for working on their own land, or imperfect substitutability of household and hired labor.

In the case of unconstrained farmers, the maximization problem follows the separation property: the household chooses the optimal amount of inputs to maximize profits and, separately, chooses consumption and leisure levels, given the optimal profit. From standard procedures, the optimal levels of inputs and output, $L^*(A,w,r)$, $M^*(A,w,r)$ and $Q^*(A,w,r)$, depend only on total factor productivity and input prices.

In the case of fully-constrained farmers, i.e., farmers unable to sell or buy inputs, the optimal input decisions are shaped by their endowments. Since the opportunity cost of land is zero, they will use all their land endowment, $M^* = E^M$. In the case of labor, however, farmers still

[19] Results would not change qualitatively if we allow for partially constrained farmers.

[20] Data show that, in the area of study, input markets are thin: around 8% of available land is rented, and only 1.4% of the total farm labor (in number of hours) is hired. As shown in Table B.4 in the Appendix, endowments are a very strong predictor of input use.

face a trade-off between leisure and income. Solving the household's problem, the optimal level of labor, $L^*(A, E^M)$, depends now of total factor productivity and input endowments.[21]

In this framework, there are two possible channels for mining to affect agricultural output, and households' consumption. First, mines could increase demand for local inputs (input competition). This may lead to increase in w and r and, through that channel, reduce input use and agricultural output among unconstrained farmers. Similar effects would occur if, for example, mines reduce supply of inputs due to land grabbings or population displacement. There would be, however, no effect on productivity, A.[22] Also note that the effect on consumption depends on the relative size of endowments. If endowments are small, so that a household is a net purchaser of inputs, then the effect would be negative. This mechanism is similar in flavor to the Dutch disease and has been favored as an explanation for the perceived reduction in agricultural activity, and increase in poverty, in mining areas (Akabzaa, 2009; Aryeetey et al., 2007).[23]

Second, mining-related pollution may affect crop's health and yields, as well as quality of inputs as discussed above. This would imply a reduction in output even if the quantity of inputs used remains unchanged. In terms of the model, this represents a drop in productivity, A. This would, unambiguously, have a negative effect on agricultural output and household's consumption. Additionally, it might reduce input use. In particular, labor use might fall either by reducing labor demand for unconstrained farmers or through a substitution of labor towards leisure for constrained farmers. In the case of land, only unconstrained farmers would reduce their land use. The empirical implication of this is that we would only observe a drop in land use in mining areas if the share of unconstrained farmers is high. Finally, contrary to what the input competition channel might deliver, input prices would decrease or remain unchanged, depending on how well markets reflect factors' marginal productivity.

This simple framework highlights several issues relevant for the empirical analysis:

1. If the main channel is through input competition, then mining would: (i) reduce agricultural output, but have no effect on A, (ii) increase input prices, (iii) decrease input

[21] For a fully constrained farmer, the household's problems simplifies to $\max U(c, l)$ subject to $c = F(A, L, E^M)$ and $L = E^L - l$. The first order condition is $U_c F_L = U_l$.

[22] This remark depends, however, on the assumption that input type does not change.

[23] For example, Duncan et al. (2009) suggests a reduction of around 15% in agricultural land use associated with the expansion of mining in the Bogoso-Prestea area. The conflict over resources seems to have exacerbated due to weak property rights (i.e., customary property rights) and poor compensation schemes for displaced farmers (Human Rights Clinic, 2010).

use among unconstrained farmers; and (iv) depending of the relative size of endowments, decrease or increase farmers' consumption.

2. If the main channel is through pollution, then mining would: (i) reduce agricultural output and productivity, A, (ii) decrease input prices, depending of the flexibility of markets, (iii) decrease input use among all farmers (except for land of constrained farmers), and (iv) unambiguously decrease farmer's consumption.

3. In the presence of imperfect input markets, household endowments are a determinant of input use.

3.2 Empirical implementation

The aim of the empirical analysis is to explore the importance of mining-related pollution on agricultural activity. To do so, our main approach is to estimate the production function, i.e., output conditional on input, and evaluate the effect of mining on total factor productivity, A. We complement this approach by also studying the effect of mining on input prices and poverty. As previously mentioned, the effect of mining on these outcomes can also be informative of the main mechanisms at play.

We start by assuming the following agricultural production function:[24]

$$Y_{ivt} = A_{ivt} M_{it}^{\alpha} L_{it}^{\beta} e^{\epsilon_{it}}, \tag{1}$$

where Y is actual output, A is total factor productivity, M and L are land and labor, and ϵ_{it} captures unanticipated shocks and is, by definition, uncorrelated to input decisions. All these variables vary for farmer i in locality v at time t. Other inputs, such as capital and materials (e.g. fertilizers, insecticides), are not widely used and thus excluded from the empirical analysis [25]. Their inclusion, however, does not change any of the results.

We assume that A is composed of three factors: farmers' heterogeneity (η_i), time-invariant local economic and environmental conditions (ρ_v) and time-varying factors, potentially related to the presence of local mining activity (S_{vt}). In particular, $A_{ivt} = \exp(\eta_i + \rho_v + \gamma S_{vt})$. Note

[24] We assume a Cobb-Douglas technology for simplicity. In the empirical section, we check the robustness of the results to using a, more general, CES production function.

[25] For example, the value of tools and other capital goods is, on average, less than 1% of total output and the value of manure, seeds, fertilizers and insecticides account for less than 5%.

that if mining affects input availability or prices (input competition channel), it will change input use but would not affect productivity A so $\gamma = 0$. In contrast, if the pollution mechanism is at play, we should observe $\gamma < 0$.

As the empirical counterpart of S_{vt}, we use cumulative gold production near a farmer's locality.[26] This variable would be a reasonable proxy for exposure to pollutants under the assumption that pollutants have a cumulative effect, i.e. they are stock pollutants. As we discuss in Section 2, several pollutants released by mining operations, such as NO_2, SO_2 and heavy metals, can have negative cumulative effects on vegetation through acid rain and soil degradation.[27]

We can anticipate two main empirical challenges. The first one is related to the fact that mining and non-mining areas may have systematic differences in productivity. This omitted variable problem may lead to endogeneity issues when estimating the coefficients of interest. To address this issue, we exploit time variation in the repeated cross section to compare the evolution of productivity in mining areas relative to non-mining areas.

This approach is basically a difference in difference with a continuous treatment. In this case, proximity to a mine defines the treated and control group, while the intensity of the treatment is the cumulative amount of gold produced in nearby mines.[28] The validity of this approach relies on the assumption that the evolution of productivity in both areas would have been similar in the absence of mining.[29]

The second problem arises because both output and choice of inputs are affected by productivity, and hence are simultaneously determined. Thus, unobserved heterogeneity in A would go into the error term and create an endogeneity problem in the estimation of the input coefficients.

We address these concern in several ways. First, we use farmers' observable characteristics

[26]In the baseline specification, we define a mining area as localities within 20 km of a mine. For those areas, S_{vt} is equal to gold production in nearby mines from 1988 to the reference year of the household survey (i.e. 1997 for GLSS 4 and 2005 for GLSS 5). For areas farther than 20 km, $S_{vt} = 0$.

[27]In the empirical analysis, we also check the robustness of the results to measures of flow pollutants, i.e. short-lived pollutants, using annual gold production (see Table 6).

[28]We also use a simpler specification replacing S_{vt} by $(mining\_area_v) \times T_t$ where $mining\_area_v$ is an indicator of being close to a mine and T_t is a time trend. The results using this discrete treatment are, however, similar (see Table B.2 in the Appendix).

[29]In the Appendix, we explore the evolution of average agricultural output in areas closer and farther from mines for three years with available data: GLSS 2 (1988), GLSS 4 (1997) and GLSS 5 (2005). Figure A.1 shows that the evolution of output is remarkably similar in the first period (1988-1997), when gold production is relatively low, but there is a trend change in mining areas in the period when gold production increases (1998-2005). Table B.1 formally tests the similarity of trends, and subsequent change, by regressing agricultural output on $(mining\ area_v) \times T_t$ for both periods. Note that the similarity of trends prior to the expansion of mining is a necessary, though not sufficient, condition for the identification assumption to be valid.

to proxy for farmer heterogeneity, η_i. We also include district fixed effects to capture differences in average product due to local characteristics.[30] With these modifications, and taking logs, the model we estimate becomes:

$$y_{ivdt} = \alpha m_{it} + \beta l_{it} + \gamma S_{vt} + \phi Z_i + \delta_d + \psi_t + \theta mining\_area_v + \xi_{ivt}, \tag{2}$$

where y, l and m represent the logs of observed output, labor and land, respectively. Z_i is a set of farmer's controls, and S_{vt} is the cumulative gold production in the proximity of a locality. δ_d and ψ_t represent district and time fixed effects, while $mining\_area_v$ is an indicator of being within 20 km of a mine. ξ_{ivt} is an error term that includes ϵ_{it} and the unaccounted farmer and locality heterogeneity. Under the assumption that use of inputs is uncorrelated to residual unobserved heterogeneity, ξ_{ivt}, we can estimate the parameters of (2) using an OLS regression.

Second, we relax the previous identification assumption and exploit the presence of some constrained farmers. In particular, we estimate a standard IV model using endowments as instruments for input use. Recall from the model that the larger the fraction of constrained households, the greater the correlation between input use and household endowments. This approach would be valid if the correlation is strong enough and if endowments affect output only through its effect on input use, i.e., endowments are not conditionally correlated to unobserved heterogeneity, ξ_{ivt}.[31].

Finally, we consider the possibility that endowments are correlated to ξ_{ivt}.This could happen, for example, if more productive farmers have systematically larger landholdings or household size. This would invalidate the exclusion restriction of the IV strategy. We can make, however, further progress by using a partial identification strategy proposed by Nevo and Rosen (2012). This methodology uses imperfect instrumental variables (IIV) to identify the set of parameter values.[32] The approach relies on two assumptions: (i) the correlation between the instrument and the error term has the same sign as the correlation between the endogenous variable and the error term, and (ii) the instrument is *less* correlated to the error than the endogenous variable. These (set) identification assumptions are weaker than the exogeneity assumption in

[30]Districts are larger geographical areas than localities v. We cannot use locality fixed effects due to the structure of the data.

[31]The interpretation of this IV strategy would be as a local average treatment effect, since the coefficients would be identified from constrained farmers only.

[32]In contrast, the standard IV approach focuses on point identification.

the standard IV and OLS approaches.[33]

3.3 Data

Our main results use a repeated cross-section of household data from the rounds 4 and 5 of the Ghana Living Standards Survey (GLSS 4 and GLSS 5).[34] These surveys were collected by the Ghana Statistical Service (GSS) between April 1998 to March 1999, and September 2005 to August 2006, respectively. Note, however, that the questions on agricultural activities refer to the previous 12 months. Thus, the surveys reflect information on agricultural input and outputs mainly for years 1997 and 2005. We use these two years as the reference years to match household data with measures of mining activity.

The survey is representative at regional level and contains several levels of geographical information of the interviewees. The higher levels are district and region. The district is the lower sub-national administrative jurisdiction, while the region is the highest.[35] The survey also distinguishes between urban and rural areas, as well as ecological zones (coastal, savannah and forest). The finer level is the enumeration area, which roughly corresponds to villages (in rural areas) and neighborhoods (in urban areas). For each enumeration area we obtain its geographical coordinates from the GSS.[36]

We are mainly interested on two set of variables: measures of mining activity, and measures of agricultural inputs and output.

Mining activity Our main measure of mining activity is the cumulative production of gold in the proximity of a household, the empirical counterpart of S_{vt}. To construct this variable, we first identify mines active during the period 1988 to 2005, and aggregate the annual production of each mine since 1988 to the survey's reference year for agricultural activities.[37] Data on mining production by mine come mainly from reports prepared by the U.S. Geological Service

[33]We refer the reader to Nevo and Rosen (2012) for a detailed exposition of the estimation method.

[34]We also use the GLSS 2, taken in 1988/89, for evaluating pre-trends in agricultural output between mining and non-mining areas. We do not use this data, however, in the estimation of the production function since it does not contain comparable information on input use. In addition, we do not use the GLSS 3 (1993/94) because there is not available information on the geographical location of the interviewees.

