Mineral Mining and Female Employment

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Abstract

We use the rapid expansion of the number of mineral mines in Sub-Saharan Africa to explore changes in local labor markets. Matching over two decades of panel data on industrial mines to survey data for half a million women and exploiting the spatial and temporal variation in the data in a difference-in-difference strategy, we find that opening of an industrial mine induces a structural shift whereby women switch from working in agriculture to services. We also find that the probability to earn cash income increases and women become less likely to work seasonally once a mine opens nearby. The results illustrate that mineral mining creates non-agricultural employment opportunities for women despite their absence from the mining workforce. The spillover effects wear off with distance from mine and the effects on service employment are reversed when a mine closes.

JEL Classification : J16, J21, O13, O18

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1 Introduction

Africa's opportunities are being transformed by new discoveries of natural resources and their rising prices (Collier, 2010). The economic importance of the mining sector has increased to the extent that the sector has become the main recipient of foreign direct investment in Sub-Saharan Africa (World Bank, 2011). Whether the discovery of natural resources is a blessing or a curse to the economy and to a country's citizens is a contentious issue (see Frankel, 2010 or van der Ploeg, 2011 for an overview) and natural resource dependence is linked to various outcomes at the national level: institutions (e.g., Mehlum et al., 2006a, 2006b), corruption (e.g., Leite and Weidmann, 2002), civil war and conflict (e.g., Collier and Hoeffler, 2004, 2005), rent appropriation by an elite (e.g., Auty, 2001, 2007), democracy (e.g., Barro, 2000; Jensen and Wantchekon, 2004), and female labor force participation (Ross, 2008, 2012).[1]

There is less knowledge on local welfare effects of extractive industries and the present paper adds to recent literature on local effects of natural resources (Aragon and Rud, 2013b; Caselli and Michaels, 2013; Michaels, 2011; Wilson, 2012). We focus on employment opportunities and ask whether large-scale mineral mining creates labor market opportunities for women. Access to employment improves women's lives and is listed among the top five priorities for promoting gender equality in the 2012 World Development Report (World Bank, 2012).

Whether industrial mining increases or decreases female employment is theoretically ambiguous. The African Mining Vision, formulated by the member states of the African Union together with the African Development Bank and the United Nations, spells out the risk of consolidation of gender disparities in economic opportunities with women at loss as a bi-product of extractive industries (UNECA 2011). Similarly, Ross (2008, 2012) claims that exploitation of natural resources hurts women's employment via both demand and supply channels. In his model, female labor supply is reduced via a household income effect, spurred by higher male incomes and/or increased government transfers. The demand for female labor decreases as export-oriented and female-dominated manufac-

[1] Most of the literature on the resource curse, including Ross (2008, 2012), has focused on the national level. The national level focus and cross country-based literature face severe endogeneity problems. Differences in resource abundance are endogenous to factors such as institutions, civil wars, and growth (Brunnschweiler and Bulte 2008a, 2008b, 2009; Brückner and Ciccone, 2010; De Luca et al. 2012). The efficiency of the economy in general (Norman, 2009) and the protection of property rights can influence the search for and exploitation of resources (Wright and Czelusta, 2003).

turing is crowded out by Dutch disease effects. He tests his theory using cross country regressions of female labor force participation on oil wealth and finds that oil rich countries have fewer women working, a finding he claims to be valid also for mineral mining. There is, however, little reason to expect these effects in Sub-Saharan Africa (SSA). First, the manufacturing sector in rural SSA is small (see Bigsten and Söderbom, 2006 or Isham et al. 2005 for an overview).[2] Second, if women may shift to the service sector, the demand for female labor need not decrease. Women are overrepresented in sales and services in SSA but underrepresented in production and manufacturing, as shown by data from ILO's Key Indicators of the Labour Market database (ILO, 2011).

The effects of natural resource extraction on the local economy are often described in terms of linkages and multipliers (e.g. Eggert, 2002; Aragon and Rud, 2013b). Local multipliers describe the effect of an employment increase in one sector on employment in other sectors. Moretti (2010) shows that an increase in the production of tradable goods leads to increased local demand for non-tradables, as the number of workers and their salaries increase. However, the multipliers for tradables depend on local changes in labor costs, since tradable goods have prices set nationally or internationally. The multiplier effects also differ with the skill level of the jobs generated; high-skilled jobs generated in the tradable sector create more jobs in the non-tradable sector than do low skilled jobs (Moretti, 2010; Moretti and Thulin, 2013).

The strand of literature on linkages and multipliers argue for positive local employment effects. If the multipliers are small, we will find economically and statistically insignificant effects. Such findings would support the traditional view of mineral mines as having little or no linkages to the local community. This "enclave" theory was first hypothesized by Hirschman (1956) and became a stylized fact in the second part of the last century (UNECA, 2011). A recent empirical study of local welfare effects around the world's second largest gold mine in Peru found support for this hypothesis, in absence of policies for local procurement of goods (Aragón and Rud, 2013b).

If the multiplier effects are stronger, we expect an increase in female labor force participation concentrated to services and sales following the gender segregation in the Sub-Sahara African labor markets. Qualitative studies have

[2] Fafchamps and Söderbom (2006) use data from nine Sub-Saharan African countries and find that the proportion of female workers is only 12 percent in manufacturing firms. The manufacturing sector in SSA has also been found to be largely non-tradable, perhaps due to a long history of import restrictions on manufactured goods (Torvik, 2001), which would reduce potential Dutch disease effects.

found that women dominate the provision of goods and services around mines in Africa (Hinton, 2006; ILO, 1999), while they are not much engaged in the mining sector directly.[3] Spillover effects on the tradable sector are less likely to substantially affect the demand for female labor since women are not strongly represented in the tradable sector, including manufacturing and construction.

The effect on women's labor supply in agriculture is a priori ambiguous. A mine expansion can change local agriculture through a variety of channels; competition over land use (expropriation and changes in land prices; UNECA, 2011), pollution (Aragon and Rud, 2013a), intra-household reallocation of labor including substitution effects, and demand changes for agricultural goods. Our data allow us to explore the reduced form effects of mining on women's labor market decisions in both agriculture and non-agricultural work in mining areas.

A novelty of the present paper is that it connects production data on 874 industrial mines starting from 1975 to DHS household survey data for women aged 15 - 49 spanning over two decades using spatial information. The unique combination of datasets with more than 500,000 sampled women in 29 countries enables us to investigate local spillover effects on women's employment by a difference-in-difference method. By exploiting the spatial and temporal variation in the data, we compare women living close to a mine with those living further away, and women living close to a producing mine with those who live in the vicinity of a mine that is yet to open. We include region fixed effects and thereby control for time-invariant differences between regions such as time-stable mining strategies, institutions, trade patterns, openness, sectoral composition, level of economic development and gender norms. In addition, by including regional specific time trends we make the identification strategy less reliant an assumption of similar trends across areas.

