Mining, Pollution and Agricultural Productivity: Evidence from Ghana*

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Abstract

Most modern mines in the developing world are located in rural areas, where agriculture is the main source of livelihood. This creates the potential of negative spillovers to farmers through competition for key inputs (such as land and labor) and environmental pollution. To explore this issue, we examine the case of gold mining in Ghana. Through the estimation of an agricultural production function using household level data, we find that mining has reduced agricultural productivity by almost 40%. This result is driven by polluting mines, not by input availability. Additionally, we find that the mining activity is associated with an increase in poverty, child malnutrition and respiratory diseases. A simple cost-benefit analysis shows that the actual fiscal contribution of mining would not have been enough to compensate affected populations.

Keywords: Natural resources, mining, pollution.

1 Introduction

The economic effects of extractive industries, such as mining and oil extraction, are usually thought in terms of a "Dutch disease": a boon of natural resources may change relative prices and crowd out industries with more growth potential -like manufacturing (van der

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Ploeg, 2011; Sachs and Warner, 2001; Corden and Neary, 1982). Less prominent in the academic and policy debate, however, are other crowding out mechanisms such as environmental degradation and loss of agricultural output. This dimension has been neglected despite the existing biological evidence linking pollution to reduction in crop yields, and the fact that most extractive operations are located in rural areas where agriculture, more than manufacturing, is the main economic activity.

To the best of our knowledge, this paper is the first in the economic literature to explore this possible negative spillover effect of extractive industries. To do so, we examine empirically the effect of mining on agricultural output and productivity in Ghana. We focus on gold mining, the most important extractive industry in Ghana in terms of export value and fiscal revenue. The industry has experienced a boom since the late 1990s, mostly driven by the expansion and opening of large-scale operations. This has placed Ghana among the top 10 producers of gold in the world. More importantly for our purposes, most gold mines are located in the vicinity of fertile agricultural lands. They also have had little economic interactions with the local economy (in terms of employment or purchases of local goods) and a poor environmental record.

To examine the effect of mining on agriculture, and its potential channels, we estimate an agricultural production function. We use household survey data available for years 1998/99 and 2005 and we also collected detailed information on the geographical location of gold mines and households. Then, we compare the evolution of total factor productivity in areas in the proximity of mines to areas farther away. The main identification assumption is that the change in productivity in both areas would be similar in the absence of mines. Using a less rich dataset from 1989, we show that indeed agricultural output in areas close and far from mines followed similar trends before the expansion of mining. This is a necessary, though not sufficient, condition for the validity of our strategy.

An additional non-trivial empirical challenge relates to 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). We are limited, however, by the lack of panel data to implement the standard solutions. Instead, we address this issue controlling for farmer's observable characteristics and district fixed effects. We complement this strategy with an instrumental variables approach. As instruments, we use farmer's input endowments such as land holdings and households size. We show that under the assumption of imperfect input markets, there is a positive correlation between input use and endowments.

The validity of these instruments might be, however, questioned. To address this concern, we use a new partial identification approach developed by Nevo and Rosen (2012). This approach uses imperfect instrumental variables (i.e. instruments that may be correlated to the error term) to identify analytical bounds in the parameters. The validity of this method relies on two assumptions: (i) the instrument and the endogenous variables should have the same direction of correlation with the error term and (ii) the instrument has to be less correlated to the error term than the endogenous variable. These assumptions are weaker than the exclusion restriction required in a standard IV, and, as we discuss below, are more likely to be met in the case we study.

We find evidence of a significant reduction in agricultural productivity. Our estimates suggest that, between 1998/99 and 2005, productivity decreased by almost 40% in areas closer to mines, relative to areas farther away. The reduction in productivity is paralleled by a similar decline in agricultural output. The negative effects extend to areas within 20 km from mines, decline with distance, and are mostly present around polluting mines. We also document reduction in yields of cacao and maize, the two main crops in south west Ghana.

We interpret these results as evidence that pollution, from mining activities, has decreased agricultural productivity. To further explore this interpretation, we would ideally need measures of key water and air pollutants. These data, however, is unavailable in the Ghanaian case. Instead, we rely on a novel approach using satellite imagery to 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 that the concentration also declines with distance in a similar fashion as the reduction in agricultural productivity.

These results relate to recent evidence showing that air pollution reduces health and productivity of agricultural workers in the U.S. (Graff Zivin and Neidell, 2011). We, however, examine total factor productivity and find much larger effects. The effects we uncover are closer in magnitude to the reduction in crop yields due to pollution documented in the natural sciences literature. This evidence suggests that pollution may have important effects on productivity through channels different than workers' health such as quality of inputs and crops' health.

Mining could also be crowding out agriculture through competition for key inputs. This is particularly relevant since mining has been linked to land grabbings and increases in the cost of living in mining areas. Either phenomenon could lead to an increase in agricultural input prices and production costs. To further explore this alternative mechanism, we explore changes in local input prices and find that, if anything, input prices have decreased. These findings are consistent with the reduction of agricultural productivity, and weaken the case for mining to be crowding out agriculture through market channels.

Our second set of results move beyond agricultural productivity and focus instead 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%. The effects are present not only among agricultural producers, but extend to other residents in rural areas.

We also explore other markers of living conditions such as children malnutrition and health. To do so, we use data from the Demographic Health Survey. We document deterioration in indicators of children nutritional status such as weight for age, as well as increase in incidence of respiratory diseases. We do not find, however, evidence of changes in indicators of chronic malnutrition, such as height for age or in the incidence of diarrhea. Together, these findings are consistent with lower local incomes and airborne pollution associated to mining.

These results highlight the importance of considering potential loss of agricultural productivity and rural income, as part of the social costs of 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. To illustrate this point, we do a simple back-of-the-envelope calculation and show that in 2005 the annual loss to affected households amounted to US$ 150 million. In contrast, the contribution of mining to the Ghanaian government's revenue, one of the most important domestic benefits from mining, was less than half this amount. Additionally, mining taxes' redistribution rules imply that only a small fraction of tax receipts might reach local communities.

This paper contributes to the economic literature studying the effect of environmental degradation on living standards. This literature has focused mostly on examining the effect of pollution on health outcomes. For example, Chay and Greenstone (2003) find that reduction in air pollution, associated with an economic slump in early 1980s in the US, has reduced infant mortality. Currie et al. (2009) use U.S. school level data and find that air pollution increases school absence, a proxy for worse children health. In the context of developing countries, Jayachandran (2009) shows that exposure to pre-natal air pollution generated by wildfires in Indonesia in 1997 has increased child mortality. In contrast, Greenstone and Hanna (2011) find that air regulation in India were effective on reducing air pollution, but did not have significant knock-on effects on infant mortality.

Others have explored the long-term effects of environmental disasters such as soil erosion (Hornbeck, 2012) and climate change (Dell et al., 2008; Guiteras, 2009). Recent papers have also started to explore the link between pollution, workers' health, and labor market outcomes. In a closely related paper, Graff Zivin and Neidell (2011) find a negative effect of air pollution on productivity of piece-rate farm workers in California's central valley. They, however, cannot estimate the effect of pollution on total factor productivity that may occur, for instance, if land becomes less productive or if crop yields decline. Hanna and Oliva (2011) use the closure of a refinery in Mexico as a natural experiment and document an increase in labor supply associated to reductions in air pollution in the vicinity of the emissions source. Our paper contributes to this literature by documenting another, non-health related, channel through which pollution may affect living standards in rural setups: reduction in agricultural productivity and household consumption.

This paper also contributes to the literature studying the effect of natural resources on development. Using country level data, this literature finds that resource abundance may hinder economic performance, specially in the presence of bad institutions (Sachs and 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 which may be more relevant at local level. For example using the Brazilian case, Caselli and Michaels (2009) find that the revenue windfall from oil wells has not improved local income. In the same setup, Brollo et al. (2010) document a political resource curse: the revenue windfall has increased corruption and deteriorated political selection. Vicente (2010) also finds an increase in corruption in Sao Tome and Principe in anticipation to oil production. On a more positive side, Aragon and Rud (n.d.) document how the expansion of a mine's backward linkages can improve the income of local populations.

The next section provides an overview of mining in Ghana and discusses the link between mining, pollution and agricultural productivity. Section 3 describes the empirical strategy and the data. Section 4 presents the main results, while section 5 present a simple cost-benefit analysis of the mining sector in Ghana. Section 6 concludes.

2 Background

2.1 Context

The importance of the mining sector in the economy of Ghana has increased substantially in the last 20 years. According to the Ghana Chamber of Mines, in 2008 mining activities generated around 45% of total export revenue, 12% of government's fiscal revenue and attracted almost half of foreign direct investment. The contribution to gross domestic product stands around 6%. This mining expansion has been attributed to the structural reforms in the 1980s that encouraged foreign investment in large-scale mines, especially in gold (Aryeetey et al., 2007).

Gold production accelerated in late 1990s due to the opening of new mines and the expansion of existing operations (see Figure 1). Gold has become the most important export product, ahead of more traditional commodities such as cocoa, diamond, manganese and bauxite and represents around of 97% of the country's mineral revenue. This expansion has placed Ghana among the top 10 gold producers in the world. In the empirical analysis, we exploit this increase in mining activities as a source of variation to identify potential spillovers of mining on other sectors, such as agriculture.

Traditionally, gold mines have been located in the Ashanti gold belt, in the south-west of Ghana. The gold belt extends over three regions: Western, Ashanti and Central. Recently, new mines have opened in the south of Brong-Ahafo, and there are several explorations and mine developments in the Eastern and Northern regions (see Figure 2).[1]

Gold is produced by large-scale capital-intensive mines, that generate around 96% of total gold production, and by small-scale artisanal operations called *galamseys* that are labor-

[1] A mine cycle consists of several stages: exploration, mine development, production, and closure.

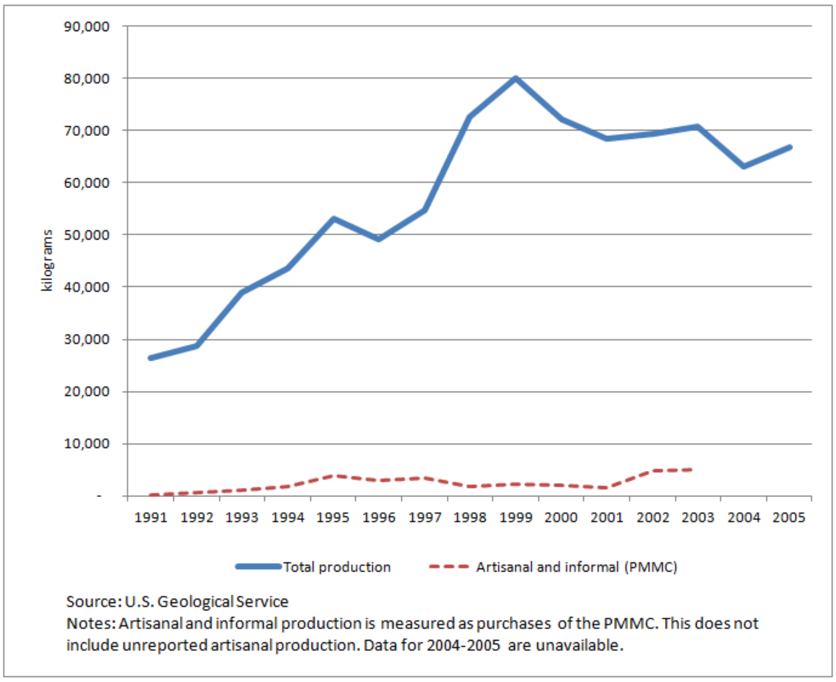

Figure 1: Evolution of gold production

intensive and, in many cases, carried out without licences or regulations. Large mines are mostly foreign owned but at least a 10% stake is held by the Ghanaian government. Similarly to other major large-scale mines in developing countries, gold mines in Ghana have little interaction with local economies: they hire few local workers, buy few local products and their profits are not distributed among local residents. As we discuss in Section 5, a small fraction of the fiscal revenue from mining is distributed among local authorities.