[35]In 2005, there were 10 regions and 138 districts.

[36]The GSS does not have location of enumeration areas for the GLSS 2. In this case, we extracted the location using printed maps of enumeration areas in previous survey reports.

[37]We use 1988 as the starting year due to data availability.

(USGS).[38] This source covers year 1991 to 2004. We complete the remaining years with data from Infomine, and Aryeetey et al. (2007).[39]

Second, we obtain geographical coordinates of each mine site.[40] Using a geographical information system (ArcGIS), we identify the enumeration areas within different distance brackets of each mine site. For reasons that will be clearer later, we define the enumeration areas within 20 km of mine sites as mining areas. Finally, we assign the cumulative production of each mine to its surrounding mining area, and zero for areas farther away.

Figure 2a displays a map of Ghana with the location of active gold mines between 1988 and 2005. Note that all mines are located in three regions: Western, Ashanti and Central. In the empirical section, we restrict the sample to these regions.[41] Figure 2b zooms in these three regions and depicts the enumeration areas and a buffer of 20 km around each mine. The areas within each buffer correspond to the mining areas (treated group), while the rest correspond to the non-mining areas (comparison group).

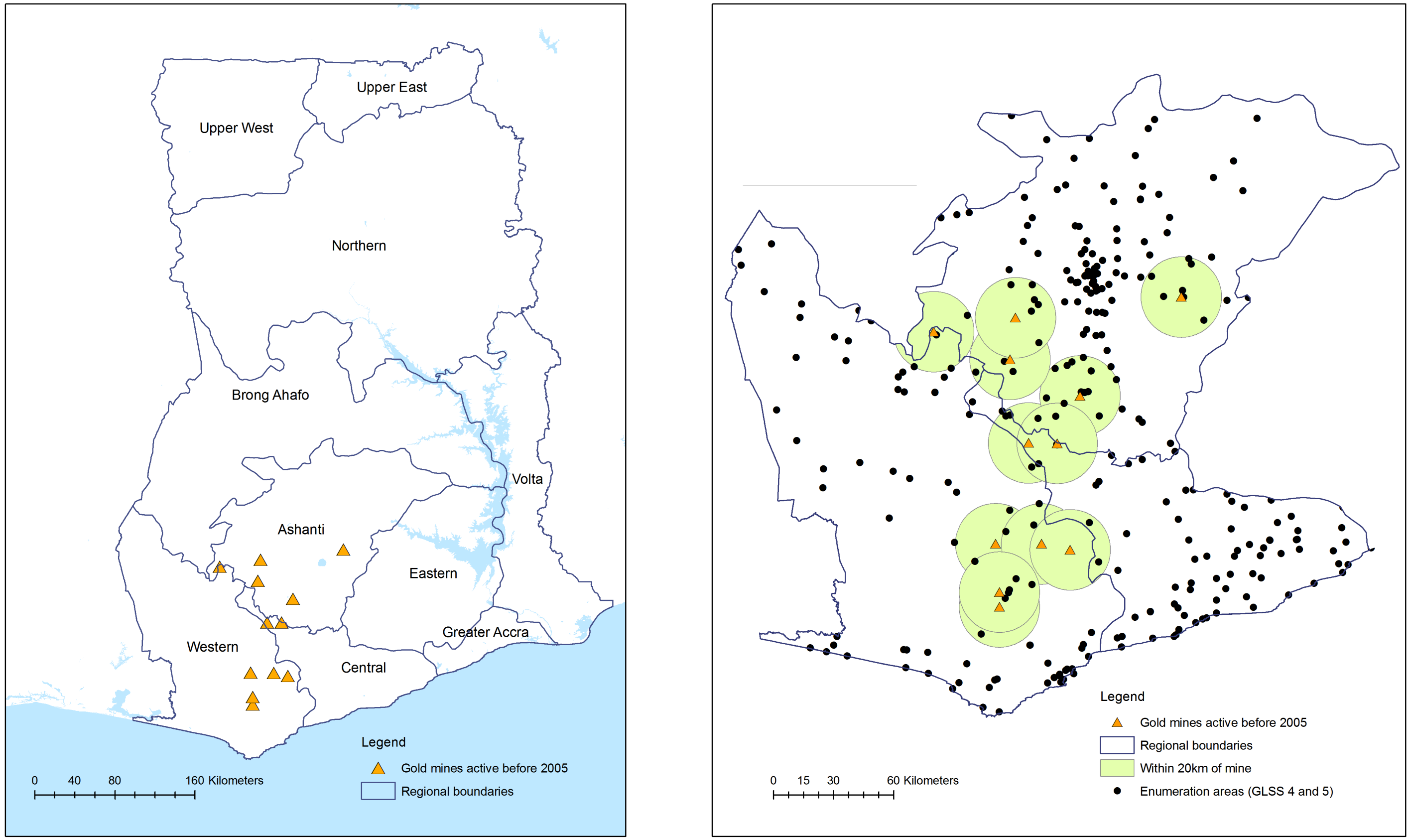
We restrict attention to medium and large-scale gold mines. We do not consider artisanal and informal gold mines for two reasons. First, the magnitude of their operations is relatively small (they represent around 4% of total gold production). Second, there is no information on their location, though anecdotal evidence suggests they are located in the vicinity of established mines. For similar reasons, we do not consider mines of other minerals (such as diamonds, bauxite and manganese). These minerals are less important than gold in Ghana's mining output. Moreover, their mine sites are concentrated in locations that overlap with existing gold operations. For example bauxite and diamonds are mined in Awaso (south of Bibiani gold mine), while manganese is extracted at the Nsuta-Wassa mine near Tarkwa. Note that the omission of these other mines would, if anything, introduce measurement error and attenuate the estimates of the effect of large-scale gold mining.

[38] See the annual editions of *The Mineral Industry in Ghana* from 1994 to 2004 available at `http://minerals.usgs.gov/minerals/pubs/country/africa.html`.

[39] Infomine (`http://www.infomine.com/minesite/`) provides production by mine for 2005, while Aryeetey et al. (2007) report aggregate production (measured by Ghana's Mineral Commission) for years prior to 1991. We impute production by mine for years 1988 to 1990 using mines' shares of gold production in 1991. Main results are, however, similar using only data from USGS for period 1991-2004.

[40] This information comes from proprietary industry reports prepared by Infomine.

[41] The results, however, are robust to using a broader sample.



(a) Location of active gold mines

(b) Area of study and enumeration area

Figure 2: Maps

Agricultural output and inputs To measure agricultural output, Y, we first obtain an estimate of the nominal value of agricultural output. To do so, we add the reported value of annual production of main crops. These category includes cash crops, staple grains and field crops such as cocoa, maize, coffee, rice, sorghum, sugar cane, beans, peanuts, etc. Then, we divide the nominal value of agricultural output by an index of agricultural prices.[42] This price index uses data from agricultural producers and varies by region and by mining and non-mining areas.[43]

We also construct estimates of the two most important agricultural inputs: land and labor. The measure of land simply adds the area of plots cultivated with major crops in the previous 12 months. To measure labor, we add the number of hired worker-days to the number of days each household member spends working in the household farm. Finally, we measure land endowment as the area of the land owned by the farmer, while the labor endowment is the number of equivalent adults in the household.

The resulting dataset contains information on agricultural inputs and output for 1,627 farmers. The farmers are located in 42 districts in three regions of south west Ghana: Western, Ashanti and Central. Table 2 presents a simplified difference-in-difference estimation of the main variables of interest, by comparing mean values in both survey rounds for farmers located in areas close and far to any mining operations (independently of their size). A first important observation is that the log of agricultural output has shown a relative decrease near the mining areas. Consistent with the consumer-producer household framework, the poverty rate in affected areas shows a relative increase. On the contrary, there is no apparent significant difference in the use of the main inputs, land and labor. There is, however, a differential change in input prices even though the sign is not, as an increase in demand from mines would suggest, positive. A reduction in input prices might simply reflect the lower marginal productivity of inputs due to pollution.

There are also no significant differences in most farmers' characteristics, except for place of birth and land ownership. These differences, however, disappear when controlling for other

[42]The results are similar using a consumer price index reported by the GSS, which varies by ecological zone and by urban and rural areas (see Table B.3 in the Appendix). This consumer price has a lower geographical resolution than the one we use in this paper.

[43]In particular, we obtain data from individual farmers on unit values of cocoa and maize, the two main crops in the area of study, and their relative share in the value of agricultural output in 1997. Then, we take the median value of prices and weights by region and by mining and non-mining area, i.e., six different values every survey, and construct a Laspeyres price index.

farmer characteristics.

Table 2: Mean of main variables, by GLSS and location

Variable	Within 20 km of mine		Outside 20 km of mine		Diff. columns
	GLSS 4	GLSS 5	GLSS 4	GLSS 5	(2-1) - (4-3)
	(1)	(2)	(3)	(4)	(5)
Cumul. gold prod. (MT)	41.7	84.6	-	-	-
ln(real agric. output)	6.6	6.2	6.5	6.6	-0.526***
					(0.174)
Land (acres)	7.2	17.9	8.3	9.4	9.671
					(9.505)
Labor (days)	377.3	358.8	343.1	366.3	-41.704
					(31.987)
Land owned (acres)	11.6	21.2	12.0	13.6	7.918
					(9.653)
Nr. adults equivalents	3.6	3.4	3.9	3.5	0.095
					(0.233)
ln(relative land price)	14.4	14.1	13.9	14.1	-0.519***
					(0.104)
ln(real wage)	8.6	8.8	8.4	8.8	-0.269***
					(0.042)
Age (years)	48.0	47.9	46.6	47.4	-0.944
					(1.956)
Literate (%)	53.1	46.6	54.5	45.3	0.027
					(0.063)
Born in village (%)	45.5	60.7	54.2	41.9	0.275***
					(0.062)
Owns a farm plot (%)	69.3	88.4	54.3	83.0	-0.095*
					(0.054)
Poverty headcount (%)	15.2	26.0	33.8	17.6	0.270***
					(0.050)
Nr. Observations	162	218	551	696	

Notes: Columns 1 to 4 report mean values for the sub-sample of farmers within and outside 20 km of a mine for every round of the GLSS. Means are estimated using sample weights. By definition, cumulative production in non-mining areas is equal to zero in both periods. Column 5 displays the difference in difference of columns 1 to 4. The standard errors are in parentheses. Total number of observations is 1627.

4 Main results

This section provides evidence that mining is associated with a significant reduction in agricultural productivity. The results are robust to various specifications and estimation techniques.

While unable to observe mining-related pollution, we use satellite imagery to show that air pollution is worse near mining areas. We also explore, and rule out, alternative explanations, such as competition for inputs, and changes in population composition, or risk of expropriation. We conclude by discussing the mechanisms through which pollution could affect productivity.

4.1 Effect on agricultural productivity

Table 3 presents the main results. In column 1, we start by exploring the relation between agricultural output and the measure of mining activity (i.e, the amount of cumulative production in nearby mines) without controlling for input use. Note that this relation is negative and significant. As previously discussed, this negative effect is consistent with mining affecting agriculture through pollution or input competition.

To explore the likely channels driving this relation, we proceed to estimate the agricultural production function laid out in equation (2). Column 2 provides OLS estimates, while column 3 estimates a 2SLS using input endowments (such as area of land owned and the number of adults equivalents in the household) as instruments for actual input use.[44] As a reference, column 4 estimates the 2SLS regression using as proxy of S_{vt} the interaction between a dummy of proximity to a mine and a time trend, so the estimate of γ represents the average change in output, conditional on inputs, of mining areas relative to non-mining areas. All regressions include a set of farmer controls, district and survey fixed effects. We also use sample weights and cluster errors at district level to account for sampling design and spatial correlation of shocks.

Both approaches suggest a large negative relation between mining and output, after controlling for input use.[45] Under the identification assumptions discussed above, we interpret this as evidence that mining has reduced agricultural productivity. This result is consistent with mining-related pollution negatively affecting agriculture.