We show that mine opening triggers a structural shift whereby women shift from agricultural work to the service sector. The results are robust to a wide battery of robustness checks such as using different measures of distance and exclusion of migrants. Our results of a shift toward service sector employment are supported by findings that women are more likely to earn cash and work less seasonally after a mine has started producing. The results are sizeable and we calculate that over 90.000 women get service sector jobs as a result of industrial

[3]One notable exception is artisanal and small scale-mining activities such as grinding, sieving etc.; i.e. activities confined to traditional mining activities. In both small- and large-scale mining, women rarely go underground into pits, for which there are often taboos and stigmas (ILO, 1999).

mining in their communities. We also investigate heterogeneous responses by marital status and find that divorced or separated women are particularly likely to increase their service sector employment. The effects of mine openings wear off with distance and are no longer statistically significant at 75 kilometers from a mine, and mine closing causes service sector employment to decrease.

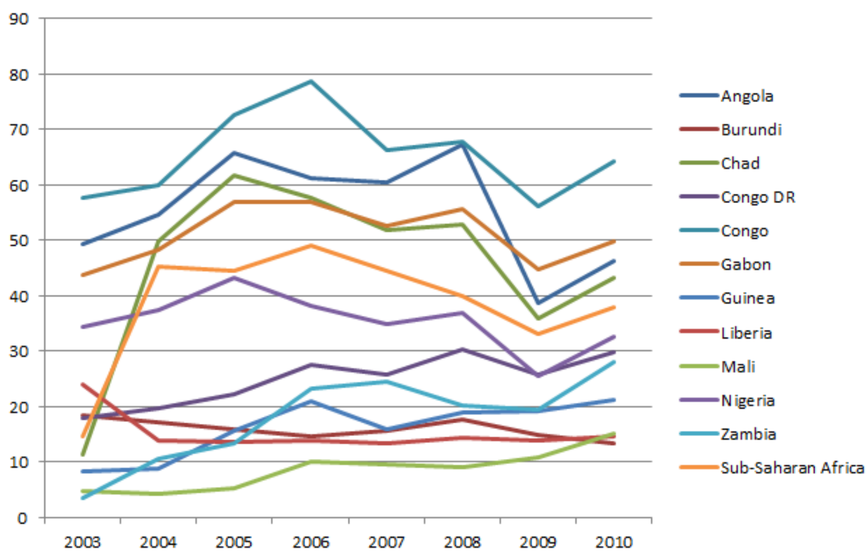
This paper is organized as follows. In the next section we discuss the context of mining in Africa and in Section 3 we present the data. In Section 4 we lay out the empirical strategy. In Section 5 we present the empirical results and in Section 6 we show robustness tests and heterogeneous effects. Finally in Section 7 we make concluding remarks.

2 Mining in Africa

Africa has a long tradition of mining and traditional mining practices remain common. Notwithstanding, since the 1990s Africa has experienced a rise in large-scale, capital-intensive production and today the continent is an important producer of gold, copper, diamond, bauxite, chromium, cobalt, manganese, and platinum (UNECA, 2011).[4] Figure 1 shows that natural resource rents as a share of GDP has been trending weakly upwards for a selection of African economies and Sub-Saharan Africa as a whole over the last decade, with the recession in 2008-2009 being the anomaly in this trend. For SSA as a whole, the resource rents as share of GDP have risen from 15 percent to almost 40 percent in only seven years. Nevertheless, the mineral base in SSA is considered underexplored. Geological surveying is associated with high financial costs and risks, and insufficient government funds and inaccessibility due to lack of infrastructure prevent explorations in Africa (Collier, 2010; UNECA, 2011). However, large growing economies like India and China, i.e. actors that until today have remained relatively small are showing growing interest in the resource endowments (UNECA, 2011). The increasing interest from both new and old actors in the continent's resources implies ample opportunities that if rightly harnessed may transform rural African economies and the livelihood of its populations. In the following sections we investigate this at the local level for a large sample of countries.

[4] Africa is a significant producer of copper and gold although its output is not sufficient to hold a dominating position in the world market for these metals.

Figure 1: Natural resources as share of GDP



Source: Authors' own. Data from World Development Indicators. The graph shows the development of total natural resources rents as share % of GDP for Sub-Saharan Africa as a whole and 11 countries (with more than 15 % of GDP stemming from natural resource rents).

3 Data

We make use of a unique longitudinal data set on large-scale mineral mines in Africa. For the purpose of the study, we link this resource data from InterraRMG to survey data for women from the Demographic and Health Surveys (DHS) using spatial information. Point coordinates (GPS) for the surveyed DHS clusters, a cluster being one or several geographically close villages or a neighborhood in an urban area, allow us to match all women to one or several mineral mines.

From a mine center point, given by its GPS coordinates, we calculate distance spans within which we place every woman. These are concentric circles with radii of 5, 10, 15, 20 km and so on, up to 200 kilometers and beyond 200 km. By matching every woman to her closest mine all women show up in at least one of these categories. However, a woman can be matched to several mines.

We construct an indicator variable that answers the questions: Is there at least one active mine within x kilometers? If not, is there at least one inactive mine within x kilometers? If still no, the woman will be coded as living in a non-mining area. If she lives within a given distance from more than one mine, she will belong to the treated group if at least one mine is producing in the year she was sampled. We assume that a woman seeks employment around any mine situated within x kilometers from her home location and that benefits from an active mine dominate those from an inactive mine. Beyond such a cut-off distance, transportation costs are assumed to be higher than benefits accruing from employment opportunities. Behind this assumption lies two subordinated assumptions, i.e., the costs in terms of transportation and information increase with distance and the footprint of a mine decreases with distance. The chosen baseline cut-off distance is 20 kilometers, but the assumptions motivate us to try different distance cut-off points.

A woman lives on average 246 kilometers away from a mine (variable *distance*) and 363 kilometers away from an active mine (*distance to active*) as given by Table 1. 1.6 % of the sample live within 20 kilometers of at least one active mine, 0.5 % live within 20 kilometers of at least one inactive mine (but no active and no suspended mines), and 1.3 % live close to a suspended mine.