Despite the success of gold mining at a macro level, it is less clear whether it has brought any benefits to the local population. There is little or no evidence that can link the expansion of the sector to poverty alleviation or to local economic development. However, the anecdotal evidence points towards a variety of negative effects and focuses on the loss of agricultural livelihoods and an increase in environmental pollution[2] (Human Rights Clinic, 2010; Akabzaa, 2009; Aryeetey et al., 2007; Hilson and Yakovleva, 2007). Because mining operations in Ghana are located in areas where agricultural production is the main economic activity, an increase in pollution of air, water and land would seriously affect farmers' ability to produce. For that reason, we turn next to the environmental hazards created by the expansion of mining activities.

[2]Reports also suggest an increase in social conflict and human rights abuse in mining areas.

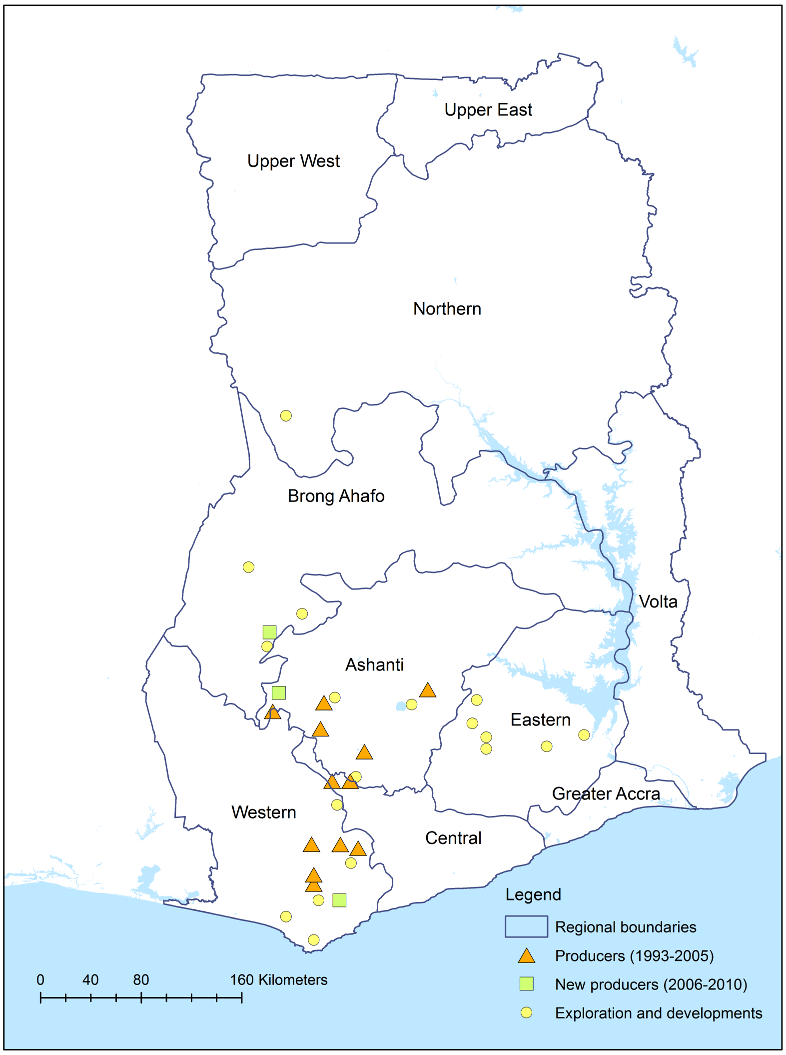

Figure 2: Gold mines in Ghana

2.2 Mining and pollution

The production process that modern mining entails has the potential to affect the environment in several ways, e.g. through acid rock drainage, contamination of ground and surface water, and emission of air pollutants.[3]

Acid rock drainage (ARD) occurs when sulphide minerals are exposed to air and water, for example during soil removal in mining operations.[4] Sulphides oxidize and form an acid effluent (sulfuric acid) which in turn leaches other metals from existing rocks. The resulting drainage can become very acidic and contain a number of harmful metals. In turn, this can have severe impacts on surrounding water bodies. ARD is considered as the most serious environmental problem for the mining industry (U.S. Environmental Protection Agency, 2000, section 3-2).

Mining operations can also affect water quality when waters (natural or wastewater) infiltrate through surface materials into the groundwater and pollutes it with contaminants such as metals, sulphates and nitrates. Wastewater may also contain sediments that increase surface water turbidity and reduces oxygen and light availability for aquatic life. In the case of gold, the use of cyanide and mercury creates an additional hazard. Cyanide is used in large-scale mining and re-processed, but some is discarded in tailings and there is a risk of spillages into surface waters. Mercury is used in artisanal mining and it is usually released into surface water or vaporized during the refining process.

Finally, mining activities produce several air pollutants such as nitrogen oxides, sulphur oxides and particulate matter.[5] These emissions are akin to any fuel-intensive technology and similar to the ones associated to industrial sites, power plants, and motor vehicles. The main direct sources of air emissions are diesel engines for haulage, drilling, heating and cooling, among others. Additionally, the process of blasting, crushing and fragmenting the rocks, followed by smelting and refining generate substantial aerial emissions in large-scale open pit mining.

In the case of Ghana, there is substantial evidence, ranging from anecdotal to scientific, that gold mining is associated with high levels of pollution. Most studies focus on gold mining areas in the Western Region such as Tarkwa, Obuasi, Wassa West and Prestea. For example,

[3] This section is based on U.S. Environmental Protection Agency (2000) , Environment Canada (2009) and Natural Resources Canada (2010).

[4] Sulphide minerals, such as pyrites, are associated to ores of base metals such as copper, lead, zinc and gold.

[5] These pollutants are contributors to smog and acid rain. Smelters and refineries may also release more dangerous particles of zinc, arsenic and lead into the air. In the area of analysis, however, there are no smelting activities.

Amegbey and Adimado (2003) and WACAM (2010) document at least eleven accidents with cyanide in mining areas (such as spills and release of cyanide-bearing tailings).

Pollution, however, extends beyond cyanide spills. 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 (PM10), an air pollutant, near or above international admissible levels.[6] Serfor-Armah et al. (2006) find high levels of arsenic in water and sediments near Prestea, while Tetteh et al. (2010) find high levels of mercury and zinc content in the topsoil of towns in Wassa West. The levels of concentration decrease with distance to mining sites, and extend beyond mining areas, probably due to the aerial dispersion of metals from mining areas.

The available data, however, are sparse. There is, for example, no historical data of water or air monitoring stations in mining regions that allow us to obtain direct measures of pollution. Only recently, since 2009, Ghana's Environmental Protection Agency (EPA) has started assessing, and reporting, the environmental compliance of mines.[7] The results are consistent with the academic evidence previously mentioned. 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. In the empirical section, we use this information to distinguish between polluting and non-polluting mines.

2.3 Pollution and agricultural productivity

An important feature of the gold mining industry in Ghana is that it is located in fertile agricultural areas. For example, the Western region is also the main producer of cocoa, the most important cash crop and agricultural export. In this context, the effect of pollution on agriculture becomes extremely relevant. If pollution has a negative effect on agriculture, then mining can potentially have a direct impact on rural income and living standards.

So far, the economic literature has disregarded this link. Other disciplines like natural and environmental sciences, however, have widely documented the effect of pollutants (mostly

[6] In a non-peer-reviewed study, WACAM (2010) collected samples from more than 200 streams and water bodies in the areas of Obuasi and Tarkwa. They also find levels of heavy metals, acidity (pH), conductivity and turbidity considerably above the permissible international standards.

[7] For further details, see `http://www.epaghanaakoben.org/`.

airborne) on crop yields (Emberson et al., 2001; Maggs et al., 1995; Marshall et al., 1997).[8] These studies, mostly in controlled environments, find drastic reductions in yields of main crops -e.g. rice, wheat, and beans- coming from the exposure to air pollutants associated to the burning of fossil fuels, such as nitrogen oxides and ozone.[9] Depending of the type of crop, the yield reductions can be as high as 30 to 60%.

The potential for mining to affect plants is also acknowledged by environmental agencies. For example, Environment Canada states that "Mining activity may also contaminate terrestrial plants. Metals may be transported into terrestrial ecosystems adjacent to mine sites as a result of releases of airborne particulate matter and seepage of groundwater or surface water. In some cases, the uptake of contaminants from the soil in mining areas can lead to stressed vegetation. In such cases, the vegetation could be stunted or dwarfed" (Environment Canada, 2009, p. 39).

3 Methods

3.1 A consumer-producer household

In this section we provide a simple analytical framework that guides the empirical strategy. As it is standard in the literature[10], we assume households are both consumers and producers of an agricultural good with price $p = 1$. They maximize utility $U(c, l)$ over consumption c and leisure l, subject to a budget constraint that accounts for household's production and income generated by market activities.

Households use labor (L) and land (M) to produce the agricultural good and have an idiosyncratic productivity A, i.e. $Q = F(A, L, M)$. A household's labor endowments E^L can be split between agricultural production (L^f), leisure (l) and market work (L^m) at a wage w. Additionally, households can hire labor at the market wage (L^h). A household's land endowments E^M can be used for agricultural production (M^f) or supplied to the land market (M^m), at a price r. Additionally, households can rent land (M^h).

We assume Cobb-Douglas utility and production functions: $U(c, l) = c^\theta l^{1-\theta}$ and $F(L, M) =$

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

[9]Tropospheric ozone is generated at low altitude by a combination of nitrogen oxides, hydrocarbons and sunlight, and can be spread to ground level several kilometers around polluting sources. In contrast, the ozone layer is located in the stratosphere and plays a vital role filtering ultraviolet rays.

[10]See (?) for a review.

$AM^{\alpha}L^{\beta}$. In brief, the household problem can be written as follows

$$\text{Max } U(c,l) \text{ subject to} \tag{1}$$

$$c + wL^h + rM^h \leq F(A,L,M) + wL^m + rM^m \tag{2}$$

$$L = L^f + L^h \ , \ M = M^f + M^h \tag{3}$$

$$E^L = L^f + L^m + l \ , \ E^M = M^f + M^m \tag{4}$$

3.1.1 Farmer heterogeneity

We assume farmers are heterogeneous in their access to markets for inputs. In particular, there are two types of farmers: a fraction τ of households that are never-constrained, i.e. they operate as in perfectly competitive markets and a fraction $1-\tau$ that are fully-constrained, i.e. they cannot buy or sell inputs[11]. In the case of land, for example, this is a reasonable assumption in the context of weak property rights such as rural Ghana. (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 [12]. Similar arguments can be made about labor markets (see (**?**)).

For never-constrained farmers, by adding $wL^f + wl + rM^f$ on both sides of the budget constraint and replacing, we obtain $c + wl \leq F(A,L,M) - wL - rM + wE^L + rE^M$. This means that the value of consumption plus the value of leisure has to be lower or equal than production profits plus the value of endowments. In this case, the maximisation problem of the household follows the separation property: the household chooses the optimal amount of inputs to maximise profits and, separately, the household chooses consumption and leisure levels, given the optimal profit. Using the above-defined Cobb-Douglas functions and defining disposable income $W = F(A,L^*,M^*) - wL^* - rM^* + wE^L + rE^M$, we can find optimal levels of inputs, consumption and leisure $L^*(A,w,r,\alpha,\beta)$; $M^*(A,w,r,\alpha,\beta)$, $c^*(\theta,W)$ and $l^*(\theta,W)$.