The magnitude of the effect is relevant: an increase of one standard deviation in the measure of mining activity is associated to a reduction of almost 10% in productivity.[46] Given the

[44]The first stage of the 2SLS reveals a positive and significant correlation between input endowments and input use. This is consistent with imperfect input markets as discussed in Section 3.1. See Table B.4 in the appendix for the first stage regressions.

[45]The estimates of α and β, i.e., the participation of land and labor, also seem plausible. We cannot reject the hypothesis of constant returns to scale. Using the 2SLS estimates, the p-value of the null hypothesis $\alpha + \beta = 1$ is 0.773. We obtain a similar result of constant returns to scale when using a CES production function.

[46]The average value of the measure of mining activity (i.e., cumulative gold production within 20 km in hundreds of MT) increased from 0.417 in 1997 to 0.846 MT in 2005. The standard deviation of this variable is 0.617.

increase in cumulative production between 1997 and 2005, this implies that average agricultural productivity in areas closer to mines decreased around 40% relative to areas farther away.[47] The estimated effect on productivity is large. Its magnitude, however, is consistent with the biological literature that documents reductions of 30-60% in crop yields due to air pollution (see Section 2). Moreover, it highlights the importance of negative spillovers from modern industries in rural environments.

Columns 5 and 6 examine the effect of mining on crop yields. Crop yields have been used as a proxy for agricultural productivity in the empirical literature and are an output of interest by themselves (see for example Duflo and Pande (2007) and Banerjee et al. (2002)). Note that crop yields use only data on physical production and land use, so they are not affected by possible errors in measuring price deflators.

We focus on the yields of cocoa and maize, the two most important crops in south west Ghana. In both cases, we estimate an OLS regression including farmer's controls and district fixed effects, but without input use.[48] Consistent with the results on productivity, we find a negative and significant relation between mining and crops yields.

Finally, we use the imperfect instrumental variable approach developed by Nevo and Rosen (2012). This approach uses instrumental variables that *may be correlated to the error term.* Under weaker assumptions that the standard IV approach, this methodology allow us to identify parameters bounds instead of point estimates. We allow both instruments to be imperfect and run the IIV specification for different combinations of values of λ_{land} and λ_{land}, the parameters that measure the ratio of correlations of the instrument and the regressor with the error term.[49] Figure 3 shows that the effect on residual productivity is negative in the large majority of the cases (more than 95%) or, in other words, we need very specific combinations of λ_j for our main results not to hold.[50]

The role of distance So far, we have assumed that areas within 20 km of mines experience most of the negative effect. Implicitly, this approach assumes that the effect of mining declines

[47]We obtain this figure using estimates in column 4.

[48]We do not control for inputs since we do not have estimates of labor use by crop. However, including total input use does not change the results.

[49]Note that $(\lambda_{land}, \lambda_{land}) = (0, 0)$ corresponds to the standard 2SLS estimate. For further details of the methodology see Nevo and Rosen (2012, section III.D).

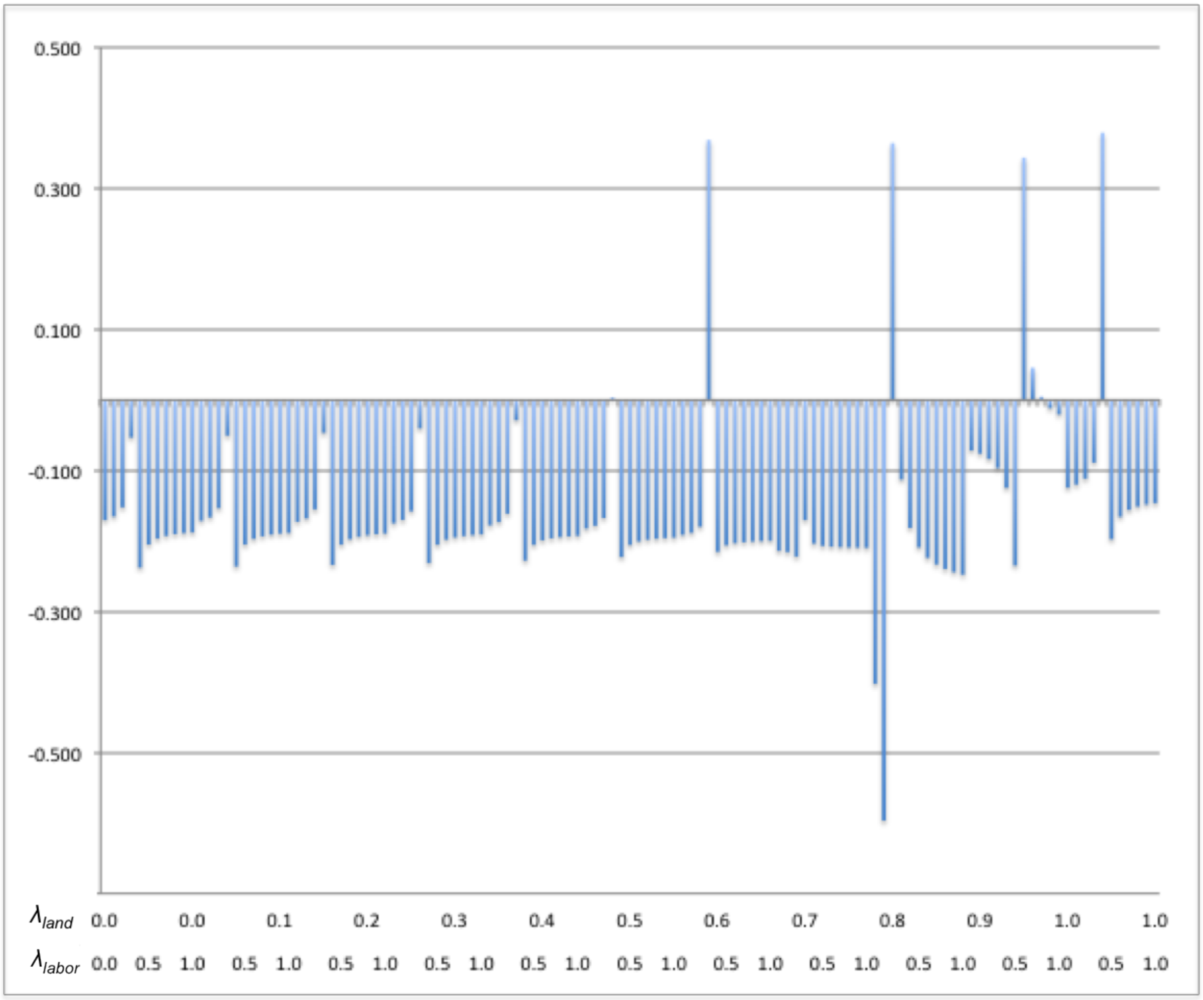
[50]For completeness, we also obtain analytical bounds proposed by Nevo and Rosen (2012) in the, more restrictive, case of only one imperfect instrument (see Table B.10).

Table 3: Mining and agricultural productivity

	ln(real agricultural output)				ln(yield cocoa)	ln(yield maize)
	(1)	(2)	(3)	(4)	(5)	(6)
Cumulative gold prod. within 20 km.	-0.149*	-0.176**	-0.170**		-0.509*	-0.420***
	(0.085)	(0.085)	(0.085)		(0.298)	(0.103)
Within 20 km of mine × GLSS 5				-0.565**		
				(0.240)		
ln(land)		0.631***	0.676***	0.678***		
		(0.038)	(0.047)	(0.046)		
ln(labor)		0.209***	0.352***	0.346***		
		(0.033)	(0.110)	(0.109)		
Estimation	OLS	OLS	2SLS	2SLS	OLS	OLS
Observations	1,627	1,627	1,627	1,627	948	605
R-squared	0.221	0.445	0.435	0.438	0.349	0.409

Notes: Robust standard errors in parentheses. Standard errors are clustered at district level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. All regressions include district and survey fixed effects, an indicator of being within 20 km of a mine, and farmer's controls. The set of farmer's controls includes: household head's age, literacy, and an indicator of being born in the village; as well as an indicator of the household owning a farm plot. Columns 3 and 4 are estimated using 2SLS. The excluded instruments are: ln(area of land owned) and ln(number of adults equivalents in the household). Cumulative gold production is measured in hundreds of metric tonnes (MT).

Figure 3: Estimates of γ with multiple imperfect IVs

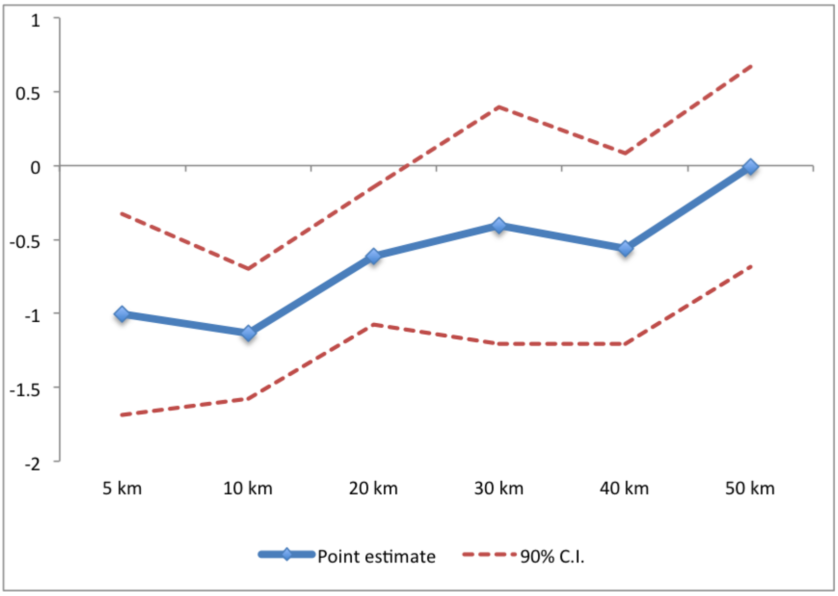


Note: Vertical axis displays estimates of γ for different values of λ_j, with $j = \{land, labor\}$. Values of λ_j in horizontal axis range from 0 to 1, with step increments of 0.1. $\lambda_j = \frac{\text{corr}(Z_j,\epsilon)}{\text{corr}(X_j,\epsilon)}$, where X is input use, Z is the instrumental variable and ϵ is the error term, measures how well the instrument satisfies the exogeneity assumption. $\lambda_j = 0$ corresponds to an exogenous, valid, instrument. The assumption that the instrument is less correlated to the error term that the endogenous variable implies that $\lambda_j < 1$.

with distance. To explore this issue further, we estimate equation (2) replacing S_{vt} by a linear spline of distance to a mine, $\sum_c \gamma^d(distance_v^d \times T_t)$ where $distance_v^d = 1$ if enumeration area v is in distance bracket d, and T_t is a time trend. This specification treats distance more flexibly and allow us to compare the evolution of farmers' productivity at different distance brackets from the mine relative to farmers farther way (the comparison group is farmers beyond 50 km).

Figure 4 presents the estimates of γ^d. Note that the effect of mining on productivity is (weakly) decreasing in distance. Moreover, the loss of productivity is significant (at 10% confidence) within 20 km of mines, but becomes insignificant in farther locations. This result provides the rationale for concentrating in a 20 km buffer around mines, as in the main results.

Figure 4: The effect of mining on agricultural productivity, by distance to a mine



Robustness checks In Table 4, we check that our results are robust to alternative specifications.[51] Column 1 estimates a parsimonious model without farmer characteristics. In contrast, column 2 adds to the baseline regression indicators of use of other inputs (such as fertilizer, manure and improved seeds), while column 3 further expands this specification by adding an array of heterogeneous trends. We include the interaction of time trends with indicators of ecological zone, proximity to coast and to region capitals. This last specification addresses concerns that

[51] Results are also robust to the inclusion of mine fixed effects, and exclusion of farmers in the vicinity of Obuasi mine (see Table B.5 in the Appendix). As discussed in Section 2, Obuasi mine's operations were of a sizable magnitude before the period of interest.

the measure of mining activity may be just picking up other confounding trends.

Column 4 excludes observations within 5 km of a mine. This addresses concerns that the effects are driven by factors such as land grabbings and population displacement. Population displacement, if required, is usually confined to the mine operating sites, i.e., areas containing mineral deposits, processing units, and tailings, These areas comprise, at most, few kilometers around the mine site.