Table 1: Descriptive statistics

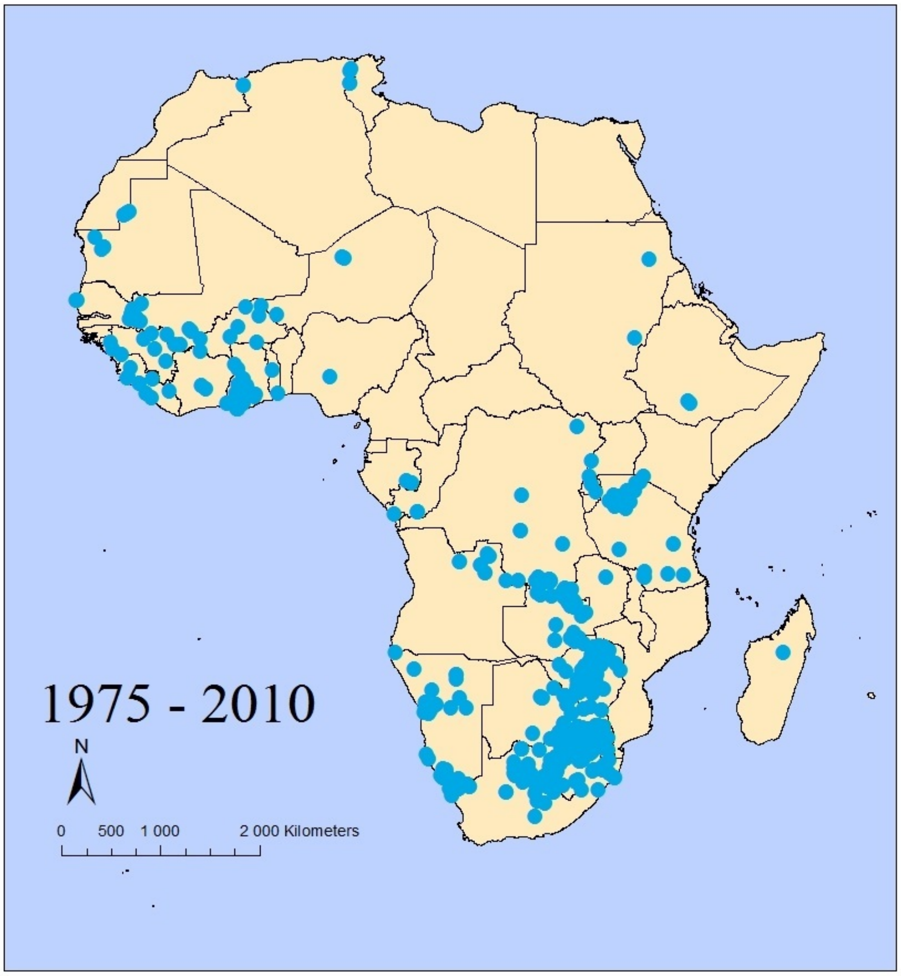
Variable	Definition	Mean	St. dev
Mine variables			
distance	Distance to closest active or inactive mine (km).	246.4	211.0
distance to active	Distance to closest active mine (km).	363.6	247.2
active (20 km)	At least one active mine within 20 km.	0.016	0.124
inactive (20 km)	At least one inactive mine within 20 km, no active.	0.005	0.067
suspended (20 km)	At least one suspended mine within 20 km, no active.	0.013	0.113
Dependent variables			
working	1 if respondent is currently working.	0.662	0.473
services	1 if respondent is working in the service sector.	0.036	0.186
sales	1 if respondent is working with sales.	0.172	0.377
agriculture	1 if respondent is working in agriculture.	0.329	0.470
seasonally	1 if respondent is working seasonally.	0.317	0.465
all year	1 if respondent is working all year.	0.573	0.495
occasionally	1 if respondent is working occasionally.	0.111	0.314
Control variables			
urban	1 if respondent is living in urban area.	0.330	0.470
age	Age in years.	28.4	9.556
schoolyears	Years of education.	4.2	4.347
christian	1 if respondent is Christian.	0.593	0.491
muslim	1 if respondent is Muslim.	0.333	0.471
Migration			
non mover	1 if respondent always lived in the same place.	0.455	0.498
Marital status			
married	1 if respondent is married or cohabitant.	0.583	0.493
married_bf_mine	1 if respondent married before mine opening.	0.247	0.431
divsep	1 if respondent is divorced or separated.	0.058	0.234
widow	1 if respondent is widow.	0.031	0.174
single	1 if respondent never has been married.	0.241	0.428

* The sample consists of 525,189 observations, except for inactive (20 km) where the sample is limited to 518,368 observations because women close to suspended mines are dropped.

3.1 Resource data

The Raw Materials Data (RMD) data comes from InterraRMG (see InterraRMD 2012). The dataset contains information on past and current industrial mines or future industrial mines with potential for industrial-scale development, geocoded with point coordinates and historic information on production levels. The panel dataset consists of 874 industrial mines across Africa. For these mines we have production levels in 1975 and then for each consecutive year from 1984 to 2010. The geographic dispersion of the mines can be seen in Figure 2, where each dot represents a mine.

Figure 2: RMG Mines in Africa



Of the 874 mines in Africa, 275 are matched to a geographical cluster in the DHS data. All clusters are matched to mines, but not all mines are matched to clusters. This is because some mines are located in remote and sparsely populated areas or are densly clustered, or because we have no DHS sample for the country (e.g., South Africa). Considering only the mines that are closest to at least one cluster, 51 mines had opened by 1984, 109 mines opened during the following 26 years, and 90 mines closed during the same period (see Appendix Table A.3). This is to our awareness the only existing mine production panel dataset, and while the quality with respect to the exact levels of production is uncertain the state of the mine (active, inactive, or suspended) is reliable.

The RMD data focuses on mines of industrial size and production methods, often with foreign or government ownership. The mines in the dataset thus constitute a subset of existing mines and deposits in the region, excluding small scale mines and informal or illegal mines. The external validity of the results from the main empirical strategy is therefore limited to large-scale mining.

Industrial mining may exist alongside or replace small-scale and artisanal mining (ASM). While the production levels of ASM-type activities are small, they are an important source of livelihood in Africa.[5] Twenty-one countries in Africa are estimated to employ more than 100,000 people each in ASM, with Ghana and Tanzania above one million people each. Together, these two countries are estimated to have 13.4 million people dependent on ASM ("dependent" implying indirect employment and families of miners) (UNECA, 2011). The current definition of small-scale mining operations includes a cap of 50 employees and that operations are labor rather than capital intensive. Artisanal mining is characterized by traditional and often hand-held tools and may be of an informal and/or illegal nature. Similarly to large-scale mining there are taboos regarding women's participation in underground work, yet women as well as children often engage in other ASM operations. In order to get a more complete picture of the effects of mining we complement the main analysis using datasets from the U.S. Geological Survey (USGS) and the Center for the Study on Civil War (CSCW) on diamond mines. The USGS data covers a wider variety of mines and deposits, but has the drawback of not including time-varying production levels. Similarly, the CSCW data includes all diamond mines but no production

[5] 3.0–3.7 million people in Africa were estimated to be engaged in small-scale or artisanal mining at the end of the last century according to ILO (1999). A more recent report from the UN and African Union (UNECA, 2011) estimates that 8.1 million people are engaged in ASM.

levels. Figues A.1 and A.2 in the Appendix show the distribution of the mines included in the USGS ans CSCW datasets, respectively.