If farmers cannot buy or sell inputs, their production is constrained by their endowments.

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

[12] Interestingly, there is variation within farmer i.e. a farmer may own some plots subject to traditional property rights and other plots subject to modern rights.

In the case of land, this is straightforward: because the marginal cost of land is zero, this type of farmers uses it all. In the case of labor, now farmers face a trade-off between leisure and income. The binding budget constraint now becomes $c = F(E^L - l, E^M)$ and the optimisation problem is reduced to the choice of leisure that maximizes the expression $U(c,l) = c^\theta l^{1-\theta} = [A(E^M)^\alpha (E^L - l)^\beta]^\theta l^{1-\theta}$.

Solving, we obtain optimal leisure $l^* = \frac{1-\theta}{1-\theta(1-\beta)} E^L$ that results in optimal in-farm labor use $L^* = \frac{\theta\beta}{1-\theta(1-\beta)} E^L$. Note that for constrained farmers, endowments are good predictors of input use. In particular, land endowment is equal to land use and labor endowments correlation with labor use depends on farmers' preference for leisure and technical labor needs in farming.

3.1.2 Expansion of mining activities: channels

In this simple framework, there are two main channel through which the expansion of mining activities can affect farmers: pollution and competition for inputs. Pollution would imply a reduction in agricultural productivity A. Note that because pollution affects the health of crops either directly (e.g. leaf tissue injury or plant growth) or indirectly (e.g. reducing resistance to pests and diseases), in the presence of pollution agricultural product would fall even if there is no change in input use.

Output could also decline due to a reduction in input use, for example, if prices for L and M increase because of a greater demand from mines or a reduction in endowments, following land grabbings and population displacement. This mechanism is similar in flavor to the Dutch disease and, as discussed in the previous section, has been flagged as a concern in the case of Ghana[13]. The second of the arguments has been favored as an explanation for the perceived reduction in agricultural activity, and an increase in poverty, in mining areas (Akabzaa, 2009; Aryeetey et al., 2007). Either way, the competition for inputs would reduce agricultural output, even if productivity remains unchanged.

Because the two proposed channels have different empirical implications, we can separate them by estimating the agricultural production function. Furthermore, the analytical framework presented above informs how consumer-producer farmers choose inputs in a way that can be

[13]For example, Duncan et al. (2009) quantify at around 15% the reduction of 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).

used to guide the estimation of the production function. Additionally, because agricultural output affects the budget constraint of farmers, the anaytical framework shows that if the mining sector is reducing farmer productivity, agricultural incomes should decrease and affect negatively consumption and poverty levels (which is simply consumption relative to a threshold)

3.2 Empirical implementation

A farmer's agricultural production function can be written as

$$Q_{ivt} = A_{ivt} M_{it}^{\alpha} L_{it}^{\beta}, \tag{5}$$

where Q is expected output, M and L are land and labor, and A is total factor productivity. All these variables vary for farmer i in locality v at time t. We define locality as the survey's enumeration area. This is the smallest recognizable jurisdiction and roughly corresponds to a village or neighborhood.

We assume that A is composed of 3 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, we assume:

$$A_{ivt} = \exp(\eta_i + \rho_v + \gamma S_{vt}). \tag{6}$$

In addition, note that we do not observe Q but only actual output Y:

$$Y_{ivt} = Q_{ivt} e^{\epsilon_{it}}, \tag{7}$$

where ϵ_{it} captures unanticipated shocks and is, by definition, uncorrelated to input decisions.

With these assumptions in mind, we can write the following relation:

$$y_{ivt} = \alpha m_{it} + \beta l_{it} + \eta_i + \rho_v + \gamma S_{vt} + \epsilon_{it}, \tag{8}$$

where y, l and m represent the logs of observed output, labor and land, respectively.

Note that the effects of mining on input availability would affect output through change in prices and the optimal choice of land and labor, but not through changes in A. As a consequence, if the pollution mechanism is at play we should obtain that $\gamma < 0$. Also, in the absence of direct measures of pollution, we use as a proxy the presence of local mining activities S_{vt}. A caveat with using this proxy, however, is that it may also capture other non-market negative spillovers associated to mining activity such as decline in quality of inputs, change in public good provision, and increase in social conflict. In the results section we examine these alternative mechanisms in more detail.

There are two main empirical challenges to estimate specification (8). The first one is related to the fact that mining and non-mining areas may have systematic differences in productivity. In terms of equation (8), this means that $E(S_{vt}\rho_v) \neq 0$ and ρ_v is unobservable. This omitted variable problem may lead to endogeneity issues when estimating the coefficients of interest. To address this issue, we exploit the time variation in the repeated cross section to compare the evolution of productivity in mining areas relative to non-mining areas. In particular, we replace S_{vt} by $mine_v \times T_t$ where $mine_v$ is an indicator of being close to a mine and T_t is a time trend.

This approach is basically a difference in difference. Its validity rely on the assumption that the evolution of productivity in both areas would have been similar in the absence of mining growth. Figure 3 illustrates this strategy. It shows the average agricultural output in areas closer and farther from mines for the three years with available data: 1988, 1998-99 and 2005. Note that the evolution of output is remarkably similar in the first period, when gold production is relatively low, but there is a trend change in mining areas in the period when gold production increases. The similarity of trends prior to mine expansion is a necessary, though not sufficient, condition for the identification assumption to be valid.

The second problem in the estimation of 8 arises because for the fraction τ of unconstrained farmers, both output and choice of inputs are affected by productivity and hence are simultaneously determined. Thus, unobserved heterogeneity captured by A, such as elements of η_i, would go into the error term and create an endogeneity problem in the estimation of the input coefficients. The empirical literature on production functions has long recognized the endogeneity of input choices and has developed several procedures to deal with it.[14] These procedures mostly rely on the availability of panel data and use instruments based on lagged input decisions. Unfortunately, we are constrained by the available survey data that does not follow a

[14]There are two main approaches: dynamic panel models and structural estimation methods. See for example Blundell and Bond (2000) Olley and Pakes (1996) and Levinsohn and Petrin (2003).

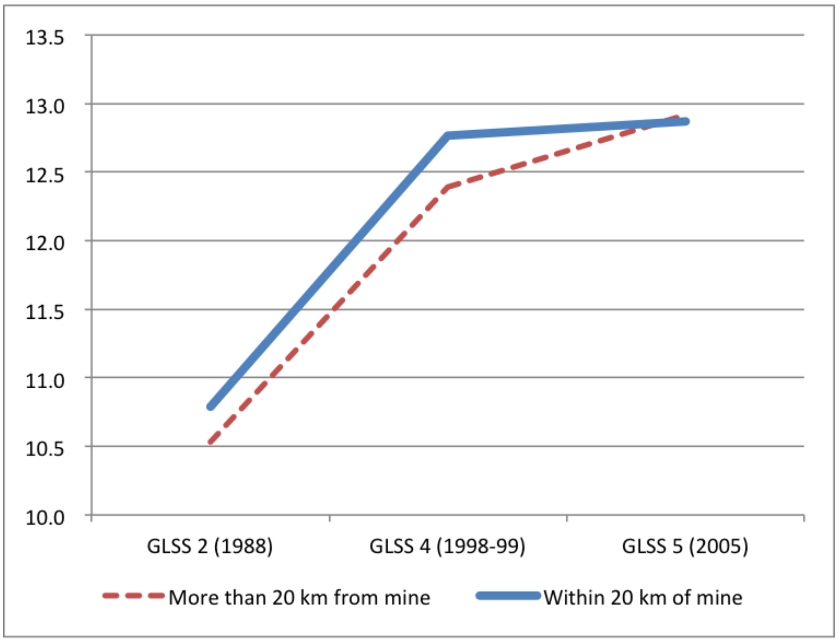

Figure 3: Evolution of the unconditional mean of ln(real agricultural output)

panel of farmers, but only repeated cross-sections.

As a first approach, we proxy η_i and ρ_v using farmer observable characteristics and district fixed effects.[15]

With these modifications, the model we estimate becomes:

$$y_{ivdt} = \alpha m_{it} + \beta l_{it} + \phi Z_i + \delta_d + \gamma(mine_v \times T_t) + \xi_{ivt}, \tag{9}$$

where d refers to district, Z_i is a set of farmer's controls, δ_d are district fixed effects, and ξ_{ivt} is an error term that includes ϵ_{it} and the unaccounted heterogeneity of η_i and ρ_v.

The set of farmer characteristics includes proxies for human capital such as age and literacy, land ownership as a proxy for wealth or political power, and place of birth to account for possible selective migration. Under the assumption that the use of inputs is uncorrelated to the residual unobserved heterogeneity ξ_{ivt}, we can estimate the parameters of (9) using a simple OLS regression. This assumption would be satisfied if farmer heterogeneity is fully captured by these controls or if $\tau = 0$, i.e. if all farmers are fully constrained.

However, the problem persists if there is a strictly positive fraction of unconstrained farmers

[15]Districts are larger geographical areas than enumeration areas. We do not include enumeration areas fixed effects, however, because each ares is observed in one survey only. Thus this set of fixed effects would be perfectly collinear to $mine_v \times T_t$.

and the set of controls does not capture fully farmers' characteristics that affect the choice of inputs. Assuming $\tau < 1$[16], we can use the presence of fully-constrained farmers to deal with input estimates. In particular, we can use endowments in an IV strategy. This works under what we consider a more plausible assumption, i.e. that endowments are not conditionally correlated to idiosyncratic productivity shocks or to an omitted variable, i.e. the (unobserved) heterogeneity not captured by our controls[17].

In the presense of a correlation between the error term and endowments that would invalidate the exclusion restriction in the IV strategy, we can make further progress by using a partial identification strategy proposed by Nevo and Rosen (2012). This approach uses imperfect instrumental variables (IIV) to identify parameter bounds.[18] An IIV is an instrument that may be correlated with the error term. Nevo and Rosen (2012) show that if (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, then it is possible to derive analytical bounds for the parameters.[19]

These (set) identification assumptions are weaker than the exogeneity assumption in the standard IV approach. The analytical framework presented above again provides the rationale for using this approach under less restrictive assumptions. First, there is a positive correlation between endowments and input use that comes from the subset of constrained farmers. There is no correlation between inputs and endowments for farmers operating in an unconstrained environment, unless it comes from an omitted variable that affects both. We only need that this omitted variable is such that higher productivity increases endowments[20]. Second, because the input is a share of endowments, for the subset of constrained farmers the correlation with the error term is the same. However, for unconstrained farmers there is a direct positive correlation

[16]Data shows that inputs markets are thin: in the area of study around 8% of available land is rented, and only 1.4% of the total farm labor (in number of hours) is hired.

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

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

[19]The parameter set could be a two- or one-sided bound depending on the observable correlation between endogenous variables and instruments. In particular, denoting X as the endogenous variable, Z as the imperfect instrument, and W other additional regressors, there is a two-sided bound if, in addition to the (set) identification assumptions, $(\sigma_{\tilde{x}x}\sigma_z - \sigma_x\sigma_{\tilde{x}z})\sigma_{\tilde{x}z} < 0$, where $\tilde{x}$ is the projection of X on W. In the complementary case, there is a one-sided bound. In the empirical section we do check that this expression has a negative value. We refer the reader to Nevo and Rosen (2012) for a detailed exposition of the estimation method.