Column 5 performs a falsification test. To do so, we estimate the baseline regression (2) including interactions between time trends and dummies of: (1) proximity to an active mine, and (2) proximity to a future mine, but not to an active one. Future mines include sites that started operations after 2005 or have not started production yet but are in the stage of advanced exploration or development.[52] The results show that the negative relation between mining and agricultural productivity occurs only in the proximity of mines active during the period of analysis, but not in future mining areas.

Finally, we relax the assumption of a Cobb-Douglas production function and assume instead a constant-elasticity-of-substitution (CES) technology. In particular, we use non-linear least squares to estimate the following model:

$$y_{ivt} = A_{ivt}[\eta M_{it}^{-\rho} + (1-\eta)L_{it}^{-\rho}]^{-\frac{\lambda}{\rho}},$$

where $A_{ivt} = \exp(\gamma S_{vt} + \phi Z_i + \delta_d + \psi_t + \theta mining\_area_v)$, M and L represent land and labor use, while S_{vt} is the measure of mining activity, i.e., cumulative gold production within 20 km. The parameter of interest is γ, the effect of mining activity on total factor productivity.

Table 5 displays the results. The implicit elasticity of substitution, $\sigma = \frac{1}{1-\rho}$, is less than one, and we cannot rule out constant returns to scale ($\lambda = 1$). Similar to the baseline results, the estimate of γ is negative, suggesting that the increase in cumulative gold production is associated to lower productivity.

[52] Note that we cannot use cumulative gold production (our preferred measure of mine activity) in this case because there is not data on production for future mines.

Table 4: Robustness checks

	ln(real agricultural output)				
	(1)	(2)	(3)	(4)	(5)
Cumulative gold	-0.169*	-0.163*	-0.166*	-0.163*	
prod. within 20 km	(0.096)	(0.084)	(0.087)	(0.087)	
Within 20 km of active					-0.800***
mine x GLSS 5					(0.280)
Within 20 km of future					0.441
mine x GLSS 5					(0.435)
ln(land)	0.669***	0.599***	0.603***	0.637***	0.630***
	(0.039)	(0.039)	(0.039)	(0.039)	(0.038)
ln(labor)	0.220***	0.207***	0.206***	0.205***	0.212***
	(0.031)	(0.032)	(0.034)	(0.033)	(0.031)
Use fertilizer		0.444***	0.446***		
		(0.098)	(0.098)		
Use manure		0.548***	0.549***		
		(0.153)	(0.154)		
Use improved seeds		-0.108	-0.111		
		(0.092)	(0.090)		
Farmer's control	No	Yes	Yes	Yes	Yes
Heterogenous trends	No	No	Yes	No	No
Sample	All	All	All	Excl. within 5 km of mine	All
Observations	1,627	1,627	1,627	1,598	1,627
R-squared	0.422	0.464	0.465	0.448	0.454

Notes: Robust standard errors in parentheses. Standard errors are clustered at district level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. All regressions are estimated using OLS, and include district and survey fixed effects, and an indicator of being within 20 km of a mine. Column 1 does not include any additional control. Column 2 replicates the baseline regression in Table 3 but includes indicators of use of other inputs, such as fertilizers, manure and improved seeds. Column 3 adds to the previous column the interaction of time trends with indicators of ecological zone, proximity to coast, and proximity to region capitals. Column 4 replicates the baseline regression but excludes farmers within 5 km of a mine. Column 5 performs a falsification test. *active mines* are mines that had some production in period 1988-2005, while *future mines* are mines that started operations after 2005 or have not started production yet, but are in the stage of advanced exploration or development.

Table 5: CES function

Parameter	Estimate	S.E.
γ	-0.165**	0.083
λ	0.911***	0.052
ρ	-0.787***	0.228
η	0.997***	0.005
Implied σ	0.560	

Note: * denotes significant at 10%, ** significant at 5% and *** significant at 1%. Regression includes district and survey fixed effects, indicators of proximity to a mine, and farmer's characteristics as in Table 3.

4.2 Is this driven by pollution?

We interpret the previous findings as evidence that agricultural total factor productivity has decreased in the vicinity of mines. We argue that a plausible channel is through the presence of mining-related pollution. As we discussed before, modern mines can pollute air with exhausts from heavy machinery and processing plants, and particulate matter from blasting. In low concentrations, these pollutants are dispersed and absorbed by the environment. In larger concentrations, however, they can deposit on the ground in the form of acid rain and have long-term cumulative effects. This is in addition to other industry specific pollutants such as cyanide, heavy metals and acidic discharges which may also have cumulative effects but are mostly dispersed through surface water.

To further explore this issue, we would need measures of environmental pollutants at local level.[53] Then, we could examine whether mining areas are indeed more polluted. Unfortunately, this information is not available in the Ghanaian case.[54]

[53] An alternative way to assess exposure to pollution is to use information collected by Ghana's Environmental Protection Agency (EPA). This agency collects information of environmental pollutants in some mining areas, and produces environmental assessments. This information has, however, two main limitations. First, the information has been collected only since 2007, hence it may not accurately reflect the environmental conditions during the period of analysis (1997-2005). Second, there are not environmental assessments for all mines that were active before 2005, nor for non-mining areas that could be used as a control group. These issues create potentially severe measurement error, and limit the use of formal regression analysis.

[54] There are, for example, air monitoring stations only in the proximity of Accra. Regarding mining areas, there are some case studies collecting measures of soil and water quality. These measures, however, are sparse, not collected systematically, and unavailable for non-mining areas. This precludes a more formal regression analysis.

Instead, we rely on satellite imagery to, indirectly, look for a smoking gun of the role of pollution.[55] The satellite imagery is obtained from the Ozone Monitoring Instrument (OMI) available at NASA.[56] This satellite instrument provides daily measures of tropospheric air conditions since October 2004. We focus on a particular air pollutant: nitrogen dioxide (NO_2). The negative effects of NO_2 can be both short-term, by directly damaging plant's tissues, or cumulative, through acid rain and the subsequent degradation of soils. The main source of NO_2 is the combustion of hydrocarbons such as biomass burning, smelters and combustion engines. Thus, it is likely to occur near large urban centers, industrial sites and heavily mechanized operations, such as large-scale mines.

There are three important caveats relevant for the empirical analysis. First, the satellite data reflect air conditions not only at ground level, where they can affect agriculture, but in the whole troposphere (from ground level up to 12 km).[57] Levels of tropospheric and ground level NO_2 are, however, highly correlated.[58] Thus, data from satellite imagery can still be informative of relative levels of NO_2 on the surface. Second, the data is available only at the end of the period of analysis (2005). For that reason we can only exploit the cross-sectional variation in air pollution. Finally, the measures of NO_2 are highly affected by atmospheric conditions such as tropical thunderstorms, cloud coverage, and rain. These disturbances are particularly important from November to March, and during the peak of the rainy season.[59] For that reason, we aggregate the daily data taking the average over the period April-June 2005. These months correspond to the beginning of the rainy season, and also to the start of the main agricultural season.

To compare the relative levels of NO_2 in mining and non-mining areas, we match the satellite data to each enumeration area and estimate the following regression:[60]

$$NO2_v = \phi_1 X_v + \phi_2 W_v + \omega_v,$$

[55]A similar approach of using satellite imagery to measure air pollutant is used by Foster et al. (2009) and Jayachandran (2009).

[56]For additional details, see `http://aura.gsfc.nasa.gov/instruments/omi.html`. Data are available at `http://mirador.gsfc.nasa.gov/cgi-bin/mirador/presentNavigation.pl?tree=project&project=OMI`.

[57]To obtain accurate measures at ground level, we would need to calibrate existing atmospheric models using air measures from ground-based stations. This information is, however, not available.

[58]The correlation between these two measures is typically above 0.6. OMI tropospheric measures tend to underestimate ground levels of NO_2 by 15-30% (Celarier et al., 2008).

[59]In southern Ghana, the rainy season runs from early April to mid-November.

[60]The satellite data are binned to 13 km x 24 km grids. The value of NO_2 of each enumeration area corresponds to the value of NO_2 in the bin where the enumeration area lies.

where $NO2_v$ is the average value of tropospheric NO_2 in enumeration area v during the period April-June 2005. X_v is an indicator of proximity to a mine ; and W_v is a vector of controls variables.[61] Note that the unit of observation is the enumeration area and that, in contrast to the baseline results, this regression exploits cross-sectional variation only.

Columns 1 in Table 6 presents the empirical results. We also replace the dummy X_v by a distance spline with breaks at 10, 20, 30 and 40 km and plot the resulting estimates in Figure 5. Note that in this figure the comparison group is farmers beyond 40 km of a mine.

The satellite evidence suggests that mining areas have a significantly greater concentration of NO_2. Moreover, the concentration of NO_2 decreases with distance to the mine in a similar fashion as the observed decline in total factor productivity. These latest findings point out to air pollution as a plausible explanation for the decline of agricultural productivity in mining areas.

Columns 2 further explores the relation between mining, air pollution and productivity. To do so, we estimate the relation between NO_2 and agricultural productivity using an indicator of proximity to a mine as an instrument for NO_2. Since we only have measures of NO_2 for 2005, we use the sample of farmers in the GLSS 5 and thus exploit only cross sectional variation. Consistent with mining-related pollution being a possible explanation, we find a significant negative correlation between NO_2 and agricultural productivity.[62]

So far, we have been using measures of the *stock* of pollutants, i.e, cumulative production.[63] We use this measure due to the potential of many mining-related pollutants (such as air emissions and heavy metals) to have cumulative effects on the environment. Here, we check whether measures of the *flow* of pollutants would be better instead. As a measure of the flow of pollution, we use the annual production of the neighboring mines in the surveys' reference years, i.e., 1997 and 2005. Columns 3 and 4 in Table 6 display the results. First, we add only the measure of flow of pollution. Then, we include both measures of stock and flow of pollution. The results suggest that the reduction in productivity is only affected by the variation in the measure of long-term exposure to pollution.

Finally, we explore the importance of pollutants carried by surface water. To do so, we

[61] NO_2 is measured as 10^{15} molecules per cm^3. The average NO_2 is 8.1 while its standard deviation is 1.1.

[62] In the first stage, the relation between NO_2 and the excluded instrument (*within 20 km of mine*) is positive and significant at 5%.

[63] We measure this variable in hundred of MT. Results using the log of cumulative production are qualitatively similar (see Table B.6 in Appendix).