3.2 DHS data

We use micro data from the Demographic and Health Surveys (DHS). The DHS data are obtained from standardized surveys across years and countries, with GPS coordinates. We combine the women's questionnaires from all 67 surveys in Sub-Saharan Africa that contain information on employment and GPS coordinates, in total 67 surveys. The total dataset includes 525,189 women aged 15-49 from 29 countries. They were surveyed between 1990 and 2011 and live in 20,967 survey clusters in 297 sub-national regions.[6] The survey clusters are shown in Figure 3. The data cover large parts of Sub-Saharan Africa; Table A.1 in the Appendix shows the distribution of the sample by country. Table A.2 in the Appendix shows the distribution of the sample by years.

Definitions and summary statistics for our dependent and control variables are shown in Table 1, the occupational status (*working*) relates to whether the respondent had been working during the last 12 months; 66 % of the women responded affirmatively. Women who are not working may be engaged in child care, household production, or backyard farming. The information on employment is disaggregated by sector of activity, and we present descriptive statistics for services, sales, and agriculture. The main focus of this paper is on these three occupational categories given their relative importance. There are five more categories that together make up 11 percent.[7] The surveys also contain demographic variables, place of residence, education and religious affiliation. Regarding migration, women state in what year they moved to their current place of residence. However, no information is collected on previous place of residence or place of birth.[8]

[6]The cluster sizes range from 1 to 108 women. The mean number of women in a cluster is 25 and the median is 24. In most cases, the regions correspond to the primary administrative division for each country. Where the coding into the primary divisions is not possible in the DHS data due to natural regions being used instead (e.g., North-East, North-West, etc.), we use the existing natural regions. We largely follow Kudamatsu (2012) to make the coding consistent over the years and we complement the classification using Law (2012), which is available on www.statoids.com and which is the updated version of Law (1999). The regions are not of equal sizes; rather, they range from having 30 sampled women to having 22,966 women. The average sample size of a region is 1,769 and the median is 1,201.

[7]The other categories are: professional, domestic, clerical, skilled manufacturing, and unskilled manufacturing.

[8]Not all survey rounds include information on migration. In the sample, year of last move

Figure 3: DHS clusters

4 Empirical Strategy

With several waves of survey data combined with detailed information on the mine expansion, the estimation relies on a difference-in-difference estimation strategy, using multiple definitions of the mine footprint area (i.e., the core

is available for 428,735 women.

treatment area) based on different proximity measures and alternative definitions of the control group.

Assuming that women seek employment at any mine falling within a cut-off distance, our main identification strategy includes three groups with the baseline distance 20 km; (1) within 20 kilometers from at least one active mine, (2) within 20 kilometers from an inactive mine (defined as not yet active mine) but not close to any active mines nor to any suspended mines, and (3) more than 20 kilometers from any mine. The baseline regressions are thus of the form

$$Y_{irvt} = \beta_1 \cdot active + \beta_2 \cdot inactive + \alpha_r + g_t + \delta_{rt} + \lambda X_i + \varepsilon_{irvt},$$

where the outcome Y of an individual i in region r, cluster v, and for year t is regressed on a dummy *(active)* for whether the woman lives within 20 kilometers from at least one active mine, a dummy *(inactive)* for whether the woman lives close to a mine that is not producing at the time of the survey, region and year fixed effects, region-specific linear time trends, and a vector X of individual level control variables. In all regressions, we control for living in an urban area, age, years of education, and indicators for religious beliefs.

Only interpreting the coefficient for *active* (20 km) builds on the premise that the production state (*active* or *inactive*) of the mine is not correlated with the population characteristics before production starts, i.e., that a mine does not open in a given location because of the availability or structure of the labor force in that geographical location. This is a debatable assumption since wage labor and population density may influence mining companies' investment decisions or could jointly vary with a third factor such as accessibility or infrastructure. The dummy variable for inactive mines allows us to compare areas before a mine has opened with areas after a mine has opened, and not only between areas close and far away from mines. For all regressions, we therefore provide test results for the difference between *active* (20 km) and *inactive* (20 km). By doing this we get a difference-in-difference measure that controls for unobservable time-invariant characteristics that may influence selection into being a mining area.

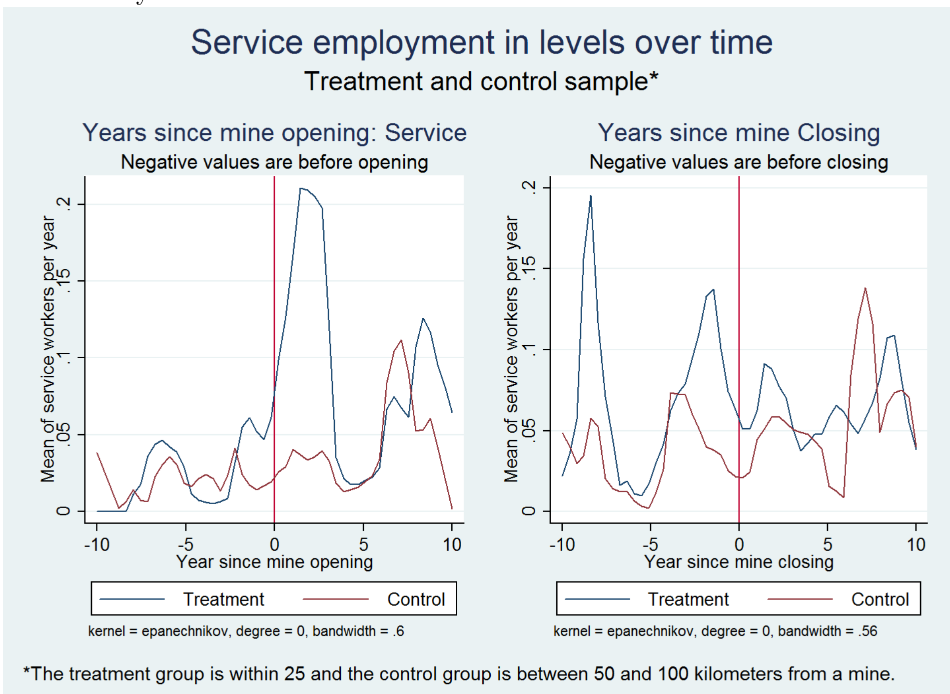
Controlling for region fixed effects, only time-variant differences should be a menace to this identification strategy. That is, we control for time-invariant regional mining strategies, institutions, level of economic development, sectoral composition, and norms regarding female work force participation. Exploiting within-country variation leads to more robust causal claims (e.g., Angrist and Kugler, 2008; Buhaug and Rød, 2006; De Luca et al., 2012; Dube and