[20]One might argue that higher productivity might be negatively correlated with household size. In that case, we only need the fraction of constrained farmers to be high enough. In the case of land, the sign of the correlations looks less controversial, but the same logic would apply.

between unobserved productivity and input use. We only need to assume that the correlation between endowments and productivity is more tenuous for this group to use IIV. In brief, point (i) above is obtained thanks to the group of constrained farmers, while point (ii) is obtained thanks to the group of unconstrained farmers.

We have laid out thre alternative ways of estimating input coefficients in the agricultural production function. However, our main interest is to test whether residual productivity has changed in mining areas, as the smoking gun for the presence of pollution-related reduction in production. A reduction in productivity should alse be reflected in lower consumption levels (and greater levels of poverty) for consumer-producer households. Crowding out of farming through other channels, such as an increase in the price of inputs, might increase household income for unconstrained households selling inputs. In that case, the average effects on consumption could even be positive.

3.3 Data

Our main results use household data from the rounds 4 and 5 of the Ghana Living Standards Survey (GLSS) These surveys were collected by the Ghana Statistical Service (GSS) in 1998-99 and 2005, respectively. [21]

The survey 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.[22] The survey also distinguishes between urban and rural areas, as well as ecological zones (i.e. 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.[23]

We are mainly interested on two set of variables: measures of proximity to gold mines, and measures of argicultural inputs and output.

[21]We also use the GLSS 2, taken in 1989, 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.

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

[23]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.

Proximity to mines To measure proximity to gold mines, we identify the sites of mines active during the period 1993 to 2004, and obtain their geographical coordinates The mining information comes from industry reports available at Infomine and U.S. Geological Service.[24] We combine the geographical information of mine sites and enumeration areas in a geographical information system (GIS) and 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.

Figure 4 displays a map of Ghana with the location of active gold mines between 1993 and 2004. Note that all mines are located in three regions: Western, Ashanti and Central. In the empirical section, we restrict the sample to these regions.[25] Figure 5 zooms in these three regions and depicts the enumeration areas and a buffer of 20 km around each mine. In the empirical analysis, the enumeration areas within each buffer correspond to mining areas ($mine_v = 1$) while the rest of enumeration areas correspond to non-mining areas ($mine_v = 0$).

We restrict attention to medium and large-scale gold mines, and do not consider neither other minerals (such as diamonds, bauxite and manganese), nor artisanal and informal gold mines (see Table 10 in Appendix for the list of mines). We focus on gold mining because is the most important mining activity both in quantity and geographical scope. Other mines are concentrated in few locations and 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-Wassaw mine near Tarkwa. Similarly, the gold production of artisanal and informal miners is relatively small (see Figure 1). Moreover, there is no information on their location, though anecdotal evidence suggests they are located in the vicinity of established mines. Finally, note that the omission of these other mines would, if anything, attenuate the estimates of the effect of mining.

Agricultural inputs and output 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

[24]See `http://www.infomine.com/minesite/` and the editions of *The Mineral Industry in Ghana* from 1994 to 2004 available at `http://minerals.usgs.gov/minerals/pubs/country/africa.html`.

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

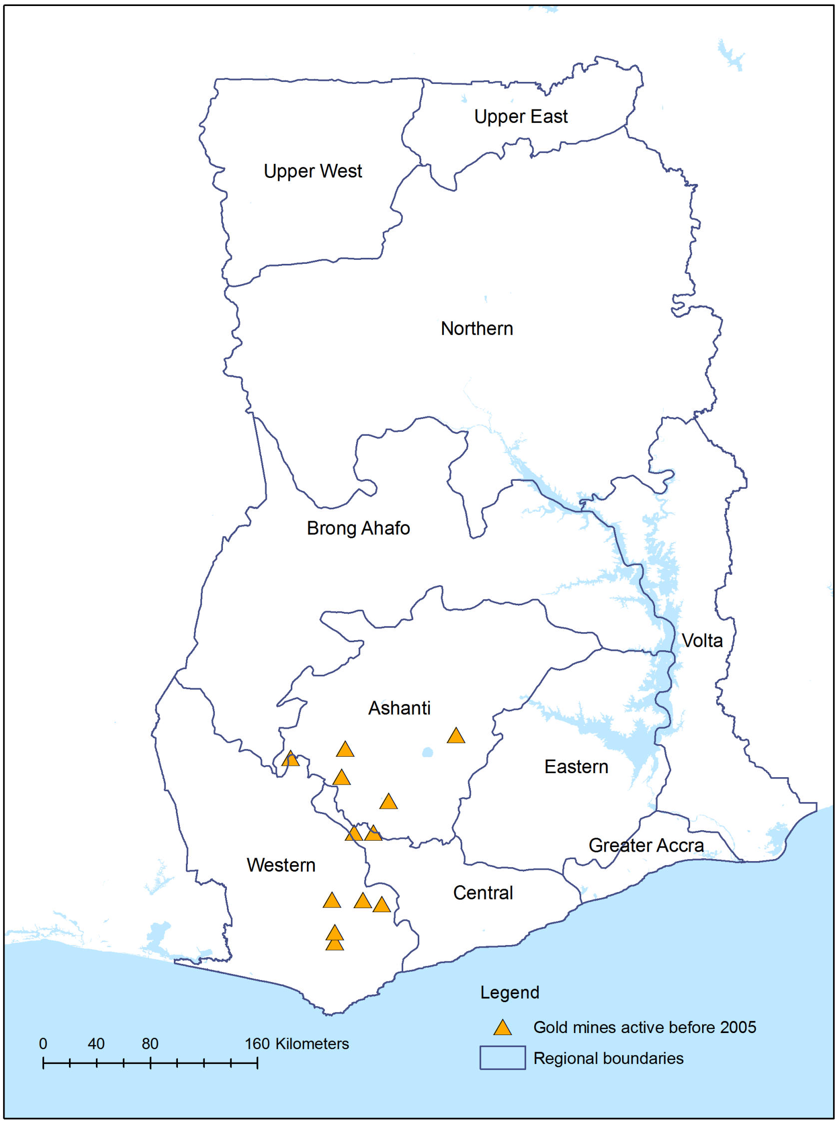

Figure 4: Location of active gold mines

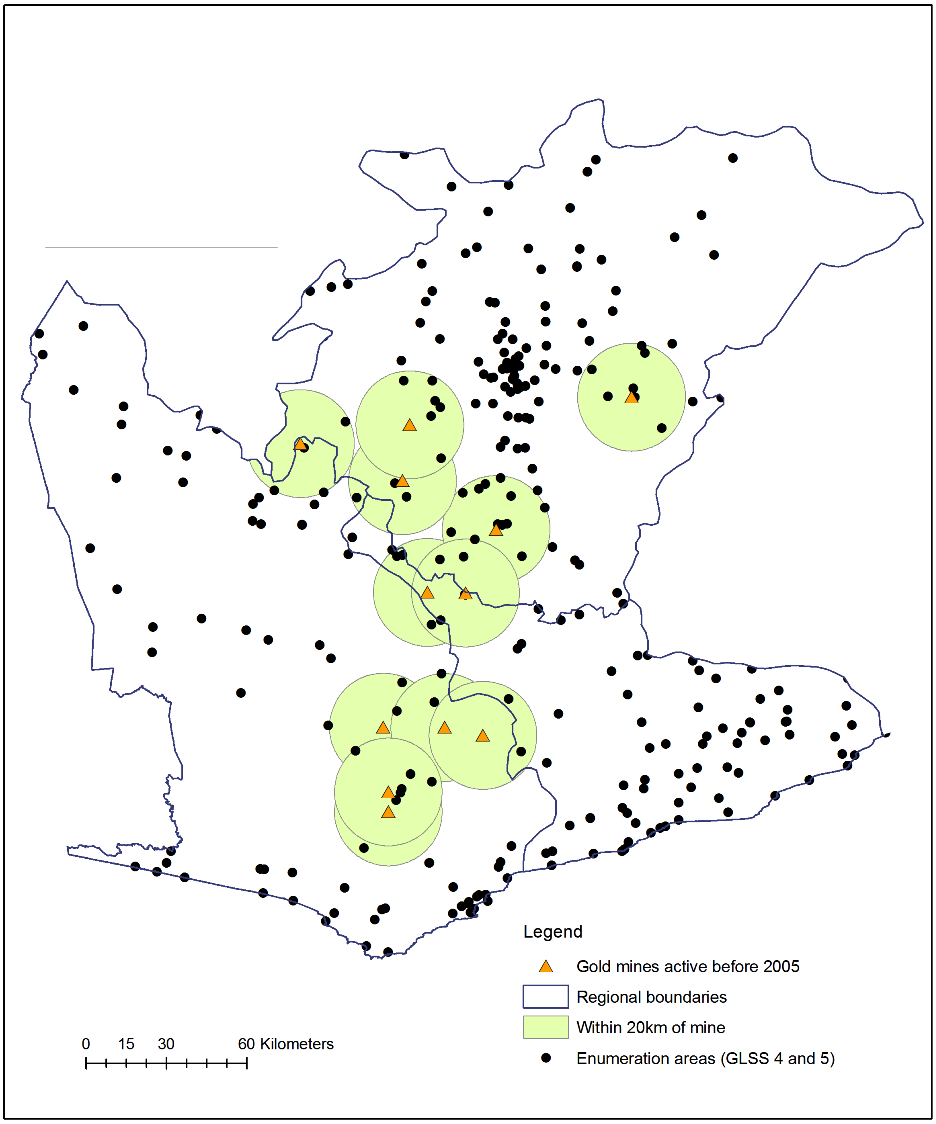

Figure 5: Area of study and enumeration areas

divide the nominal value of agricultural output by the value of the poverty line.The poverty line is estimated by the GSS and measures the value of a minimum consumption basket, mostly composed of food. This variable is available for Accra, rest of urban areas, and rural areas in each ecological zone.

In addition, we construct estimates of yields of the two main crops in the area of study: cocoa and maize. These measures provide us with alternative ways to explore the effect of mining on agricultural productivity.

We 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 in years 1998-99 and 2005. The farmers are located in 42 districts in 3 regions of south west Ghana: Western, Ashanti and Central. Table 1 presents some summary statistics.

Table 1: Mean of main variables

Variable	GLSS 4	GLSS 5
Within 20 km of mine (%)	22.5	26.8
ln(real agricultural output)	13.3	13.5
Land (acres)	9.9	15.1
Labor (days)	376.9	387.7
Land owned (acres)	12.2	16.6
Nr adults equivalents	3.8	3.5
ln(relative land price)	14.0	14.1
ln(real wage)	8.4	8.8
Age (years)	45.9	47.8
Literate (%)	55.2	43.7
Born in village (%)	55.2	45.9
Owns a farm plot (%)	64.2	86.2
Poverty headcount (%)	29.2	20.3
ln(household consumption p.c.)	13.8	13.9
Nr. Observations	713	914

Note: Means are estimated using sample weights.

4 Results

4.1 Mining and agricultural productivity

We start by examining whether mining areas have experienced a reduction in agricultural product, relative to areas in the same region that are farther away from mining sites. We do this by running a reduced form regression of household agricultural output on $mine_v \times T_t$. Column 1 in Table 2 uses data from GLSS 4 and 5 and compares the change in output between 2005 and 1998/99. Column 2 uses data from GLSS 2 and 4 to check a necessary condition for the validity of the difference in difference strategy i.e. that the evolution of output in mining and non-mining areas before the acceleration of mining production was similar.[26] Consistent with Figure 3, both results show significantly lower levels of agricultural production in mining areas between 1998/99 and 2005, but not before.