Table 6: Mining and pollution

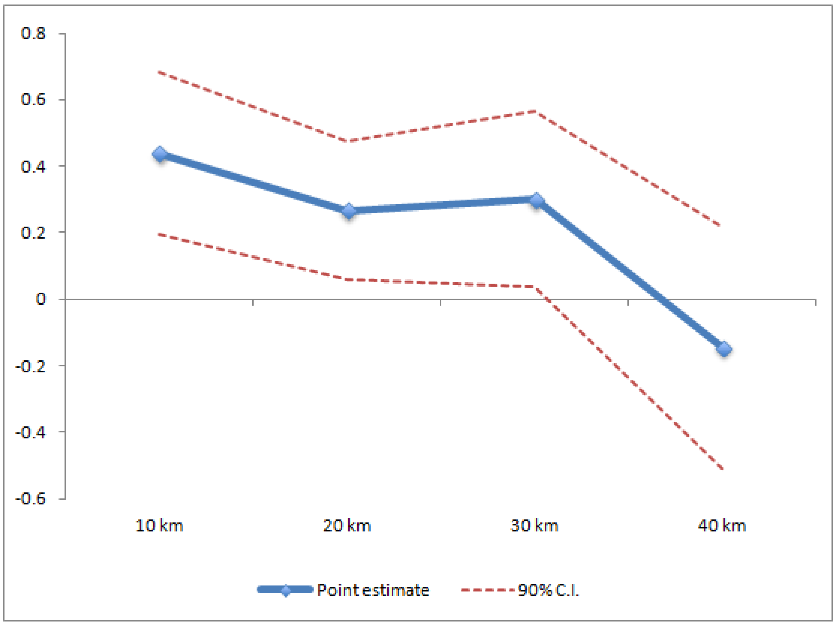
	ln(real agricultural output)				
	Average NO_2	Using mining as IV	Stock vs flow pollution		Upstream vs downstream
	(1)	(2)	(3)	(4)	(5)
Within 20 km of mine	0.325***				
	(0.111)				
Average NO_2		-1.554*			
		(0.837)			
Cumulative gold prod. within 20 km				-0.220**	-0.193**
				(0.093)	(0.094)
Annual gold prod. within 20 km			-0.057	1.644	
			(1.324)	(1.802)	
Cumul. gold prod. within 20km × downstream					-0.012
					(0.086)
Estimation	OLS	2SLS		OLS	OLS
Farmer's controls	No	Yes		Yes	Yes
Controlling for inputs	No	Yes		Yes	Yes
Observations	399	914	1,627	1,627	1,627
R-squared	0.238	0.029	0.443	0.445	0.447

Notes: Robust standard errors in parentheses. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. Standard errors in columns 2 to 5 are clustered at district level. Columns 1 and 2 use data for 2005 only. Column 1 uses as unit of observation the enumeration area and includes as additional controls indicators of ecological zones, urban area, and region fixed effects. Column 2 presents 2SLS estimates of the agricultural production function using only the sample of farmers in GLSS 5. It treats *Average* NO_2 as an endogenous variable and uses *within 20 km of mine* as the excluded instrument. This specification includes the additional controls: indicators of ecological zone, urban area, region fixed effects, as well as farmer's characteristics and measures of input use as in the baseline regression (see notes of Table 3). Column 3 and 4 replicates baseline OLS regression (column 2 in Table 3) adding *annual gold production within 20 km* as a proxy for flow pollutants. This variable measures the production of gold (in hundreds of MT) from nearby mines in years 1997 and 2005. Column 5 adds to the baseline OLS regression an interaction term of the measure of mining activity and *downstream*, a dummy equal to one if household is downstream of an active mine. This regression also includes *downstream* and its interaction with *within 20 km of mine*. .

identify areas downstream of active mines and examine whether the negative effects of mining are stronger in these areas. Note that this is a crude way to assess exposure to pollution since some pollutants (like heavy metals and dust) can be carried by water and air, so areas upstream and downstream of mine can both be negatively affected.

We replicate the baseline regression including an interaction term between our measure of mining activity and a dummy *downstream* equal to one if the household is located downstream of an active mine. The results, displayed in Column 5 in Table 6, suggest that there is no significant difference in the effect of mining between areas downstream and upstream of a mine. Though this may be due to lack of statistical power, a conservative interpretation is that pollution of surface waters may not be driving the main results.[64]

Figure 5: Increase in concentration of NO_2, by distance to a mine



4.3 Alternative explanations

4.3.1 Competition for inputs

Mining could also affect agriculture through competition for key inputs. A first, and most obvious, way involve direct appropriation of inputs, such as diversion of water sources and land

[64]Additionally, there is no variation in productivity that can be explained by the direction of winds. Ghana has two main winds that come from opposite directions: the Harmattan, a dry and dusty wind, that blows from the Sahara, i.e., north east, and another wind, warm and moist, coming from the Atlantic ocean, i.e., south-west. Hence, air pollutants may be dispersed in all directions around a mine.

grabbings. A concern is that the drop in productivity simply reflects the relocation of farmers to less productive lands.[65] It is unlikely, however, that this factor fully accounts for the observed reduction in productivity. As shown in Table 4, the results are similar excluding farmers within 5 km of a mine. This is the population most likely to suffer from displacement.

A second way involves the increase in price of local inputs, i.e., the input competition channel discussed in Section 3.1. Mines may reduce supply of agricultural land through land grabbings, or increase demand for farming inputs such as unskilled labor. Alternatively, mines' demand for local goods and services may increase price of non-tradables (such as housing) and indirectly drive up local wages. In any case, the increase in input prices may lead to a decline in input demand, and agricultural output. This phenomena cannot be studied by equation (2) since it already controls for input use and thus it is only informative of the effect of mining on total factor productivity.

To explore this issue further, we study the relation between mining and input prices. Recall that the input competition channel has a different empirical implication for input prices than the pollution channel. If output is decreasing due to input competition, there would be a positive correlation between mining and input prices. In contrast, if results are driven by a negative shock on productivity, the relation should be negative or insignificant, depending on how competitive input markets are.

We also explore the relation between mining and input demands. Note that both channels (input competition and pollution) would predict a weakly negative relation, though for different reasons. In the first case, it would be due to an increase in input prices; while in the second, it would be due to reduction in factors' productivity. This distinction is relevant because, in the presence of lower productivity, input use may drop even if prices do not change.

Table 7 displays the results. As measure of input prices, we use the daily agricultural wage from the GLSS community module and the price of land per acre self-reported by farmers.[66] To estimate input demands, we regress input use on measures of input prices, farmer's endowments and proxies of total factor productivity, including mine activity.[67]

[65]These phenomena are documented in the Ghanaian case and are deemed a source of conflict and increased poverty in mining areas (Duncan et al., 2009; Botchway, 1998).

[66]We take the average of these variables by enumeration area, and divide them by the consumer price index to obtain relative input prices.

[67]We check the robustness of these results to using annual gold production, instead of cumulative production, as proxy of mining activity, and including agricultural output as an additional control in the estimation of input demands (see Table B.7 in the Appendix).

Note that the relation between mining and input prices is insignificant. This result weakens the argument that mining crowds out agriculture through increase in factor prices. Instead, it points out to a reduction in productivity as the main driver of reduction in agricultural output. The results on input demands are consistent with this interpretation. Despite no changes in input prices, demand for labor decreases with mining. This is expected in the presence of a negative productivity shock, as discussed in Section 3.1. The lack of response of input prices to this productivity shock could be due to imperfect input markets. In turn, this may explain why land demand does not change while labor demand decreases. As laid out in the analytical framework, in the absence of input markets, the opportunity cost of land is low so the whole endowment is used. In contrast, labor use is more responsive to productivity shocks since the labor endowment can always be consumed as leisure.

Table 7: Mining, input prices and input demands

	ln(relative wage) (1)	ln(relative land rent) (2)	ln(labor) (3)	ln(land) (4)
Cumulative gold prod. within 20 km.	-0.012 (0.029)	-0.040 (0.078)	-0.144** (0.062)	-0.007 (0.037)
ln(relative wage)			-0.093 (0.153)	0.019 (0.117)
ln(relative land rent)			-0.085 (0.071)	0.009 (0.038)
ln(nr. adult equivalents)			0.528*** (0.062)	0.022 (0.021)
ln(land owned)			0.130*** (0.029)	0.914*** (0.030)
Farmer's controls	No	No	Yes	Yes
District fixed effects	No	No	Yes	Yes
Observations	194	201	1,342	1,342
R-squared	0.277	0.007	0.267	0.803

Notes: Robust standard errors in parentheses. Standard errors are clustered at district level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. All regressions include survey fixed effects and an indicator of being within 20 km of a mine. Columns 3 and 4 also include district fixed effects, and a set of farmer's controls similar to regressions in Table 3.

4.3.2 Compositional effects, and risk of expropriation

We next turn our attention to changes in the composition of farmers as an alternative explanation for the observed phenomena. A particular concern is that the reduction in productivity is just reflecting an increase in the relative size of low productivity farmers. This is possible, for example, if high-productivity farmers are emigrating away from mining areas, or switching to non-agricultural activities.

To assess this alternative explanation, we examine whether mining activity is associated to changes on observable population characteristics (see Table 8). First, we look at the probability that an individual in working age is employed, self-employed or engaged in domestic production. Second, we look at the probability that a worker is engaged in agriculture (either as a producer or laborer). In the presence of occupational change towards non-agricultural activities we could expect a negative correlation. Third, we examine measures of agricultural workers' demographics and mobility, such as probability of being a male in prime age (20-40 years), or being born in the same village where they reside, Finally, we explore measures of human capital of agricultural workers, such as literacy and having completed secondary school.[68] This result is informative, however, under the assumption that farming ability is positively correlated with educational attainment. This sounds a plausible assumption, given that in our baseline regression the measure of literacy is associated with an increase in agricultural product and productivity. We find, however, no evidence of any change in these population characteristics.

An alternative story that could explain lower agricultural productivity is related to weak property rights. In the case of Ghana, two phenomena are at play: customary and weakly-defined land rights, and the right of the State to grant licenses for the use of land where mineral wealth is located (Botchway, 1998). Farmers near mining sites might fear expropriation and might choose to reduce agricultural investments, such as planting cocoa trees, as in Besley (1995). We first check whether there is a change in land ownership. Then, we examine whether there is any perceptible decrease in the share of cocoa or planting of new cocoa trees. Finally, we also explore changes in other agricultural practices, such as crop diversification and use of fertilizers, that could change as a way to mitigate the effect of pollution.[69]

[68]Levels of completion of primary school are high, i.e., around 86%, while literacy levels (47.8%) and secondary school completed (36.3%) show greater variation. Results hold when using data on completed primary school.

[69]Recall that farmer could ameliorate the effects of soil degradation by increasing use of fertilizers. Similarly, if crops' sensitivity to pollution is heterogeneous, farmers may reduce the impact on their income by changing

Table 9 displays the results. We do not find a decrease in cocoa planting nor significant changes in land ownership or use of fertilizers. If anything there has been an increase in planting of cocoa trees. These results are the opposite of what the property rights story would suggest, and weaken the argument that the reduction in productivity is driven solely by changes in perceived risk of expropriation. Interestingly, we find an increase in crop concentration. While far from conclusive, this finding could be indicative of farmer's actions to ameliorate the negative effect of pollution.

4.4 Exploring the mechanisms

An important question is how mining-related pollution would affect total factor productivity. As discussed in Section 2.2, there are least three possible mechanisms. First, pollution could affect crops' yields and health. Second, pollution could deteriorate quality of key inputs, such as soil. Third, through its effects on human health, pollution could affect labor productivity.

To formally discuss these factors, consider the following augmented Cobb-Douglas production function:

$$Y = q_T(q_M M)^\alpha (q_L L)^\beta \tag{3}$$

where Y is agricultural output, M and L are the observable quantities of land and labor. q_L and q_M are input-specific quantity shifters, that we could think of as labor productivity and quality of soil, respectively, while q_T captures all other unobserved factors, including crops' health and yields. Our previous discussion suggests that pollution could potentially affect any of these factors.

In this setup, total factor productivity $A = q_T q_M^\alpha q_L^\beta$. This is the object that we can observe, as a residual, when we estimate an agricultural production function. Our empirical analysis shows that mining-related pollution reduces A, but cannot identify its effect on each component. To do so, we would need data on quality of soil, crops' health and labor productivity. These data are, however, unavailable in the case we study.

Instead, we use an indirect approach to show that the effect is unlikely to have been entirely driven by reduction in labor productivity, q_L. We do it in three ways. First, note that, under the assumption that all the reduction in A is driven by changes in labor productivity, $\Delta \ln A =$

crops' composition.

Table 8: Population characteristics

	Do any work (1)	Do any work (2)	Works in agriculture (3)	Male in prime age (4)	Born in village (5)	Literacy (6)	Completed secondary (7)
Cumulative gold prod. within 20 km	-0.001	-0.018	-0.032	-0.001	-0.006	-0.004	-0.013
	(0.006)	(0.017)	(0.042)	(0.018)	(0.024)	(0.021)	(0.016)
Sample	Males in working age	Females in working age	All workers	Agricultural workers	Agricultural workers	Agricultural workers	Agricultural workers
Observations	4,787	5,688	8,932	4,978	4,929	4,971	4,978
R-squared	0.453	0.319	0.359	0.029	0.127	0.044	0.134

Notes: Robust standard errors in parentheses. Standard errors are clustered at district level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. All regressions include district and survey fixed effects, an indicator of being in a mining area, and indicators of ecological zone and urban area. *Do any work* is an indicator equal to one if individual is employed, self-employed or participates in domestic production. Working age is between 15 to 65 years. *Works in agriculture* is an indicator equal to one if individuals works in agriculture as a laborer or producer. *Male in prime age* is an indicator equal to one if individual is male between 20 to 40 years old. *Born here* is an indicator equal to one if individual was born in the same village where she resides. All regressions are estimated using a linear probability model. Columns 1 to 3 include as additional controls: age, age^2, religion, place of birth, literacy status, and household size. Columns 6 and 7 examine the educational attainment of agricultural workers conditional on age and age^2.