Vargas, 2013 on conflicts, Wilson, 2012 on sexual risk taking behavior in Zambia's copper belt; and Aragon and Rud, 2013b on the local economy in Peru). Nonetheless, the exact location of a mine within a country or region may still be influenced by factors other than abundance of resources. The placement of mineral deposits is random (Eggert, 2002), but the discovery of such deposits is not. In particular, the literature suggests it should depend on three other factors (Krugman, 1991 and Isard et al., 1998): (i) access to and relative price of inputs, (ii) transportation costs, and (iii) agglomeration costs. If selection into being a mining area, even within a country or region, is based on factors other than mineral endowments that are stable over time, we can exploit the temporal variation in the data to control for such factors. We further control for region specific time trends and the setup thereby allows for different time trends across sub-national regions and makes the identification of effects even less reliant on the similar trends assumption.

4.1 Further empirical issues

Our identification strategy allows us to control for unobservable time-invariant region characteristics that may influence selection into being a mining area. The identifying assumption in such a difference-in-difference approach is that absent the mine opening, the trends in the areas close to mines would have been the same as those further away. We present the trends in service level employment for those within 20 kilometers and those between 50 and 100 kilometers from a mine in Figure 4. The left side of the figure shows that there are no differences in either trends or levels of service employment for the treatment and control groups before the mines open. In contrast, service employment increases sharply once the mine opens and there is more service employment in the treatment area up until around five years after the mine has opened. That the levels are equal after five years may be due to a spreading of the effects over time as the control group is also within 100 km. There is also a small increase in service sector employment in the last year prior to mine opening, potentially due to increased activity during the investment phase. The right-side figure shows that service employment is higher close to mines that are going to close but have not yet done so. This difference in service level employment disappears once the mine closes. Similar trends are obtained if we have the residuals after controlled regressions instead of levels (figures are available upon request).

Figure 4: Trends before and after openings and closings for those close and further away from mines



Note that we control for region-specific time trends in the regressions, which further reduces the danger of non-paralell trends. One remaining threat to the validity of the identifying assumption, however, is selective migration. Since the data is repeated cross-sectional data, it is implicitly assumed that women are sampled from the same populations before and after mine opening. Migration is likely to be spurred by natural resource and mining booms and there is evidence of the creation of mining cities (Lange, 2006 in Tanzania), consumption cities (cocoa booms in Ghana and Ivory Coast; Jedwab, 2012), urban-rural migration (Hilson, 2009) as well as work-migration (Corno and de Walque, 2012). This means that we may have a selection issue where women have moved to mining areas for work. While urbanization and inward migration are possible channels through which the multipliers work, we are interested in knowing if the original population benefited from the expansion. Excluding all women who have ever moved allows us to explore this aspect (leaving a sample of 356,958 women). This also controls for selective outward migration.

Another worry is that something else happens parallel to and irrespective of the mine opening, and that the results capture such effects rather than mine effects. In particular, it may be that both mine industrialization and employment are driven by improvements in infrastructure. In order to test this potential channel, we incorporate data on roads to check whether the results remain stable.

Different fixed effects, for the closest mines and for different types of minerals, are included to verify the robustness of the results. In all regressions we cluster the standard errors at the DHS cluster level, but we also present results where the standard errors are clustered at the regional level, at the level of the closest mine, and for multi-way clustering at both the DHS cluster and the closest mine. A last empirical issue is that the control group living far away from mines may be inherently too different from the population living in mining areas. Several measures are taken to ensure that the results are not driven by such dissimilarities, including using region fixed effects and geographically limiting the area from which the control group is drawn.

5 Results

The main results following the empirical strategy previously outlined are reported in Table 2, with the first four columns using the whole sample and the last four columns using a subsample of women within 200 kilometers from a mine. The variable of main interest is *active (20 km)* capturing the difference in outcomes between women living close to a producing mine and those living further away. The coefficient is positive and statistically significantly correlated with the woman working and working in the service sector but is not statistically significantly correlated with being in sales or agriculture.

Due to the possibility of non-random mine placement, we use a difference-in-difference strategy whereby the effect of a mine opening can be read out as the difference between the coefficients for *active (20 km)* and *inactive (20 km)* and test results are presented for this difference ($\beta_1 - \beta_2 = 0$) henceforth. First of all we see that there is a decline in the probability that a woman is working by 5.5 percentage points when a mine opens in the area (which is calculated by the difference between *active* and *inactive*: 2.6-8.1). Investigating the sectoral composition of the effect, it is clear that the decline in overall employment is driven by a decline in agriculture. In fact, we see an increase in service sector employment. The increase in the likelihood of working in the service sector has a lower span of 1.8 percentage points (from the regression with sample limitation) and an upper limit of 2 percentage points. The sample mean of engaging in service sector jobs is 3.6 %, so the size of the increase in likelihood is thus substantial at over 50 %. When reducing the sample to only include a control group within 200 km, we lose around half the sample. Nonetheless, all effects point in the same direction and are still statistically significant. Trying to quantify the effect of mine opening on female service sector employment, we make a simple back-of-the-envelope type calculation and estimate that if only considering those living within 25 kilometers from a mine, 93,550 women have benefited from service sector jobs generated by the industrial mining sector.[9]

With respect to selection, it is also interesting to interpret the coefficient for *inactive* as the correlation between being a mining area and our outcomes before the mines have any industrial-scale production. The statistically significant results for *inactive* show that there may be selection into being a mining area, which is not fully accounted for by including region fixed effects. We posit three possible reasons why the likelihood of women working is higher around inactive mines: (1) these are geographical areas with agricultural focus where women are more likely engaged in economic activities outside of the household; (2) the coefficient captures pre-opening effects (e.g., jobs generated in the prospecting and investment phase); and (3) the prevalence of artisanal and small scale mining activities that may employ women directly in addition to indirectly generating employment.