To explore the likely channels of this drop, we proceed to estimate the agricultural production function laid out in equation (9). Column 3 provides OLS estimates of input coefficients and

[26] GLSS 2 and 4 were collected in 1989 and 1998/99 respectively.

explores whether exposure to mining has reduced residual productivity, under the assumption that the identifying conditions discussed above hold. In column 4, we estimate a 2SLS using input endowments (such as area of land owned and the number of adults equivalents living in the household) as instruments for actual input use. All regressions include farmer controls and district fixed effects to account for the endogeneity in input use. The estimates use sample weights and cluster errors at district level to account for the sampling design and geographically correlated shocks, respectively.

The main observation is that both OLS and 2SLS estimates suggest a drastic reduction in agricultural productivity.[27]. The estimate of the interaction term "within 20 km × year 2005" for the whole sample is around -0.55. This implies that, between 1998-99 and 2005, the average agricultural productivity of farmers in the vicinity of mines declined by around 40%, relative to farmers located farther away. The reduction in productivity is high, and consistent with the results documented in biological literature (see Section 2.3).

Columns 5 and 6 use the imperfect instrumental variable approach developed by Nevo and Rosen (2012). As previously discussed, this approach uses instrumental variables that *may be correlated to the error term* to identify parameters bounds instead of point estimates. The key identification assumptions are that (i) the instrument and the endogenous regressor have the same direction of correlation with the error term and (ii) the instrument is less correlated to the error term than the endogenous variable. These are weaker assumptions than the exogeneity required in standard IV. We allow one instrument at a time to be imperfect.[28] We include similar controls as in the OLS and 2SLS estimates and also use sample weights.

We report the estimated lower and upper parameter bounds and also the confidence interval of the identified set.[29] Note that the identified parameter sets of α and β remain mostly positive, though the range is quite broad. Despite this, the estimated effect of mining on agricultural productivity (γ) remains negative with values ranging between -0.551 and -0.358.[30]

[27]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 X. The F-test statistic of excluded instruments is 59.41. See Table 11 in the appendix for further details.

[28]Nevo and Rosen (2012) obtain analytical bounds only in the case when there is one endogenous regressor with imperfect instruments. In the case of multiple endogenous variables, the parameter set can be, however, obtained by simulations. The estimates of γ in this more flexible case are similar (see Table 12 in the Appendix).

[29]In columns 5 and 6, the values of the expression $(\sigma_{\tilde{x}x}\sigma_z - \sigma_x\sigma_{\tilde{x}z})\sigma_{\tilde{x}z}$ are, respectively, -0.059 and -0.229. Recall that when this expression is negative there is a two-sided bound of the parameters. The 95% confidence intervals of the identified sets are obtained by adding (subtracting) 1.96 standard deviations to the upper (lower) bounds.

[30]A sensitivity analysis confirm that the results are very robust to alternative assumptions in the values of α

These results suggest that the negative effect on total factor productivity is robust to a series of specifications and estimation methods to (partially) identify input coefficients in the production function. What is reassuring for our purposes is that even allowing for production function coefficients to vary within a wide range of combinations (within the expected set where $\alpha + \beta \leq 1$) does not affect the finding that residual productivity has deteriorated over time near mining areas.

Finally, columns 7 and 8 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)). 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. Note that the sample size is smaller, since we only use data of farmers engaged in cocoa or maize production. Consistent with the results on productivity, we find a significant reduction (around 58%) in crops yields.

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 with distance. To explore this issue further, we estimate equation (9) replacing "$mine_v$" by a linear spline of distance to a mine, $\sum_c \gamma_c distance_{cv}$ where $distance_{cv} = 1$ if enumeration area v is in distance bracket c. 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 6 presents the estimates of γ_c. First, the effect of mining on productivity is (weakly) decreasing in distance. Second, 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.

4.1.1 Is this driven by pollution?

We interpret the previous findings as evidence that agricultural productivity has decreased in the vicinity of mines. We argue that a plausible channel is through the presence of mining-

and β. See Appendix A.1.

Table 2: Mining and agricultural productivity

	ln(real agricultural output)						ln(yield cocoa)	ln(yield maize)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Within 20 km of mine × year 2005	-0.502*		-0.554**	-0.554**	[-0.493 -0.358]	[-0.551 -0.540]	-0.882**	-0.846**
	(0.270)		(0.250)	(0.259)	(-0.520 -0.297)	(-0.556 -0.530)	(0.402)	(0.374)
Within 20 km of mine × year 1998/99		0.067						
		(0.333)						
ln(land)			0.627***	0.673***	[0.191 0.673]	[0.737 0.673]		
			(0.037)	(0.048)	(-0.031 0.770)	(0.772 0.612)		
ln(labor)			0.218***	0.356***	[0.664 0.356]	[0.118 0.356]		
			(0.034)	(0.115)	(0.806 0.294)	(-0.013 0.584)		
Estimation	OLS	OLS	OLS	2SLS	IIV	IIV	OLS	OLS
Farmer's controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Imperfect IV for:					Land	Labor		
Observations	1,627	1,479	1,627	1,627	1,627	1,627	1,076	933
R-squared	0.245	0.533	0.462	0.453			0.250	0.272

Notes: Robust standard errors in parentheses. Standard errors are clustered at district level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. 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. Column 2 uses data from GLSS 2 and 4, the rest of columns use data from GLSS 4 and 5. Column 4 uses land and labor endowmentes as instruments. Column 5 and 6 identify parameter bounds using the imperfect instrumental variable approach in Nevo and Rosen (2012). Identified parameter bounds are in brackets while the 95% confidence interval is in parenthesis. Confidence intervals are calculated adding (subtracting) 1.96 standard deviations to the upper (lower) bound.

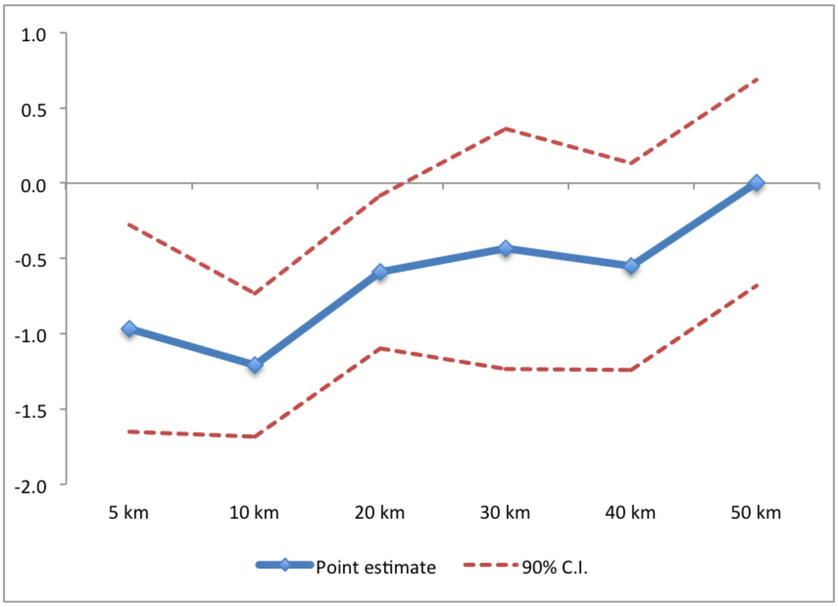

Figure 6: The effect of mining on agricultural productivity, by distance to a mine

related pollution. As we discussed before, several studies show that water and soil in mining areas have higher than normal levels of pollutants (see section 2.2).

To further explore this issue we would need measures of water and air pollutants at local level. Then, we could examine whether mining areas are indeed more polluted. Unfortunately, these data are unavailable in the Ghanaian case.[31] Instead, we rely on three indirect ways to assess the role of pollution.

First, we explore heterogeneous effects between areas located downstream and upstream of mine sites. This is a crude way to assess the importance of pollutants that could be carry by surface water. Second, we examine heterogeneous effects in areas near polluting and non-polluting mines. This classification is based on Ghana EPA's environmental assessments.[32] Finally, we obtain indicators of air pollution using satellite imagery, and examine the relative levels of pollution in mining and non-mining areas.

Column 1 and 2 in Table 3 estimates the baseline regression allowing for heterogeneous effects between between areas upstream and downstream of a mine, as well as between polluting

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

[32]See `http://www.epaghanaakoben.org/rating/listmines2` for details. The earliest environmental assessments were published in year 2009. We classify a mine as polluting if it is red-flagged by EPA as failing to comply environmental standards. As previously mentioned, these mines are considered to pose serious environmental risks.

and non-polluting mines. To do so, we include an interaction of "within 20 km $\times$ year 2005" with an indicator of being downstream of a mine, or being near a polluting mine. The results suggest that there is no heterogeneous effect of mining in areas downstream and upstream of a mine. The coefficient of the triple interaction is negative but insignificant. Though this may be due to lack of statistical power, a conservative interpretation is that pollution of superficial waters may not be driving the main results. In contrast, column 1 shows that most of the decline in productivity occurs in the proximity of mines red-flagged by the Ghana EPA as having poor environmental practices. There are, however, two important caveats. First, the environmental assessments are based on information collected since 2007, and hence may not accurately reflect the mine environmental status during the period of analysis. Second, there are no environmental assessments for all mines that were active before 2005. For that reason, we impute a non-polluting status to mines with missing data. These issues may create measurement errors and lead to an attenuation bias of the estimates.

Taken together these results are suggestive that environmental pollution may play a role. To get more conclusive evidence, we examine indicators of air pollution obtained from satellite imagery. The satellite imagery is obtained from the Ozone Monitoring Instrument (OMI) available at NASA.[33] This satellite instrument provides daily measures of tropospheric air conditions since October 2004.

We focus on a particular air pollutant: nitrogen dioxide (NO_2). NO_2 is a toxic gas by itself and also an important precursor of tropospheric ozone -a gas harmful to both human and crops' health.[34] The main source of NO_2 is the combustion of hydrocarbons such as biomass burning, smelters and combustion engines.[35] Thus, it is likely to occur near highly mechanized operations, such as large-scale mining.

There are three important caveats relevant for the empirical analysis. First, the data provides only a proxy of the cross sectional distribution of NO_2 at ground level. Note that the satellite data reflect air conditions in the troposphere (from ground level up to 12 km). Tropospheric and ground-level NO_2 are correlated, but to obtain accurate measures at ground level we need to calibrate existing atmospheric models.[36] This requires ground-based air pollution

[33]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`.

[34]NO_2 gives the brownish coloration to smog seen above many polluted cities.

[35]There are also natural sources of NO_2 such as lightning and forest fires.