Table 9: Agricultural investment and practices

	Owns farm (1)	New cocoa plants (2)	Share of cocoa (3)	Crop concentration (4)	Use fertilizer (5)	Use manure (6)
Cumulative gold prod. within 20 km	-0.010	0.066*	0.021	0.043**	-0.005	-0.015
	(0.029)	(0.039)	(0.036)	(0.017)	(0.045)	(0.026)
Observations	1,627	1,627	1,627	1,627	1,627	1,627
R-squared	0.225	0.159	0.446	0.118	0.140	0.102

Notes: Robust standard errors in parentheses. Standard errors are clustered at district level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. All regressions include district and survey fixed effects, an indicator of being in a mining area, and indicators of ecological zone and urban area. Columns 2 to 6 also include farmer's controls as the agricultural production function in Table 3. All regressions are estimated using linear OLS. *Owns farm* is equal to 1 if farmer owns any plot. *New cocoa plants* equals one if the farmer has planted new cocoa trees in the previous 12 months. *Share of cocoa* is the share of cocoa revenue in the value of total agricultural output. *Crop concentration* is the Herfindahl concentration index of crops' value. Outcomes in columns 5 and 6 are indicators equal to one if farmer uses chemical fertilizers or manure, respectively.

$\beta \Delta \ln q_L$. In Table 3 column 4, we estimate $\Delta \ln A = -0.565$ and $\beta = 0.346$. This implies a reduction in q_L of almost 80%. Thus, to fully account for the observed reduction in A, the reduction in labor productivity should have been very large. To put this figure in context, note that previous estimates of the relation between air pollution and labor productivity in U.S. find that one standard deviation in ozone levels decreases labor productivity by roughly 7% (Graff Zivin and Neidell, 2012).

Second, we examine indicators of workers' health. We use self-reported data on incidence and duration of illness.[70] Then, we examine the relation between these measures of health and our measure of mining. We focus on the sample of working age population (age 15 to 65) and split the sample between urban and rural populations. Table 10 displays the results. In all cases, we find no evidence of an increase in the likelihood of being ill nor on the duration of illness. This is contrary of what we could expect if the sole channel was through human health.

Finally, we examine the effect of mining on urban workers, not directly linked to the agricultural sector. This group include employed and self-employed workers. We focus on two available outcomes: number of hours worked and employment income. Under reasonable assumptions, if the effect was transmitted entirely through reduction in labor productivity, we should also

[70]The survey questions are: In the last two weeks, have you been ill? If yes, how many days have you been ill?.

Table 10: Mining and self-reported illness

	Ill in previous 2 weeks			ln(number of days ill)		
	(1)	(2)	(3)	(4)	(5)	(6)
Cumulative gold	-0.015	0.013	-0.022	0.019	-0.182***	0.038
prod. within 20 km.	(0.022)	(0.046)	(0.026)	(0.032)	(0.034)	(0.034)
Sample	All	Urban	Rural	All	Urban	Rural
Observations	11,713	4,498	7,215	2,842	1,041	1,801
R-squared	0.055	0.066	0.071	0.062	0.089	0.081

Notes: Robust standard errors in parentheses. Standard errors are clustered at district level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. All regresssions are estimated using OLS and include district and survey fixed effects, an indicator of being within 20 km of a mine, and individual controls such as: age, age^2, gender, an indicator of rural area and ecological zone. *Ill in previous 2 weeks* is a dummy variable equal to 1 if individual reports being ill during the last 2 weeks. It does not include accidents. Column 4 to 6 include only individuals that reported being ill.

observe a decrease in these labor outcomes.[71] The results are displayed in Table 11. Column 1 and 3 use the sample of all urban workers, including agricultural workers, while columns 2 and 4 narrow it down to non-agricultural workers. Note that all regressions exclude mining workers, who can be directly affected by mining operations. In all cases, there is no significant change in number of hours nor on employment income.

Taken together, this evidence does not rule the possibility that the effects reflect, in part, reduction in labor productivity. However, they suggest that it is unlikely that this mechanism fully accounts for the observed phenomena.

[71] These assumptions are: (1) labor demand for urban workers depend of their productivity, (2) mining did not increase labor demand in urban areas, and (3) mining did not affect urban labor supply. The first assumption is more reasonable given the existence of urban labor markets. The last two assumptions are likely to be met given the limited economic interactions between gold mines and local economies in the Ghanaian context.

Table 11: Mining and labor outcomes of urban workers

	ln(hours work)		ln(real employment income)	
	(1)	(2)	(3)	(4)
Cumulative gold prod. within 20 km.	-0.062 (0.042)	-0.064 (0.064)	0.222 (0.260)	0.139 (0.250)
Sample	All urban workers	Urban non-agric. workers	All urban workers	Urban non-agric. workers
Observations	2,580	2,062	1,936	1,564
R-squared	0.152	0.090	0.389	0.319

Notes: Robust standard errors in parentheses. Standard errors are clustered at district level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. All regressions include district and survey fixed effects, an indicator of being in a mining area, and indicators of ecological zone and urban area. Columns 1 and 2 include as additional controls: age, age^2, religion, place of birth, literacy status, and household size. Columns 3 and 4 add as additional control the log of number of hours worked. All regressions exclude mining workers. Columns 2 and 4 also exclude agricultural workers.

5 Effects on poverty

The standard consumer-producer household framework presented above links a household's utility function, that depends on consumption levels, to income from agricultural production. As a consequence, we expect that our previous results indicating a sizable reduction in agricultural productivity and output imply a knock-on effect on local living standards, such as measures of poverty. There are reasons to believe that this channel can be averted. Mining companies or the government could, for example, promote local development projects, employ local workers, compensate local residents, or transfer part of the mining surplus. These policies are often implemented by the industry to mitigate potential negative side-effects of mining, and may offset the decline in productivity.

To examine this issue, we use data from the GLSS on poverty to estimate the following regression:

$$poverty_{idvt} = \phi_1 S_{vt} + \phi_2 W_i + \delta_d + \omega_{it} \tag{4}$$

where *poverty* is an indicator of the household being poor, and W_i is a set of household controls.[72] The rest of the specification is similar to equation (2).[73] The parameter of interest is ϕ_1 which captures the difference in the evolution of poverty in mining areas, relative to non-mining areas. Note that the identification strategy is a difference in difference, similar to the one used in the estimation of the production function.

Figure A.2 depicts the evolution over time of poverty headcount in areas close and far from mines. There are two relevant observations. First, poverty declined steadily between 1988 and 2005 in areas far from mines. This trend is similar to the dramatic poverty reduction experienced in the rest of Ghana since the early 1990s (Coulombe and Wodon, 2007). Second, during the 1990s, mining areas were less poor than non-mining areas, and poverty evolved similarly in both areas. Since 1997, however, poverty increased in mining areas and they become poorer than non-mining areas.[74] Note that this increase in poverty parallels the reduction in agricultural output (see Figure A.1).

Table 12 presents the estimates of equation (4) using poverty as the outcome variable.[75] Column 1 shows results for all households using our preferred specification. As a reference, column 2 uses as proxy of S_{vt} the interaction between a dummy of proximity to a mine and a time trend to obtain the average effect of mining on poverty. Columns 3 and 6 split the rural sample between urban and rural households, respectively. Column 4 looks at rural households that are engaged in household production (and thus were included in the estimation of the agricultural production function,) while column 5 looks at rural households that did not report any agricultural production.[76] We also check the robustness of the results to using a continuous measure of real household expenditure (see table B.8 in the Appendix).[77]

The picture that emerges is similar to the one observed in Figure A.2. There is a positive and significant relation between mining activity and poverty. The magnitude of the effect is sizable: the increase in gold production between 1997 and 2005 is associated to an increase

[72] We use the poverty line used by the Ghana Statistical Service, i.e., 900,000 cedis per adult per year in 1999 Accra prices. The poverty line includes both essential food and non-food consumption (Ghana Statistical Service, 2000). We check the robustness of the results to alternative poverty lines such as USD 1.25 PPP a day.

[73] We also estimate this model by OLS using sample weights and clustering the errors at district level.

[74] Recall that during this period, gold production reached higher levels and the number of mines increased.

[75] We estimate equation (4) using only data from the last two rounds of the GLSS. We do not use data from GLSS 2, which are available, in order to keep the estimates comparable to the results on agricultural productivity. The results including this survey round are, however, similar.

[76] Note that households whose members are engaged in farming as wage laborers are around 65% of the sample.

[77] To construct the measure of real expenditure, we deflate nominal expenditure per capita with the index of local agricultural prices used to obtained measures of real agricultural output. The results using the official consumer price index are, however, similar.

of almost 16 percentage points in poverty headcount. The effect is concentrated among rural inhabitants, regardless of whether the households are producers or not. Non-producers could be affected either directly, by the reduction in agricultural wages associated to lower total factor productivity, or indirectly, if they sell good or services locally.[78]

The reduction in indicators of economic well-being is consistent with the decline in agricultural productivity in areas where farming activities are the main source of livelihood. Table C.1 in the Appendix shows two additional results among children that are also consistent with levels of poverty induced by pollution: malnutrition and acute respiratory diseases have both increased in mining areas.

Taken together, these findings suggest that compensating policies and positive spillovers from mines, if any, have been insufficient to offset the negative shock to agricultural income.

Table 12: Mining and poverty

	Poverty					
			Rural			Urban
	All households		All	Farmers	Non-farmers	
	(1)	(2)	(3)	(4)	(5)	(6)
Cumul. gold prod. within 20 km.	0.059***		0.071***	0.056**	0.084**	0.054
	(0.015)		(0.019)	(0.021)	(0.032)	(0.036)
Within 20 km of mine × GLSS 5		0.186***				
		(0.055)				
Observations	5,527	5,527	3,393	2,540	853	2,134
R-squared	0.212	0.216	0.227	0.237	0.224	0.199

Notes: Robust standard errors in parentheses. Standard errors are clustered at district level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. All regressions are estimated using ordinary least squares, and include district and survey fixed effects as well as household controls, such as: age, age^2, religion, place of birth and literacy status of household head, household size, and an indicator of urban areas. All columns include an indicator of being within 20 km of a mine.

6 Concluding remarks

This paper examines an important externality that polluting industries may impose on rural areas, namely reduction on agricultural productivity. We find robust evidence that agricultural productivity has decreased in mining areas, relative to areas in the same region but located

[78] Aragon and Rud (2013) discuss the conditions under which these effects would be present and show evidence for the households in the area of influence of a gold mine in Peru.

at a greater distance from mining activities. The reduction is economically significant: around 40% between 1997 and 2005. We also document an increase in rural poverty associated to the decline in agricultural productivity The magnitude of these effects is, however, specific to the Ghanaian case we study, and should not be extrapolated to other contexts.

These findings have an important implication for environmental and industrial policies. In particular, they suggest that environmental assessments should consider the possible impact of polluting industries on agricultural productivity and farmers' income.

These potential costs are usually neglected in the academic and policy debate. For instance, in the case of extractive industries, the debate usually focuses on the benefits they could bring in the form of jobs, taxes or foreign currency. These benefits are weighted against environmental costs such as loss of biodiversity, or human health risks. However, local living standards may be also directly affected by the reduction in agricultural productivity. In fertile rural environments, these costs may offset the benefits from extractive industries, and hinder the ability to compensate affected populations. In turn, this may have substantial re-distributive effects.

A simple back of the envelope using the Ghanaian case illustrates this argument. In 2005, mining-related revenues amounted to US$ 75 millions, which represent around 2-3% of total government revenue. Most of this revenue (around 80%) was channeled to the central government.[79] In contrast, the average annual loss by farming households in mining areas, according to our main results, is in the order of US$ 97 millions.[80] These rough numbers show that the amount of tax receipts might not be enough to compensate losing farmers and that this situation is even worsened by the fact that a only small proportion of the tax receipts go back to affected localities.