5.1 Heterogeneous effects by distance

The empirical strategy relies on decrasing footprint with distance from a mine. As seen in Table 3, there are large and highly statistically significant effects of mine openings up to 25 kilometers away, and there is a shift from agriculture to service sector jobs. The largest effects are found using a cut-off of 5 kilometers and the most statistically significant effects are for a distance of 10 kilometers.

[9] We use our baseline results. According to the World Bank Indicators for 2011, the Sub-Saharan African female population aged 15-65 is estimated to 236,241,202 people. In our sample, approximately 1.6 % percent live within 20 kilometers from an active mine. In the whole sample, 3.6 percent of the women work in the service sector, but this increases to 5.4 % close to mines. Our estimates show that 1.8 % - 2 % of the women close to mines benefit from service sector employment, amounting to 68,037 to 75,597 women. Using the 25 kilometers distance span from an active mine, we estimate that 93,550 women gained employment in the service sector.

Table 2: Effects of mining on main outcomes: Within 20 km from an active or inactive mine with and without sample restrictions.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	No restriction				Sample restricted to within 200 km			
VARIABLES	Working	Service	Sales	Agriculture	Working	Service	Sales	Agriculture
active (20 km)	0.026***	0.020***	0.001	-0.009	0.025***	0.020***	-0.001	-0.008
	(0.010)	(0.005)	(0.008)	(0.012)	(0.010)	(0.005)	(0.008)	(0.013)
inactive (20 km)	0.081***	0.000	-0.014	0.065***	0.067***	0.002	-0.015	0.051**
	(0.020)	(0.005)	(0.015)	(0.024)	(0.020)	(0.005)	(0.015)	(0.025)
urban	-0.055***	0.033***	0.117***	-0.259***	-0.048***	0.030***	0.137***	-0.267***
	(0.003)	(0.001)	(0.003)	(0.004)	(0.004)	(0.002)	(0.004)	(0.006)
age	0.011***	0.000***	0.004***	0.004***	0.011***	0.000***	0.004***	0.005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
schoolyears	-0.004***	0.001***	-0.004***	-0.018***	-0.005***	0.000**	-0.006***	-0.016***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
christian	-0.013***	0.010***	0.030***	-0.066***	-0.013***	0.006***	0.032***	-0.069***
	(0.003)	(0.001)	(0.003)	(0.005)	(0.004)	(0.002)	(0.004)	(0.005)
muslim	-0.065***	0.005***	0.080***	-0.146***	-0.018***	-0.002	0.106***	-0.106***
	(0.005)	(0.001)	(0.004)	(0.006)	(0.005)	(0.002)	(0.006)	(0.008)
Observations	518,368	518,368	518,368	518,368	269,276	269,276	269,276	269,276
R-squared	0.198	0.091	0.141	0.354	0.222	0.094	0.164	0.394
F test: active-inactive=0	6.154	7.152	0.751	7.423	3.613	5.896	0.637	4.480
p value	0.0131	0.00750	0.386	0.00645	0.0574	0.0152	0.425	0.0343

Robust standard errors clustered at the DHS cluster level in parentheses. All regressions control for year and region fixed effects, regional time trends, living in an urban area, age, years of education, and religious beliefs.
*** p<0.01, ** p<0.05, * p<0.1

The probability of having a service sector job within 10 kilometers from an active mine is 2.8 percentage points higher and this gives a total effect (coefficient for *active* – coefficient for *inactive*) of 4.0 percentage points. Similarly, the probability of working in agriculture within 10 kilometers from active mine is 4.9 percentage points less (*active*) and the effect of mine opening at this distance is a reduction of 16.1 (*active* – *inactive*) percentage points. The footprint of mines extends to 50 kilometers with respect to services, but wears off at 75 kilometers. Women living within 50 and 75 kilometers from a mine are more likely to work, but there is no extra effect of the mine opening. Table A.4 in the Appendix shows the sample sizes broken down by treatment status (*active*, *inactive* and *suspended*) for the different distances.

We choose a baseline distance of 20 kilometers from the mine. Although this distance cut-off does not maximize the effect size, we find it reasonable for four reasons: (1) the geocoordinates in the DHS data are randomly displaced up to 5 kilometers, and for 1 % of the sample up to 10 kilometers why small distance spans may introduce a higher share of noise; (2) the geocoordinates in the mining data reflect the centroid of the mining area so that with a too small area around it we are likely to capture the actual mining site of the mine rather than the surrounding communities; (3) the sample size increases rapidly when increasing the distance spans, which increases the robustness of the results with respect to outliers; and (4) using longer distances than 20 kilometers, we fail to capture the mine footprint. As shown in Table 4, we get consistent results using continuous measures to the closest active mine. *Distance to closest active mine* captures the distance in kilometers (scaled by a hundred) from the DHS cluster to the closest active mine (Panel A), limited to 200 kilometers (Panel B), or taken in logs (Panel C). The results from these regressions show that being further away from an active mine is correlated with less employment, less service sector employment, and less agriculture. We also do a horse race with the logged distance to the closest mine regardless of activity (*distance to closest mine*) and the logged distance to the closest active mine. In accordance with previous results, we find that mining areas have higher work participation and more agriculture (a selection effect) and that distance to an active mine dominates for services. The shorter the distance to an active mine, the larger the share of the female population engaged in services. We see the opposite results for agriculture - the distance to an active mine is positive but the distance to any mine is negative. In Panel E we show results from a spline indicating that the strongest effects for services are found wihtin 10 km from an active mine. The probability of working in services is 3.2 percentage points higher for women living within 10 kilometers from an active mine, whereas the likelihood of an agricultural job is 3.8 percentage points lower.

5.2 Other measures of occupation

To further assess the effects on employment changes, we investigate the effects of mining on remuneration and seasonality of work. We have data on how the women are paid for work done outside the household and on whether they work all year, seasonally, or occasionally. The sample is smaller as the question is not asked in all DHS survey rounds. The remuneration results are shown in Panel A of Table 5. We see that being close to an inactive mine is associated with a higher probability of earning in-kind only. This is in line with the previous results that mining areas have a higher share of agricultural workers prior to production. The probability of earning cash increases by 6.5 percentage points (0.016 - (-0.049)) with a mine opening and this effect is statistically significant at the 6 % level (p-value 0.052). We also see a statistically significant effect of reduced probability of being paid in-kind only or being paid both cash and in-kind. In Panel B we show the results on seasonality of employment and note that women become less likely to work seasonally after mine openings. We also see that the probability of engaging in work activities on an occasional basis increases. These effects are further indications that the labor market opportunities for these women change, and they are in line with our previous findings that the probability of engaging in agriculture decreases with mine opening and that women are more likely to work in the service sector, which ought to vary less with the seasons.