[36]The correlation between these two measures is typically above 0.6. OMI tropospheric measures tend, however,

Table 3: Mining and pollution

	ln(real agricultural ouput)		Average NO_2		ln(real agric. output)
	Upstream vs downstream	Ghana EPA assessment			
	(1)	(2)	(3)	(4)	(5)
Within 20 km of mine × year 2005	-0.498*	-0.391			
	(0.274)	(0.279)			
Within 20 km of mine × year 2005 × downstream	-0.115				
	(0.421)				
Within 20 km of mine × year 2005 × polluting mine		-0.773**			
		(0.318)			
ln(land)	0.626***	0.633***			0.718***
	(0.036)	(0.037)			(0.066)
ln(labor)	0.218***	0.215***			0.136**
	(0.034)	(0.034)			(0.056)
Within 20 km of mine			0.342**	0.439***	
			(0.137)	(0.123)	
Average NO_2					-0.759*
					(0.407)
Farmer's controls	Yes	Yes	No	No	No
District fixed effects	Yes	Yes	No	No	No
Region fixed effects	No	No	No	Yes	Yes
Observations	1,627	1,627	399	399	918
R-squared	0.462	0.464	0.063	0.209	0.265

Notes: Robust standard errors in parentheses. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. Column 1 and 2 includes input use, district fixed effects and farmer's control variables as in the baseline regression (see notes of Table 2). Columns 1, 2 and 4 reports standard errors clustered at district level. Columns 3 to 4 uses the sample of enumeration areas and satellite data for 2005. They include ecological zone fixed effects and indicators of urban areas. Columns 4 also include region fixed effects. Column 5 presents 2SLS estimates of the agricultural production function using only the sample of farmers in GLSS 5. It uses‘' Within 20 km of mine" as instrument for NO_2. The control variables are fixed effects for region and ecological zone.

measures from monitoring stations in some of the dates and locations covered by the satellite.[37] Second, the data is available only from late 2004. Hence, we cannot study levels of air pollution during the period of analysis (1998 to 2005), but only at the end. While this approach does not allow us to study the change in air pollutants associated to mining, it can still be informative of the relative levels of pollution at local level. Finally, the measures of NO_2 are highly affected by atmospheric conditions such as tropical thunderstorms, cloud coverage, and rain.[38]. These disturbances are particularly important from November to March, and during the peak of the rainy season.[39] For that reason, we aggregate the daily data taking the average over the period April-May 2005. These months are at the beginning of the rainy season. This period also corresponds to the beginning of the main agricultural season in southern Ghana.

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:[40]

$$NO2_v = \phi_1 mine_v + \phi_2 W_v + \omega_v, \tag{10}$$

where $NO2_v$ is the average value of tropospheric NO_2 in enumeration area v during the period April-May 2005, $mine_v$ is an indicator of being within 20 km of a mine, and W_v is a vector of controls variables.[41] 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 3 and 4 in Table 3 present the empirical results. Column 3 estimates (10) including only indicators of ecological zones and urban areas. Column 4 populates the model with region fixed effects. Finally, we replace the dummy $mine_v$ by a distance spline with breaks at 10, 20, 30 and 40 km and plot the resulting estimates in Figure 7. 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.[42] Moreover, the concentration of NO_2 decreases with distance to the mine in a similar

to underestimate ground levels of NO_2 by 15-30 % (Celarier et al., 2008).

[37]Similar data would be necessary to estimate tropospheric ozone.

[38]Lighting tends to increase NO_2 while rain reduces it.

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

[40]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.

[41]NO_2 is measured as 10^15 molecules per cm^2. The average NO_2 is 8.9 while its standard deviation is 1.2.

[42]We also find a negative correlation between NO_2 and agricultural productivity. These results, not reported, exploit only cross sectional variation.

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. This result is consistent with the biological evidence linking air pollution to reduction in crop yields and the increase in respiratory diseases that we document in Section 4.2.

Column 5 further explores the relation between mining, air pollution and productivity. To do so, we estimate the relation between NO_2 and agricultural productivity using proximity to a mine as an instrument for NO_2. Since we only have measures of NO_2 for 2005, we use only the sample of farmers in the GLSS5. Thus, this regressions exploits only cross sectional variation. Consistent with mining-related pollution being an important mechanism, we find a significant negative correlation between NO_2 and agricultural productivity.[43]

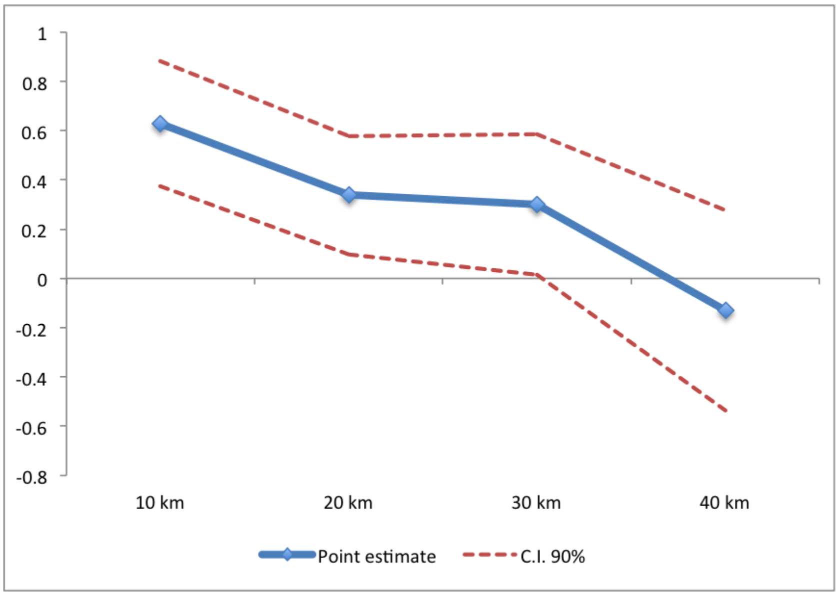

Figure 7: Increase in concentration of NO_2, by distance to a mine

4.1.2 Competition for inputs

Mining could also affect agricultural output through competition for key inputs. The most obvious way involve direct appropriation of inputs such as diversion of water sources and land grabbings. 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).

[43] In the first stage the relation between NO_2 and the excluded instrument ''within 20 km of a mine" is positive and significant at 5%.

A possibility is that the loss in productivity reflects the reduction in quality of inputs associated with farmers' displacement. For example, farmers may have been relocated to less productive lands or to isolated locations.[44]

It is unlikely, however, that this factor fully accounts for the observed reduction in productivity. 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. For example, Bibiani mine has a license over 19 km^2; Iduapriem mine has a mining lease of 33 km^2 while Tarkwa leases cover 260 km^2. Note that not all lands in mining concessions are inhabited nor all its population is displaced. In contrast, we document drops in productivity in a much larger area i.e. within 20 km of a mine, this represents an area of more than 1,200 km^2 around a mine.[45]

Mines may also compete with farmers for scarce local inputs, such as unskilled labor. Similarly, the mine's demand for local goods and services may increase price of non-tradables (such as housing). In either case, mining activities would increase input prices, and farmer's production costs. In turn, this may lead to a decline in output, and demand of inputs.[46] This phenomena cannot be studied by equation (9) 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 effect of mining on input prices. 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.[47] We take the average of these variables by enumeration area, and divide them by the poverty line to obtain relative input prices. Then, we regress the log of the relative input price on the interaction term "within 20 km $\times$ year 2005". We also include geographical controls (such as region fixed effects, ecological zone fixed effects, and indicators of proximity to the coast or a region's capital) and their interaction with a time trend to account for unobserved market conditions.

Table 4 display the results. Columns 1 and 3 start by estimating a parsimonious model

[44] Note that our previous results are conditional on being a farmer, hence they underestimate the loss of agricultural output due to change of land use from agriculture to mining, or farmer's leaving the industry.

[45] Another possibility is that the drop in productivity is driven by migrants with either lower human capital or occupying poorer lands. We discuss this alternative explanation in the robustness checks.

[46] This effect could be offset if mines' demand for local inputs has a positive effect on local income. The income effect may increase demand for, and price of, local agricultural goods. In that case, agricultural output and farmer's income would actually increase (Aragon and Rud, n.d.).

[47] The results using the rental price of land are similar, though the sample size is much smaller and the estimates, less precise.

without control variables, while columns 2 and 4 include a full set of covariates. Note that input prices do not increase in mining areas. Instead, the point estimates suggest a reduction on land prices and wages of around 15%, though this reduction is only significant for wages.

These results weaken the argument that mining crowds out agriculture through increase in factor prices. Instead they are consistent with a decline in factor demand associated to the fall in productivity. Moreover, they suggest that the reduction in productivity associated to pollution may be a more important negative mining spillover for farmers, than the change in input prices.

Table 4: Mining and input prices

	ln(relative wage)		ln(relative land price)	
	(1)	(2)	(3)	(4)
Within 20 km of	-0.159*	-0.162*	-0.328	-0.160
mine × year 2005	(0.091)	(0.088)	(0.281)	(0.264)
Geographical control	No	No	Yes	Yes
Heterogeneous trends	No	No	Yes	Yes
Observations	194	194	201	201
R-squared	0.284	0.355	0.011	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%..The unit of obsrevation is the enumeration areas. Columns 2 and 3 include a set of geograhical controls such as region fixed effects, ecological zone fixed effects, indicators of proximity to the coast or a region's capital as well as their interaction with a time trend.

4.1.3 Additional checks

Compositional effects We next turn our attention to changes in the composition of farmers or crops 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 from mining areas, or switching to non-agricultural activities. Similarly, it could reflect changes in crop composition. For example, farmers may perceive a higher risk of expropriation in the vicinity of mines and reduce the share of crops with high productivity but a long growing cycle (such as cocoa).

As a first check, we investigate whether workers in mining areas are changing occupation relative to control households. Columns 1 and 2 in Table 5 estimate the probability that a worker is engaged in the agricultural sector (as a producer or laborer). Column 1 focuses on all workers, while column 2 focuses on household heads only. In both cases, there is no significant change in the likelihood of working in agriculture. If anything, point estimates are slightly positive.[48]

Second, we look at measures of farmer's education. 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. Columns 3 and 4 look at the sample of producers only and check whether literacy levels and a measure of educational attainment (e.g. secondary school completed) have dropped[49]. The results do not suggest that mining areas have a relative decrease in measures of farmer's education.

Finally, we examine whether farmer's have changed crop composition. We focus on the share of cocoa in total agricultural value. Note that cocoa is the main cash crop, but it also has a long maturity cycle. In addition, we use a Herfindhal concentration index of all main crops. Columns 5 and 6 suggest that there is no significant change in either variable in mining areas.[50]

Taken together, these results weaken the argument that the reduction in productivity is driven by changes in occupational choice, farmer's ability or crop choice.

Alternative specifications In table 6, we check that our results are robust to alternative specifications. Column 1 estimates a parsimonious model without farmer characteristics and district fixed effects. In contrast, column 2 saturates the baseline regression with an array of heterogeneous trends. We include the interaction of time trends with indicators of ecological zone, region, proximity to coast and to region capitals. This specification addresses concerns that the interaction term "within 20 km $\times$ year 2005" may be just picking up other confounding trends. Columns 3 and 4 split the sample between local and non-local farmers. We define a

[48]These results are robust to a series of specifications, with and without controls, and using other measures of farming activity, such as proportion of farmers in the household.

[49]Levels of completion of primary school are really high, i.e. around 88%, while literacy levels (47.7%) and secondary school completed (37.2%) show greater variation. Results hold when using data on completed primary school.

[50]Additionally, we did not find any evidence of a reduction in the shares of maize, the second most important crop.