A main limitation of this paper is that we cannot clearly assess the relative importance of several plausible mechanisms through which pollution could affect productivity —such as effects on labor productivity, quality of soil, and crops' health and growth. Similarly, we cannot examine in detail changes in farmers' decisions to ameliorate the effect of pollution. While beyond the reach of this paper, examination of these issues warrant further research.

[79]Local authorities (such as District Assemblies, Stools and Traditional Authorities) receive only 9% of mining royalties.

[80]This number is obtained by multiplying the number of producing households in mining areas, around 210,000, to the average reduction in households' annual consumption, i.e., US$ 460.

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— NOT FOR PUBLICATION—

ONLINE APPENDIX

A Additional figures

Figure A.1: Evolution of the unconditional mean of ln(real agricultural output)

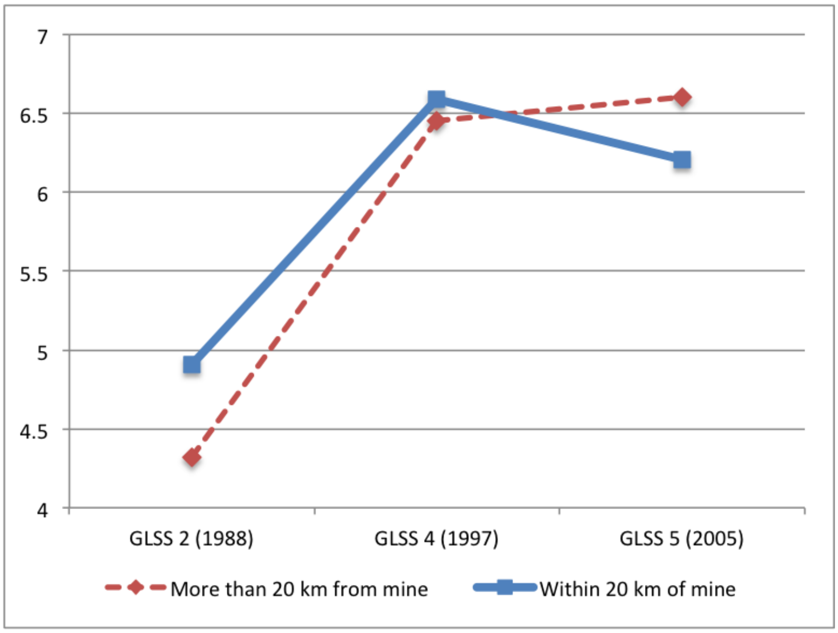
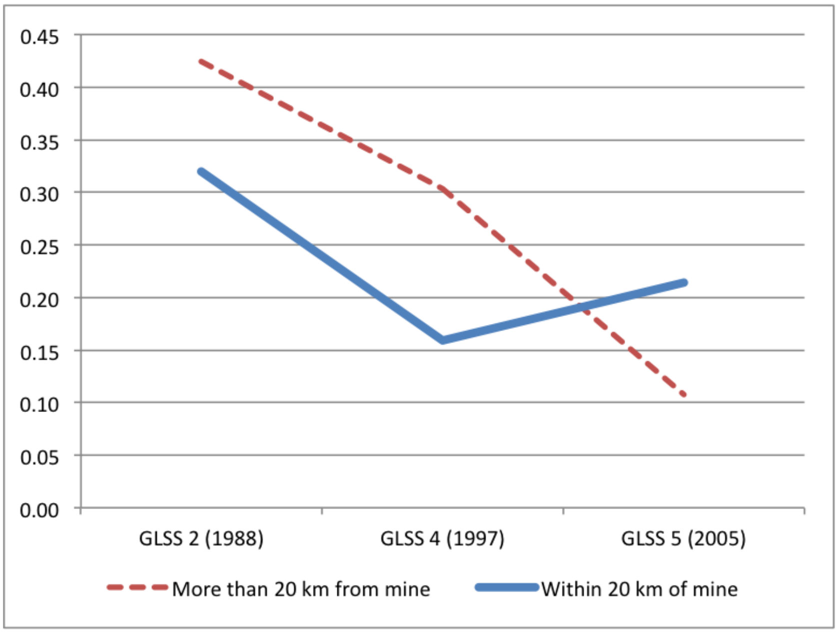


Figure A.2: Evolution of poverty headcount



B Additional results

Table B.9: Imperfect instruments with multiple endogenous variables

$(\lambda_{land}, \lambda_{labor})$	$\hat{\gamma}$	$\hat{\alpha}$	$\hat{\beta}$
(0, 0)	-0.170	0.676	0.352
(0, 0.1)	-0.165	0.657	0.422
(0, 0.2)	-0.152	0.610	0.601
(0, 0.3)	-0.053	0.249	1.967
(0, 0.4)	-0.238	0.921	-0.577
(0, 0.5)	-0.205	0.802	-0.126
(0, 0.6)	-0.197	0.771	-0.009
(0, 0.7)	-0.193	0.757	0.045
(0, 0.8)	-0.190	0.749	0.075
(0, 0.9)	-0.189	0.743	0.095
(0, 1)	-0.188	0.740	0.109
(0.1, 0)	-0.171	0.687	0.344
(0.1, 0.1)	-0.166	0.668	0.413

Continue on next page

Table B.9 – continued from previous page

$(\lambda_{land}, \lambda_{labor})$	$\hat{\gamma}$	$\hat{\alpha}$	$\hat{\beta}$
(0.1, 0.2)	-0.154	0.620	0.590
(0.1, 0.3)	-0.051	0.235	1.998
(0.1, 0.4)	-0.236	0.928	-0.539
(0.1, 0.5)	-0.205	0.813	-0.115
(0.1, 0.6)	-0.197	0.782	-0.004
(0.1, 0.7)	-0.193	0.768	0.047
(0.1, 0.8)	-0.191	0.760	0.077
(0.1, 0.9)	-0.190	0.755	0.096
(0.1, 1)	-0.189	0.751	0.110
(0.2, 0)	-0.173	0.702	0.335
(0.2, 0.1)	-0.168	0.683	0.402
(0.2, 0.2)	-0.155	0.634	0.575
(0.2, 0.3)	-0.047	0.215	2.045
(0.2, 0.4)	-0.234	0.937	-0.491
(0.2, 0.5)	-0.205	0.826	-0.102
(0.2, 0.6)	-0.197	0.797	0.002
(0.2, 0.7)	-0.194	0.783	0.051
(0.2, 0.8)	-0.192	0.775	0.079
(0.2, 0.9)	-0.190	0.770	0.097
(0.2, 1)	-0.190	0.766	0.110
(0.3, 0)	-0.175	0.723	0.322
(0.3, 0.1)	-0.170	0.703	0.386
(0.3, 0.2)	-0.158	0.653	0.553
(0.3, 0.3)	-0.040	0.183	2.120
(0.3, 0.4)	-0.231	0.949	-0.431
(0.3, 0.5)	-0.205	0.845	-0.085
(0.3, 0.6)	-0.198	0.816	0.011

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Table B.9 – continued from previous page

$(\lambda_{land}, \lambda_{labor})$	$\hat{\gamma}$	$\hat{\alpha}$	$\hat{\beta}$
(0.3, 0.7)	-0.195	0.803	0.055
(0.3, 0.8)	-0.193	0.795	0.081
(0.3, 0.9)	-0.192	0.790	0.098
(0.3, 1)	-0.191	0.786	0.110
(0.4, 0)	-0.178	0.753	0.303
(0.4, 0.1)	-0.173	0.734	0.362
(0.4, 0.2)	-0.161	0.683	0.521
(0.4, 0.3)	-0.028	0.120	2.264
(0.4, 0.4)	-0.228	0.964	-0.351
(0.4, 0.5)	-0.205	0.870	-0.060
(0.4, 0.6)	-0.199	0.843	0.023
(0.4, 0.7)	-0.196	0.831	0.062
(0.4, 0.8)	-0.194	0.823	0.085
(0.4, 0.9)	-0.193	0.818	0.100
(0.4, 1)	-0.192	0.815	0.111
(0.5, 0)	-0.183	0.802	0.272
(0.5, 0.1)	-0.178	0.783	0.324
(0.5, 0.2)	-0.167	0.732	0.466
(0.5, 0.3)	0.004	-0.048	2.651
(0.5, 0.4)	-0.223	0.985	-0.241
(0.5, 0.5)	-0.206	0.908	-0.025
(0.5, 0.6)	-0.201	0.884	0.041
(0.5, 0.7)	-0.198	0.873	0.072
(0.5, 0.8)	-0.197	0.867	0.091
(0.5, 0.9)	-0.196	0.862	0.103
(0.5, 1)	-0.195	0.859	0.111
(0.6, 0)	-0.191	0.893	0.215

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Table B.9 – continued from previous page

$(\lambda_{land}, \lambda_{labor})$	$\hat{\gamma}$	$\hat{\alpha}$	$\hat{\beta}$
(0.6, 0.1)	-0.188	0.879	0.250
(0.6, 0.2)	-0.180	0.836	0.353
(0.6, 0.3)	0.369	-1.959	7.055
(0.6, 0.4)	-0.215	1.016	-0.079
(0.6, 0.5)	-0.206	0.969	0.034
(0.6, 0.6)	-0.203	0.953	0.071
(0.6, 0.7)	-0.202	0.946	0.089
(0.6, 0.8)	-0.201	0.941	0.100
(0.6, 0.9)	-0.200	0.938	0.107
(0.6, 1)	-0.200	0.936	0.113
(0.7, 0)	-0.214	1.129	0.067
(0.7, 0.1)	-0.216	1.139	0.047
(0.7, 0.2)	-0.222	1.177	-0.022
(0.7, 0.3)	-0.170	0.862	0.554
(0.7, 0.4)	-0.204	1.066	0.182
(0.7, 0.5)	-0.207	1.085	0.146
(0.7, 0.6)	-0.208	1.093	0.132
(0.7, 0.7)	-0.209	1.097	0.125
(0.7, 0.8)	-0.209	1.099	0.120
(0.7, 0.9)	-0.210	1.101	0.117
(0.7, 1)	-0.210	1.102	0.115
(0.8, 0)	-0.402	3.079	-1.160
(0.8, 0.1)	-0.597	4.768	-2.774
(0.8, 0.2)	0.364	-3.591	5.213
(0.8, 0.3)	-0.113	0.562	1.245
(0.8, 0.4)	-0.182	1.160	0.674
(0.8, 0.5)	-0.209	1.399	0.446

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Table B.9 – continued from previous page

$(\lambda_{land}, \lambda_{labor})$	$\hat{\gamma}$	$\hat{\alpha}$	$\hat{\beta}$
(0.8, 0.6)	-0.224	1.528	0.322
(0.8, 0.7)	-0.233	1.609	0.245
(0.8, 0.8)	-0.240	1.664	0.193
(0.8, 0.9)	-0.244	1.704	0.154
(0.8, 1)	-0.248	1.734	0.125
(0.9, 0)	-0.072	-0.347	0.995
(0.9, 0.1)	-0.076	-0.190	1.080
(0.9, 0.2)	-0.084	0.052	1.213
(0.9, 0.3)	-0.096	0.476	1.444
(0.9, 0.4)	-0.124	1.403	1.951
(0.9, 0.5)	-0.235	5.060	3.949
(0.9, 0.6)	0.344	-14.114	-6.529
(0.9, 0.7)	0.046	-4.244	-1.135
(0.9, 0.8)	0.005	-2.881	-0.390
(0.9, 0.9)	-0.012	-2.339	-0.094
(0.9, 1)	-0.020	-2.048	0.065
(1, 0)	-0.124	0.198	0.652
(1, 0.1)	-0.120	0.226	0.757
(1, 0.2)	-0.112	0.281	0.962
(1, 0.3)	-0.089	0.435	1.539
(1, 0.4)	0.379	3.546	13.184
(1, 0.5)	-0.197	-0.289	-1.170
(1, 0.6)	-0.166	-0.078	-0.381
(1, 0.7)	-0.156	-0.013	-0.137
(1, 0.8)	-0.151	0.019	-0.018
(1, 0.9)	-0.148	0.038	0.052
(1, 1)	-0.146	0.050	0.098

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Table B.9 – continued from previous page

$(\lambda_{land}, \lambda_{labor})$	$\hat{\gamma}$	$\hat{\alpha}$	$\hat{\beta}$

Notes: Table displays estimates used to construct Figure 3.