We have found that the probability of a woman working is higher in mining areas and that active industrial mines lead to more service sector employment. Next we show that women do not benefit from direct employment in the mining activities. A subset of the surveys include information on whether a woman or her partner works in mining. The categorization unfortunately differs between DHS survey rounds, and hence these variables can only be taken as indicators of engagement in mine activities.[10] We run regressions on whether a woman or her partner is engaged in mining using three different mine datasets (RMG,

[10]Possible categories include: mine blasters and stone cutters; laborers in mining; miners and drillers; miners and shot firers; laborers in mining and construction; gold panners; extraction and building; mining and quarrying; and laborers in mining, construction and manufacturing.

Table 3: Effects of mining on main outcomes with different cut-off distances

VARIABLES	(1) Working	(2) Service	(3) Sales	(4) Agriculture	*Observations*
active (5 km)	0.038	0.023	-0.016	-0.008	
	(0.025)	(0.016)	(0.017)	(0.033)	
inactive (5 km)	0.215***	-0.022	0.035	0.132***	
	(0.043)	(0.014)	(0.032)	(0.023)	
p value: active-inactive=0	0.000367	0.0307	0.151	0.000559	524,151
active (10 km)	0.020	0.028***	0.010	-0.049***	
	(0.017)	(0.011)	(0.013)	(0.019)	
inactive (10 km)	0.154***	-0.012	0.016	0.112***	
	(0.033)	(0.011)	(0.025)	(0.021)	
p value: active-inactive=0	0.000355	0.00745	0.838	1.03e-08	521,285
active (15 km)	0.018	0.024***	0.000	-0.025*	
	(0.012)	(0.007)	(0.009)	(0.015)	
inactive (15 km)	0.137***	-0.001	-0.001	0.111***	
	(0.024)	(0.009)	(0.019)	(0.023)	
p value: active-inactive=0	9.10e-06	0.0305	0.935	8.40e-07	519,842
active (20 km)	0.026***	0.020***	0.001	-0.009	
	(0.010)	(0.005)	(0.008)	(0.012)	
inactive (20 km)	0.081***	0.000	-0.014	0.065***	
	(0.020)	(0.005)	(0.015)	(0.024)	
p value: active-inactive=0	0.0131	0.00750	0.386	0.00645	518,368
active (25 km)	0.023***	0.018***	0.003	0.000	
	(0.009)	(0.005)	(0.007)	(0.011)	
inactive (25 km)	0.064***	0.000	-0.013	0.045*	
	(0.017)	(0.004)	(0.014)	(0.023)	
p value: active-inactive=0	0.0349	0.00697	0.283	0.0822	515,321
active (50 km)	0.038***	0.004	-0.010*	0.040***	
	(0.008)	(0.003)	(0.006)	(0.010)	
inactive (50 km)	0.024*	0.000	-0.012	0.025	
	(0.012)	(0.002)	(0.012)	(0.018)	
p value: active-inactive=0	0.304	0.314	0.905	0.452	498,947
active (75 km)	0.050***	0.007***	-0.005	0.046***	
	(0.008)	(0.002)	(0.006)	(0.010)	
inactive (75 km)	0.029***	0.003*	-0.004	0.032**	
	(0.010)	(0.002)	(0.010)	(0.015)	
p value: active-inactive=0	0.0838	0.271	0.860	0.463	490,704

Robust standard errors clustered at the DHS cluster level in parentheses. All regressions control for year and region fixed effects, regional time trends, living in an urban area, age, years of education, and religious beliefs. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4: Effects of mining using continuous distance measures and distance spline

VARIABLES	(1) Working	(2) Service	(3) Sales	(4) Agriculture
Panel A : Distance				
Distance to closest active mine	-0.016***	-0.001	-0.000	-0.011***
	(0.003)	(0.001)	(0.002)	(0.003)
Panel B : Distance with sample limit to 200 km				
Distance to closest active mine	-0.030***	-0.009***	0.005	-0.030***
	(0.007)	(0.002)	(0.005)	(0.010)
Panel C : Log distance				
ln Distance to closest active mine	-0.023***	-0.007***	0.002	-0.015***
	(0.004)	(0.002)	(0.003)	(0.005)
Panel D : Horse race log distance				
ln Distance to closest active mine	-0.000	-0.005***	-0.001	0.011*
	(0.005)	(0.002)	(0.004)	(0.006)
ln Distance to closest mine	-0.028***	-0.002*	0.005*	-0.031***
	(0.004)	(0.001)	(0.003)	(0.004)
Panel E: Spline with distance to active mine				
Distance to closest active mine (0 to 10 km)	0.027	0.032***	0.003	-0.038*
	(0.018)	(0.011)	(0.013)	(0.020)
Distance to closest active mine (10 to 20 km)	0.028**	0.019***	-0.015	0.021
	(0.012)	(0.006)	(0.010)	(0.016)
Distance to closest active mine (20 to 30 km)	0.022**	0.001	-0.008	0.033**
	(0.011)	(0.005)	(0.008)	(0.013)
Distance to closest active mine (30 to 40 km)	0.004	0.010**	-0.026***	0.024*
	(0.011)	(0.005)	(0.008)	(0.014)
Distance to closest active mine (40 to 50 km)	0.022**	-0.003	-0.019**	0.047***
	(0.011)	(0.004)	(0.008)	(0.014)
Observations	495,832	495,832	495,832	495,832

Robust standard errors clustered at the DHS cluster level in parentheses. All regressions control for year and region fixed effects, regional time trends, living in an urban area, age, years of education, and religious beliefs. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5: Effects of mining on payment and seasonality

	(1)	(2)	(3)	(4)
Panel A : Remuneration of work				
VARIABLES	Cash	Cash & Kind	Kind	Not Paid
active (20 km)	0.016	-0.029***	0.015*	-0.002
	(0.015)	(0.011)	(0.008)	(0.012)
inactive (20 km)	-0.049	0.016	0.059***	-0.026
	(0.030)	(0.020)	(0.018)	(0.030)
Observations	254,029	254,029	254,029	254,029
F test: active-inactive=0	3.777	4.165	4.653	0.568
p value	0.0520	0.0413	0.0310	0.451
Panel B : Seasonality of work				
VARIABLES	Seasonal	All year	Occasional	
active (20 km)	-0.074***	0.057***	0.017**	
	(0.014)	(0.013)	(0.008)	
inactive (20 km)	-0.004	0.027	-0.023	
	(0.030)	(0.026)	(0.015)	
Observations	306,087	306,087	306,087	
F test: active-inactive=0	4.541	1.135	5.588	
p value	0.0331	0.287	0.0181	