Table 5: Robustness checks: compositional changes

	Work in agriculture		Literacy	Completed secondary	Share of cocoa	Crop concentration
	(1)	(2)	(3)	(4)	(5)	(6)
Within 20 km of mine × year 2005	0.057	0.031	0.025	0.026	-0.089	-0.009
	(0.072)	(0.072)	(0.094)	(0.047)	(0.080)	(0.049)
Sample	All workers	All working HH heads	Head of agric. households		Agricultural households	
Observations	8,932	4,970	1,627	1,627	1,627	1,627
R-squared	0.359	0.386	0.123	0.162	0.447	0.111

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 district fixed effect. Columns 1 to 4 are estimated using a linear probability model. Columns 1 and 2 examine the probability that an individual or the head of household, respectively, is engaged in farming activities. Column 3 and 4 examine the educational attainment of heads of agricultural households. Columns 5 uses the share of cocoa in total value of production, and column 6 looks at a Herfindhal concentration index of main crops. Column 1 uses the sample of all workers, while column 2 focuses on household heads. Columns 3 to 6 use the sample of agricultural producers. Columns 1 and 2 control for worker characteristics such as: age, age^2, religion, place of birth, literacy status, household size, and indicators of ecological zone and of being in a rural area. Columns 3 and 4 use similar controls without literacy status. Column 5 and 6 use same farmer's controls as the agricultural production function in Table 2.

farmer as local if she was born in the same village where she resides. This specification responds to concerns that the change in productivity may be driven by migrants to mining areas with lower human capital or occupying marginal, unproductive, lands. Note that in all cases, the estimates of the effect of mining on productivity (γ) are negative and statistically significant.

Column 5 relaxes the assumption of a Cobb-Douglas production function and estimates a translog production function, i.e. a second order Taylor approximation to unknown aggregate production function. In practice, this amounts to including squared terms for inputs and interaction terms between the inputs.[51] Allowing for a more general production function does not change the effect of exposure to mining on productivity, neither in magnitude nor significance.[52]

4.2 Poverty, malnutrition and health

The previous results indicate a sizable reduction in agricultural productivity associated to polluting mines. Because agriculture is the main source of livelihood in rural Ghana, a reduction

[51] Note that the coefficients for the squared terms are multiplied by 1/2 when expanding the production function

[52] Results hold similar when estimating a CES production function using non-linear least squares.

Table 6: Alternative specifications

	ln(real agricultural output)				
			Locals	Non-locals	
	(1)	(2)	(3)	(4)	(5)
Within 20 km of mine × year 2005	-0.593**	-0.562**	-0.643***	-0.692*	-0.542**
	(0.239)	(0.261)	(0.215)	(0.394)	(0.252)
ln(land)	0.698***	0.630***	0.615***	0.662***	0.916***
	(0.045)	(0.037)	(0.048)	(0.048)	(0.217)
ln(labor)	0.225***	0.225***	0.290***	0.174***	-0.502**
	(0.042)	(0.034)	(0.054)	(0.042)	(0.222)
ln(land) × ln(land)					0.035
					(0.032)
ln(labor) × ln(labor)					0.059***
					(0.016)
ln(land) × ln(labor)					-0.054
					(0.034)
Farmer's control	No	Yes	Yes	Yes	Yes
District fixed effects	No	Yes	Yes	Yes	Yes
Heterogeneous trends	No	Yes	No	No	No
Production function	C-D	C-D	C-D	C-D	Translog
Estimation method	OLS	OLS	OLS	OLS	OLS
Observations	1,633	1,627	780	847	1,627
R-squared	0.337	0.468	0.468	0.510	0.471

Notes: Robust standard errors in parentheses. Standard errors are clustered at district level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. Column 1 does not include any control. Column 2 includes farmer controls and the interaction of time trends with indicators of ecological zone, region, proximity to coast, and proximity to region capitals. Columns 3 and 4 split the sample between locals and non-locals. C-D stands for Cobb-Douglas. Column 5 estimates a translog production function..

in agricultural production could be associated with lower levels of living standards[53].

We focus first on poverty and household consumption. The decline in agricultural output and wages suggests a possible channel for mining to increase poverty, specially in rural areas. The net effect, however, is unclear. 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 and household consumption. to estimate the following regression:

$$poverty_{idvt} = \phi_1(mine_v \times T_t) + \phi_2 W_i + \delta_d + \omega_{it} \tag{11}$$

where *poverty* is an indicator of the household being poor and W_i is a set of household controls.[54] We also estimate this regression using the log of household consumption as an outcome variable. The rest of the specification is similar to equation (9).[55] 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 8 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. During the expansion of mining, however, there is a significant trend change: poverty increases in mining areas between 1998-99 and 2005. As a result, mining areas become actually poorer than non-mining areas. Note that this increase in poverty parallels the reduction in agricultural output (see Figure 3).

[53]This can result from a standard framework where households utility function depends on consumption levels that, in turn, are directly linked to income levels. In a subsistence framework most income is consumed.

[54]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.

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

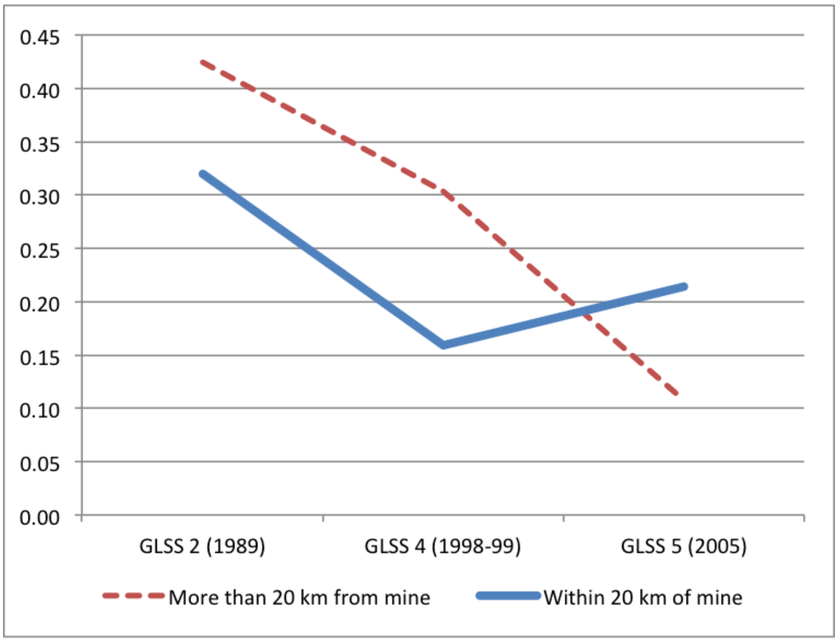

Figure 8: Evolution of the poverty headcount

Table 7 presents the estimates of equation (11).[56] Columns 1 to 5 use poverty as the outcome variable. In column 1 we show results for all households, while columns 2 and 5 split the rural sample between urban and rural households, respectively. Column 3 looks at rural households that are engaged in household production (and thus were included in the estimation of the agricultural production function) while the following column looks at rural households that did not report any production. [57] Columns 6 to 8 use as outcome the log of household consumption and also show results for all households and the split between rural and urban.

The picture that emerges is similar to the one observed in Figure 8. There a significant and sizable increase in poverty in areas around 20 km of mines relative to areas farther away. The estimates suggest a reduction of around 18% in household consumption and a similar increase in poverty, that is concentrated among rural inhabitants. This effect is present 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.[58] The reduction in indicators of economic well-being is

[56]We estimate equation (11) using only data from the last two rounds of the GLSS. We can include observations from GLSS 2. We do not use these data, however, to keep the estimates comparable to the results on agricultural productivity. The results including this survey round, not reported, are similar.

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

[58]Aragon and Rud (n.d.) discuss the conditions under which these effects would be present and show evidence

consistent with the reductions in agricultural productivity found above, in an area where farming activities are the main source of livelihood. Also, this suggests that compensating policies, if any, may have been insufficient to offset the negative shock to agricultural income. Interestingly, there is no effect of mining on urban poverty or urban household consumption.

Child malnutrition and health So far we have not examined 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, however, does not have this information. 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 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 infections (ARI). Height and weight are based on anthropometric measures, while child health indicators are based on mother's perception of symptoms.

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

$$D_{idvt} = \lambda_1(mine_v \times post2003_t) + \lambda_2 M_{it} + \delta_d + \upsilon_{it}, \tag{12}$$

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. $post2003_t$ is a dummy equal to 1 if survey year is 2003 or later, and 0 if year is 1993 or 1998. This specification is similar to (11) and compares the difference in outcomes over time in mining areas relative to non-mining areas.

We construct an indicator of proximity to a mine, $mine_v$, in a similar way than in section 4.1 i.e. a dummy equal to 1 if the clusters lies within 20 km of a mine. To do so, we use the

for the households in the area of influence of a gold mine in Peru.

Table 7: Mining, poverty and household consumption

	Poverty					ln(household consumption per capita)		
	All	Rural			Urban			
		All	Producers	Non-producers		All	Rural	Urban
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Within 20 km of	0.186***	0.309***	0.297***	0.313***	0.036	-0.195*	-0.365***	-0.051
mine × year 2005	(0.055)	(0.056)	(0.064)	(0.064)	(0.062)	(0.099)	(0.103)	(0.142)
Households controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,527	3,393	2,540	853	2,134	5,527	3,393	2,134
R-squared	0.216	0.239	0.249	0.233	0.198	0.489	0.440	0.469

Notes: Robust standard errors in parentheses. Standard errors are clustered at district level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. Household controls include: age, age^2, religion, place of birth and literacy status of household head, household size, and indicators of ecological zone and of being in a rural area. Producers are defined as households with positive agricultural production. Non-producers includes wage workers in producers' farms. All regressions are estimated using OLS.

coordinates of sampling clusters reported by the DHS.[59]

Table 8 shows the estimates of regression (12). In line with the increase in poverty and the reduction in consumption, column 1 finds a reduction in the average weight of children under 5. This results suggests a direct effect on nutrional intake for children in affected areas. Columns 2 and 3 show no effect on indicators of height or incidence of diarrhea. The latter would be expected in the presence of water contamination. However, not that there is substantial evidence (see WACAM (2010) for example) that the local population is aware of the location of contaminated water and avoids these sources of water. Finally, column 4 shows a slight increase in acute respiratory diseases that might result from lower quality of air near mining sites.

Table 8: Mining, child nutrition and health

	Nutritional status			Acute
	Under 5 weight-for-age	Under 5 height-for-age	Diarrhea	respiratory disease
	(1)	(2)	(3)	(4)
Within 20 km of mine	-26.4**	2.9	0.020	0.054*
× post-2003	(12.6)	(14.8)	(0.032)	(0.031)
Mother and child controls	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes
Observations	3,304	3,236	3,522	3,520
R-squared	0.039	0.190	0.048	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%. 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. Post-2003 is a dummy equal to 1 if survey year is 2003 or 2008. All regressions include district fixed effects and a flexible time trend, and are estimated using OLS.

5 Mining: contributions and costs

The costs and benefits of the mining activity are usually unevenly distributed. Benefits such as job creation and an increase in fiscal revenue often accrue to urban dwellers and to the central government. In contrast, most of the costs are born by local populations in the form of displaced settlements, increased pollution, and poorer health.

[59]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.

This is clearly the case in Ghana. As we have shown in the previous section, mining is associated to a reduction in agricultural product and productivity, and an increase in poverty. These negative effects are suffered by rural households in the proximity of mines. The benefits of mining, however, are perceived to be concentrated in urban centers, such as Accra, due to the paucity of local backward linkages and a scheme of centralized revenue collection (Aryeetey et al., 2007).

The increase in poverty suggests that existing policies and institutions have not offset the adverse distributional impact of mining.[60] A remaining policy question, however, is whether the benefits, accrued to the Ghanaian government, exceed farmers' losses.[61] This question is important because a positive answer is a necessary, though not sufficient, condition for the success of any governmental compensation scheme. There is also an efficiency rationale: if mines' tax bills are smaller than farmer losses, mining companies would not fully internalize the negative spillovers of their activities.