Table B.1: Evolution of agricultural output in mining vs non-mining areas

	ln(real agricultural ouput)	
	(1)	(2)
Within 20 km of mine × GLSS 4	-0.261	
	(0.370)	
Within 20 km of mine × GLSS 5		-0.515*
		(0.256)
Sample	GLSS 2 and 4	GLSS 4 and 5
Estimation	OLS	OLS
Farmer's controls	Yes	Yes
Controlling for inputs	No	No
Observations	1,473	1,627
R-squared	0.251	0.223

Notes: Robust standard errors in parentheses. Standard errors are clustered at district level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. All regressions include district and survey fixed effects, as well as a set of farmer characteristics as in Table 3. *GLSS 4* and *GLSS 5* are indicators equal to 1 if survey is GLSS 4 or 5, respectively. *Within 20 km of mine* is a dummy equal to 1 if household is in a mining area.

Table B.2: Main results using time trend as treatment variable

	ln(real agricultural ouput)			ln(yield cocoa)	ln(yield maize)
	(1)	(2)	(3)	(4)	(5)
Within 20 km of mine × GLSS 5	-0.515*	-0.566**	-0.565**	-0.913**	-1.173**
	(0.256)	(0.236)	(0.247)	(0.430)	(0.519)
ln(land)		0.631***	0.678***		
		(0.037)	(0.047)		
ln(labor)		0.210***	0.346***		
		(0.032)	(0.112)		
Estimation	OLS	OLS	2SLS	OLS	OLS
Farmer's controls	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	1,627	1,627	1,627	948	605
R-squared	0.223	0.447	0.438	0.344	0.410

Notes: Robust standard errors in parentheses. Standard errors are clustered at district level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. For further details on control variables and instruments see notes of Table 3.

Table B.3: Main results using official CPI as price deflator

	ln(value agricultural ouput / CPI)		
	(1)	(2)	(3)
Within 20 km of mine × GLSS 5	-0.155*	-0.183**	-0.176*
	(0.085)	(0.085)	(0.088)
ln(land)		0.631***	0.673***
		(0.038)	(0.048)
ln(labor)		0.202***	0.358***
		(0.033)	(0.114)
Estimation	OLS	OLS	2SLS
Farmer's controls	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes
Observations	1,627	1,627	1,627
R-squared	0.243	0.459	0.447

Notes: Robust standard errors in parentheses. Standard errors are clustered at district level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. For further details on control variables and instruments see notes of Table 3. CPI is the consumer price index reported by GSS. This index has a lower geographical resolution than the price index used in the paper's main results.

Table B.4: First stage regressions of Column 3 in Table 3

	ln(land)	ln(labor)
	(1)	(2)
ln(land owned)	0.917***	0.172***
	(0.027)	(0.038)
ln(nr adult equivalents)	0.024	0.475***
	(0.019)	(0.056)
F-test excl. instruments	781.6	76.8
Observations	1,627	1,627
R-squared	0.798	0.243

Notes: Robust standard errors in parentheses. Standard errors are clustered at district level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. All columns include district and survey fixed effects, an indicator of being within 20 km of a mine, and farmer's characteristics. See Table 3 for details on the second stage.

Table B.5: Additional robustness checks - mine fixed effects, exclusion of Obuasi mine

	ln(real agricultural output)	
	(1)	(2)
Cumulative gold prod. within 20 km	-0.652***	-0.163*
	(0.224)	(0.087)
ln(land)	0.635***	0.637***
	(0.038)	(0.039)
ln(labor)	0.210***	0.205***
	(0.034)	(0.033)
Mine fixed effects	Yes	No
Sample	All	Excl. Obuasi mine
Observations	1,627	1,627
R-squared	0.422	0.464

Notes: Robust standard errors in parentheses. Standard errors are clustered at district level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. All regressions are estimated using OLS, and include district and survey fixed effecst, an indicator of being within 20 km of a mine and farmer's controls as the baseline specification in Table 3. . Columns 1 also include a set of mine fixed effect. Column 2 excludes farmers within 20 km of Obuasi mine.

Table B.6: Robustness checks - using log of gold production

	ln(real agricultural output)			
	(1)	(2)	(3)	(4)
Cumulative gold prod.	-0.350	-0.540**	-0.339	-0.520**
within 20 km	(0.208)	(0.252)	(0.208)	(0.261)
Annual gold prod.		2.596		2.487
within 20 km		(2.223)		(2.316)
ln(land)	0.630***	0.634***	0.676***	0.677***
	(0.038)	(0.038)	(0.047)	(0.047)
ln(labor)	0.210***	0.207***	0.349***	0.353***
	(0.033)	(0.033)	(0.110)	(0.109)
Estimation	OLS	2SLS	OLS	2SLS
Observations	1,627	1,627	1,627	1,627
R-squared	0.445	0.445	0.435	0.435

Notes: Robust standard errors in parentheses. Standard errors are clustered at district level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. All regressions include district and survey fixed effect, indicator of being within 20 km of a mine, and farmer's controls as in the baseline regression in Table 3. Columns 2 and 4 are estimated using 2SLS. The excluded instruments are: ln(area of land owned) and ln(number of adults equivalents in the household).

Table B.7: Mining, input prices and input demands - robustness checks

	ln(relative wage) (1)	ln(relative land rent) (2)	ln(labor) (3)	ln(land) (4)
Annual gold prod. within 20 km	0.220 (0.627)	1.326 (1.558)		
Cumulative gold prod. within 20 km.			-0.123** (0.055)	0.008 (0.035)
ln(relative wage)			-0.101 (0.157)	0.013 (0.119)
ln(relative land rent)			-0.097 (0.070)	0.000 (0.039)
ln(nr. adult equivalents)			0.507*** (0.061)	0.008 (0.020)
ln(land owned)			0.064** (0.029)	0.867*** (0.041)
ln(real agric. output)			0.095*** (0.025)	0.067*** (0.021)
Farmer's controls	No	No	Yes	Yes
District fixed effects	No	No	Yes	Yes
Observations	194	201	1,342	1,342
R-squared	0.277	0.009	0.279	0.808

Notes: Robust standard errors in parentheses. Standard errors are clustered at district level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. All regressions include survey fixed effects and an indicator of being within 20 km of a mine. Columns 1 and 2 use annual instead of cumulative gold production (see notes of Table 6 for details). Columns 3 and 4 replicate results in Table 7 adding a measure of agricultural output as additional control variable.

Table B.8: Mining and household expenditure

	ln(real expenditure per capita)					
			Rural			Urban
	All households		All	Farmers	Non-farmers	
	(1)	(2)	(3)	(4)	(5)	(6)
Cumulative gold prod. within 20 km.	-0.055		-0.048	-0.084*	0.041	-0.115
	(0.053)		(0.065)	(0.045)	(0.111)	(0.073)
Within 20 km of mine × GLSS 5		-0.214**				
		(0.102)				
Observations	5,527	5,527	3,393	2,540	853	2,134
R-squared	0.570	0.571	0.489	0.446	0.583	0.585

Notes: Robust standard errors in parentheses. Standard errors are clustered at district level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. All regressions are estimated using ordinary least squares, and include district and year fixed effects as well as household controls, such as: age, age^2, religion, place of birth and literacy status of household head, household size, and an indicator of urban areas. All columns include an indicator of being within 20 km of a mine.

Table B.10: Mining and agricultural productivity - IIV approach assuming only one imperfect instrument

	ln(real agricultural ouput)	
	(1)	(2)
Cumulative gold	[-0.180, -0.164]	[0.043, -0.097]
prod. within 20 km.	(-0.189, -0.149)	(0.109, -0.125)
ln(land)	[0.740, 0.676]	[0,198, 0.676]
	(0.774, 0.616)	(-0.026, 0.773)
ln(labor)	[0.109, 0.352]	[0.652, 0.352]
	(-0.019, 0.576)	(0.793, 0.291)
Estimation	IIV	IIV
Farmer's controls	Yes	Yes
District fixed effects	Yes	Yes
Imperfect IV for:	Labor	Land
Valid IV for:	Land	Labor
Observations	1,627	1,627

Notes: Robust standard errors in parentheses. Standard errors are clustered at district level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. All regressions include district and survey fixed effects, an indicator of being within 20 km of a mine, and farmer's controls. For further details see notes of Table 3. Columns 1 and 2 identify parameter bounds using the imperfect instrumental variable approach in Nevo and Rosen (2010) assuming there is only one imperfect instrument. Identified parameter bounds are in brackets while the 95% confidence interval is in parenthesis. Confidence intervals are calculated adding (substracting) 1.96 standard deviations to the upper (lower) bound. Cumulative gold production is measured in hundreds of MT.

C Child malnutrition and health

As a complement of the results on poverty, we also examine other relevant measures of living standards, such as child malnutrition and health. These outcomes may be affected by the increase in poverty and pollution. The GLSS does not have, however, information on these outcomes. To overcome this limitation, we use data from the Ghana Demographic and Health Surveys (DHS). We use a dataset of repeated cross-sections covering the years 1993, 1998, 2003 and 2008, and focus on the same study area as in previous results, i.e., Western, Ashanti and Central regions.

We focus on nutrition and health of children under 5 years. As measure of nutritional status, we use Z-scores of weight-for-age and height-for-age. The first one measures current nutritional status, while the second is often used to measure chronic malnutrition. We also study two measures of child health: incidence of diarrhea and acute respiratory disease (ARD). Height and weight are based on anthropometric measures, while child health indicators are based on mother's self-reporting of symptoms.

To examine the effect of mining on these outcomes, we estimate the following model:

$$D_{idvt} = \lambda_1 \ln S_{vt} + \lambda_2 M_{it} + \delta_d + \upsilon_{it}, \tag{5}$$

where D is the nutrition or health indicator of child i in year t. v and d stand for sampling cluster, the DHS equivalent of enumeration area, and district respectively. M_{it} is a vector of mother and child controls such as mother's education, age, gender, access to piped water, an indicator of being in a rural area, and year fixed effects. S_{vt} is our preferred measure of mining activity, i.e., cumulative gold production within 20 km of the household.[81]

Table C.1 shows the estimates of regression (5). In line with the increase in poverty, column 1 finds a reduction in the average weight of children under 5. This results suggests a direct effect on nutritional intake for children in affected areas. Columns 2 and 3 show no effect on indicators of height or incidence of diarrhea. This result may be driven by avoidance behavior of the local population. There is, for example, anecdotal evidence that the local population is

[81] We obtain measures of distance to mines using coordinates of sampling clusters reported by the DHS. Note, however, that the DHS reports geographical coordinates with a random error of 5 km in rural areas and 2 km in urban areas. This introduces a measurement error that may attenuate the estimates.

aware of the location of contaminated water and avoids these sources of water (WACAM, 2010). Finally, column 4 shows a slight increase in acute respiratory diseases that might result from lower quality of air near mining sites.

Table C.1: Mining, child nutrition and health

	Under 5 weight-for-age		Under 5 height-for-age		Diarrhea		Acute respiratory disease	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(cumul. gold prod. within 20 km	-1.144		-1.099		0.001		0.004**	
	(1.049)		(1.084)		(0.003)		(0.002)	
Within 20 km of mine x post 2003		-26.407**		2.852		0.020		0.054*
		(12.570)		(14.785)		(0.032)		(0.031)
Observations	2,554	3,304	2,486	3,236	2,711	3,522	2,712	3,520
R-squared	0.047	0.039	0.206	0.190	0.047	0.048	0.041	0.033

Notes: Robust standard errors in parentheses. Standard errors are clustered at district level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. All regressions are estimated using OLS and include district and survey fixed effects, an indicator of being within 20 km of a mine, and mother and child controls. Mother and child controls include: mother education, child age and its square, child gender, access to piped water, and an indicator of being in a rural area.