Mining contributes to the Ghanaian government's revenue in three ways: corporate taxes and royalties, dividends from government-owned mining shares, and mining workers' income tax. Table 9 shows a breakdown of mining-related revenue. In 2005, mining-related revenues amounted to US$ 75 millions, which represent around 2-3% of total government revenue.[62] Note that this figure includes contribution of all mining companies, not only gold mines. Most of these revenue is channeled to the central government. Local authorities (such as District Assemblies, Stools and Traditional Authorities) receive only 9% of mining royalties. Between 1999 and 2005, this represented in total around US$ 8 million.[63]

How does the contribution of mining to government revenue compare to the loss faced by the local population? To answer this question, we estimate the aggregate loss imposed on farmers by gold mines. We use the actual household consumption in 2005 in mining areas and the

[60]A similar finding is documented by Duflo and Pande (2007) in the context of Indian dams.

[61]There may be, of course, other benefits of mining to a domestic economy. We focus, however, on rents captured by the government since they are the ones available to fund the additional cost of a compensation scheme without further changes in fiscal policies.

[62]The low contribution of mining to fiscal revenue has been attributed to relatively low royalties (Akabzaa, 2009). For example, in the period of analysis, royalties were fixed at 3% of profits, even thought the regulatory framework set by the Minerals Royalties regulations allowed for rates of up to 12%.

[63]Mining taxes (corporate and personal) and dividends accrue directly to the central government. Mineral royalties are distributed as follows: 80% goes to central government, 10% to a Mineral Development Fund, 1% to the Office of Stool Lands (OASL) and the remaining 9% distributed among local authorities. In turn, this is distributed between District Assemblies (4.95%), Stools (2.25%) and Traditional Authorities (1.8%) (World Bank, 2006, p. 91).

coefficient obtained in column 6 in Table 7 to estimate the counter-factual consumption, i.e. what the household would have consumed in the absence of exposure to mining. We obtain the total loss by multiplying the average loss times the number of households in mining areas. The results are shown in table 9.

This back-of-the-envelope calculation suggests that farmer losses, associated to mining activities, are sizable. We calculate that the average household consumption dropped by US$400 per year (or US$ 0.29 per person per day). In aggregate, this represents a loss of almost US$ 158 million, more than double the revenue received by the government from the mining sector as a whole[64].

[64]If we only use results for rural households in column 7, their individual loss is around US$818 per year. Since 69% of households within mining areas are rural in our sample, the aggregate loss would amount to US$ 221 million.

Table 9: Mining tax contributions and households' loss

	2005	Average 1998-2005
Contribution to gov. revenue		
Dividends	1.8	1.4
Corporate taxes	29.8	9.5
Royalties	26.0	21.4
Workers' PAYE	17.0	13.3
Other	0.0	1.4
Total contribution	74.6	47.1
Reduction in annual household consumption		
A. Actual household consumption in 2005 (US$)	1,857	
B. Counterfactual household consumption in 2005 (US$)	2,257	
C. Nr. households within 20 km of mines	394,631	
D. Estimated total loss of household consumption $(B - A) \times C$	-157.8	

Notes: Other includes a recreational levy applied from 2001-2004. Exchange rate for 2005: 1 US$ = 9062 cedis. Counter-factual consumption calculated using estimates from table 7. PAYE stands for Pay As You Earn.
Source: Akabzaa (2009) and authors' calculations

6 Conclusion

Modern mines in many developing countries are located in rural areas, where agriculture is an important economic activity and the main source of livelihood for a large proportion of the population. Most importantly, mines have the potential to generate significant negative spillovers to farmers such as pollution and competition for key inputs like land and labor. We use the case of gold mining in Ghana to investigate how mining affects agricultural product and productivity and, subsequently, local living standards in rural areas.

We find that total factor productivity, and crop yields have decreased in mining areas. Our estimates suggest a reduction of up to 40% in agricultural productivity between 1998 and 2005. The negative effect is associated to polluting mines and decreases with distance. The reduction in agricultural productivity is associated to an increase in rural poverty. During the analyzed period, measures of living standards have improved all across Ghana. However, households engaged in agricultural activities (whether as producers or workers) in areas closer to mining sites have been excluded from this process. As a consequence, measures of household consumption and poverty levels have deteriorated for them.

We also find that mitigation and compensation policies may be insufficient to offset local negative effects. In the case of Ghana, this is due mainly because the level of taxation was lower than the losses generated to farmers and because the distribution of mining taxes has favored the central government. Even though the costs are exclusively born locally, less than 10% of the receipts are received by district governments and traditional authorities in the affected areas.

The results of this paper suggest that in cases where mining occurs in the proximity of agricultural areas, environmental policy should consider the possible impact of mine-related pollution on crop yields and local income. In particular, the loss of agricultural productivity, and farmers' income should be an important part of the policy debate on the costs and benefits of mining. Usually this policy debate focuses on the benefits mining could bring in the form of jobs, taxes or foreign currency. These benefits are weighted against environmental costs such as loss of biodiversity or health risks. However, local living standards may be also directly affected by the reduction in agricultural productivity. In fertile rural environments, such as Ghana, these costs may offset the country's benefits from mining. It also means that the scope of mitigation and compensation policies should be much broader. Usually mitigation and compensation policies focus on populations directly displaced by mining. The negative effects of air and water pollution, however, can extend to a broader population, beyond the boundaries of mining licenses. These groups should also be considered in the area of influence of a mine.

As a consequence, activities such as mining may introduce substantial redistributive effects on the economic activity and wealth of a country. Mining can bring broader benefits to a country at the expense of localized costs (such as loss of agricultural output), some of them born by already poor disadvantaged groups. This redistribution should be considered to better understand local opposition to mining projects and demands for better compensation. Failing to recognize this social cost would grossly overestimate the net contribution of mining to an economy.

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A Additional tables

Table 10: List of gold mines

	Mine	Type	Cum. Production 1993-2004 (in Metric Tons)
1	Bibiani	open pit	47.6
2	Bogoso/Prestea	open pit, underground and tailings	52.4
3	Central Ashanti (Ayanfuri)	open pit	9.7
4	Damang	open pit	65.9
5	Dunkwa placer	placer	0.7
6	Esaase placer	placer	12.4
7	Iduapriem/Teberebi	open pit	104.6
8	Konongo/Obenemasi	open pit	1.5
9	Obotan	open pit	19.4
10	Obuasi	open pit, underground	262.8
11	Tarkwa	open pit, underground	96.9
12	Wassa	open pit	8.2

A.1 Sensitivity analysis

A simple examination of equation (9) shows that if we knew the values of α and β, we could estimate γ directly from the residual output. This observation suggests a way to examine the sensitivity of results to potential inconsistencies in the estimation of the production function. In particular, we calculate the residual output $y^*_{ivdt} = y_{ivdt} - \alpha^* m_{it} - \beta^* l_{it}$ for different values of α^* and β^*. Then, we estimate the model $y^*_{ivdt} = \phi Z_i + \delta_d + \gamma(mine_v \times T_t) + \xi_{ivt}$.

Figure 9 shows the results of this sensitivity analysis for α^* and β^* ranging from 0.05 to 1.15, with a 0.05 incremental step. The points above the solid line represent values (α^*, β^*) such that the estimate of γ remains negative and significant. As a benchmark, the circle on the left quadrant indicates the OLS estimates of α and β. Note the baseline results are robust to a wide range of possible values of α and β.

Table 11: First stage

	ln(land) (1)	ln(labor) (2)
ln(land owned)	0.917***	0.177***
	(0.019)	(0.025)
ln(nr adult equivalents)	0.024	0.466***
	(0.022)	(0.041)
Within 20 km of mine × year 2005	-0.048	-0.106
	(0.076)	(0.113)
Farmer's controls	Yes	Yes
District fixed effects	Yes	Yes
Observations	1,627	1,627
R-squared	0.798	0.247

Notes: Robust standard errors in parentheses. Standard errors are clustered at district level. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. See Table 2 for details on the second stage.

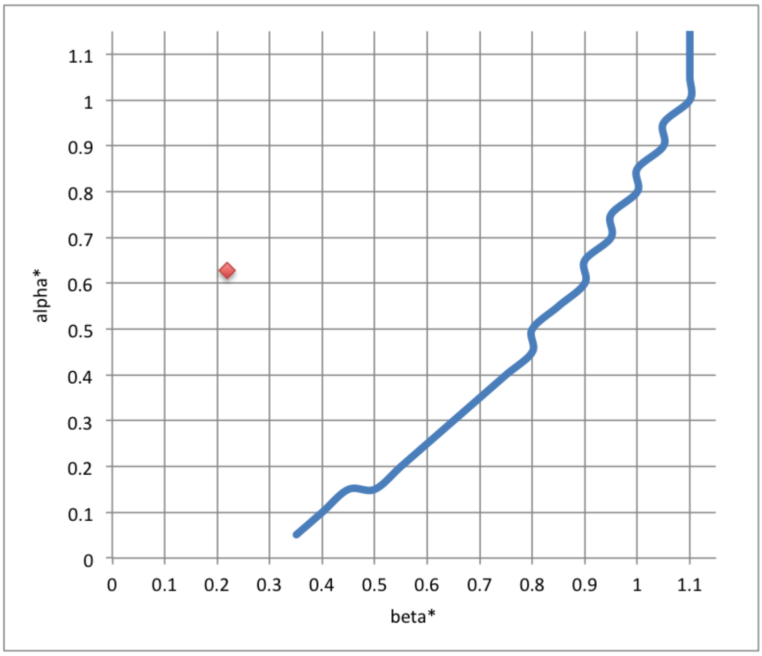

Figure 9: Sensitivity of main results to values of α and β

Table 12: Imperfect instruments with multiple endogenous variables

$(\lambda_{land}, \lambda_{labor})$	$\hat{\gamma}$	$\hat{\alpha}$	$\hat{\beta}$
(0,0)	-0.554	0.673	0.356
(0,0.2)	-0.541	0.610	0.594
(0,0.4)	-0.608	0.930	-0.605
(0,0.6)	-0.574	0.769	-0.002
(0,0.8)	-0.569	0.746	0.083
(0.2,0)	-0.557	0.700	0.339
(0.2,0.2)	-0.544	0.634	0.567
(0.2,0.4)	-0.606	0.945	-0.512
(0.2,0.6)	-0.576	0.795	0.009
(0.2,0.8)	-0.572	0.773	0.086
(0.4,0)	-0.563	0.752	0.306
(0.4,0.2)	-0.550	0.685	0.512
(0.4,0.4)	-0.604	0.969	-0.360
(0.4,0.6)	-0.580	0.842	0.030
(0.4,0.8)	-0.576	0.822	0.092
(0.6,0)	-0.579	0.896	0.214
(0.6,0.2)	-0.570	0.843	0.340
(0.6,0.4)	-0.599	1.015	-0.071
(0.6,0.6)	-0.589	0.953	0.078
(0.6,0.8)	-0.587	0.941	0.106
(0.8,0)	-0.845	3.236	-1.282
(0.8,0.2)	0.000	-3.622	5.209
(0.8,0.4)	-0.587	1.139	0.703
(0.8,0.6)	-0.635	1.533	0.330
(0.8,0.8)	-0.653	1.679	0.192

Note: $\lambda_X = \frac{\rho_{Z_X,\epsilon}}{\rho_{X,\epsilon}}$ where $X = land, labor$ and Z_X is the instrument for X i.e. the endowment of input X. λ_X measures how well the instrument satisfies the exogeneity assumption. $\lambda_X = 0$ corresponds to an exogenous, valid, instrument. Note that the assumption that the instrument is less correlated to the error term that the endogenous variable implies that $\lambda_X < 1$. Table displays estimates of main parameters for values of $\lambda_X \in (0.0, 0.8)$