Robust standard errors clustered at the DHS cluster level in parentheses. All regressions control for year and region fixed effects, regional time trends, living in an urban area, age, years of education, and religious beliefs.
*** p<0.01, ** p<0.05, * p<0.1

USGS or the CSCW diamond dataset). Table 6 shows that there is no effect of industrial scale mining on employment in mining for women. Neither do we find any statistically significant correlation for USGS mines. The USGS mine measure does not contain information on the type, timing, or significance of the mining activities. Anecdotal evidence suggests that it is common for women to engage in some type of artisanal and small-scale mining (ASM) activities, which this mine measure partly captures. No correlation is found for women using the diamond dataset from CSCW. In contrast, being within 20 kilometer of a mine is significantly and positively associated with the woman's partner being engaged in mining for all three mine estimates and there is an effect of mine industrialization in the RMG data. Mine openings increase the likelihood of the husband being a miner by 4 percentage points, which is a large increase relative to the sample mean of 2.6 %. These estimates cannot be generalized to the whole male population in these areas close to mines, and are only representative for husbands/partners of women residing close to mines.

While mineral mining is associated with men engaging in mining, it does not correlate with the probability of women being miners. However, women may benefit from more service sector jobs in the vicinity of mineral mines, and mine openings offer more opportunities to earn cash income.

6 Robustness and heterogeneous impacts

6.1 Robustness and extensions

Selective migration and access to roads

A potential threat to our identification strategy is that women move to mining areas to work, and that we capture this selection effect rather than generated employment opportunities. By restricting the sample to women who state that they have never moved, we show that our effects are not driven by inwardly or outwardly migrated women. The results can be seen in Table 7 and resemble the baseline results both in terms of direction of effects and statistical significance.

Another fear is that we capture unobserved time-variant heterogeneity across clusters rather than the effects of mines. Access to infrastructure is one possible factor at work, and therefore we include proximity to roads as an extra control variable to see if the results remain robust. Unfortunately, the road data

Table 6: Effects of mining on the probability of the respondent or the respondent's partner being a miner.

	(1)	(2)	(3)	(4)	(5)	(6)
	RMG mine data		USGS mine data		Diamond mine data	
VARIABLES	Woman Miner	Husband Miner	Woman Miner	Husband Miner	Woman Miner	Husband Miner
active (20 km)	0.005*	0.054***				
	(0.003)	(0.011)				
inactive (20 km)	0.012	0.014				
	(0.010)	(0.020)				
usgs mine (20 km)			0.001	0.009***		
			(0.001)	(0.002)		
diamond mine (20 km)					-0.001	0.039***
					(0.003)	(0.012)
Observations	251,207	175,460	256,609	178,579	256,609	178,579
R-squared	0.027	0.073	0.026	0.070	0.026	0.071
F test: active-inactive=0	0.409	2.987				
p value	0.522	0.0840				

Robust standard errors clustered at the DHS cluster level in parentheses. All regressions control for year and region fixed effects, regional time trends, living in an urban area, age, years of education, and religious beliefs.
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Effects of mining for a sub-sample of women who have never moved.

VARIABLES	(1) Working	(2) Service	(3) Sales	(4) Agriculture
active (20 km)	0.018	0.026***	0.019	-0.029*
	(0.014)	(0.008)	(0.012)	(0.017)
inactive (20 km)	0.116***	0.007	-0.000	0.071***
	(0.026)	(0.007)	(0.018)	(0.026)
Observations	194,103	194,103	194,103	194,103
R-squared	0.218	0.091	0.143	0.341
F test: suspended-active=0	11.22	3.164	0.797	10.44
p value	0.000811	0.0753	0.372	0.00124

Robust standard errors clustered at the DHS cluster level in parentheses. All regressions control for year and region fixed effects, regional time trends, living in urban area, age, years of education, and religious beliefs.
*** p<0.01, ** p<0.05, * p<0.1

is not time variant and is only available for a subset of countries. The results are presented in Table A.11 in the Appendix using data from the African Development Bank for Benin, Central African Republic, Cameroon, DRC, Mali, Niger, Senegal, and Togo. We see that the effects of mine openings are similar but that the sample size is significantly reduced when we restrict the sample to these countries and control for being within 50 kilometers of a road.

Mine suspension, intensity, fixed effects, and clustering

We further examine the effects of having a mine closing in the area on women's employment. The results are shown in Table 8. The effects of mine closings are not entirely symmetrical to the effects of mine openings. Initially, mine openings induced an increase in the likelihood of service sector employment, an effect that is offset by the time of mine suspension. Agricultural employment increases but the effect is not statistically significant and the magnitude is much smaller than the decline induced by mine openings. These results indicate that the localized structural shifts spurred by mine openings are not reversible; i.e., women seem inhibited to go back to agricultural production after mine closings.

Intuitively, living near several active mines should affect labor market opportunities more than living close to only one mine. To investigate whether agglomeration of mines creates stronger effects, we include a measure of mining

Table 8: The effect of mine suspension on our main outcomes.

VARIABLES	(1) Working	(2) Service	(3) Sales	(4) Agriculture
suspended (20 km)	0.026*	0.002	0.007	0.013
	(0.014)	(0.006)	(0.009)	(0.017)
active (20 km)	0.024**	0.020***	0.001	-0.010
	(0.010)	(0.005)	(0.008)	(0.012)
Observations	525,180	525,180	525,180	525,180
R-squared	0.197	0.091	0.141	0.355
F test: suspended-active=0	0.00895	5.377	0.265	1.341
p value	0.925	0.0204	0.607	0.247

Robust standard errors clustered at the DHS cluster level in parentheses. All regressions control for year and region fixed effects, regional time trends, living in an urban area, age, years of education, and religious beliefs.
*** p<0.01, ** p<0.05, * p<0.1

intensity. The intensity score, which equals the number of active mines within 100 kilometers, is significantly associated with our main occupational outcomes. As shown in Table A.5 in the Appendix, an extra mine within 100 km is correlated with an increased likelihood of women working and working in services and agriculture, but decreases the likelihood of women working in sales. The magnitude of the effects also increase if we consider treatment intensity. For example, having two extra mines within 100 kilometers would increase the probability of working in services by 3.3 percentage points (1.5+0.6*3+0), and this increase is statistically significant at the one percent level.

All our regressions include region fixed effects, regional time trends, and year fixed effects in addition to our individual level control variables. We also cluster the standard errors at the DHS cluster level. In Table A.6 in the Appendix, we show that our main findings are robust to inclusion of fixed effects for the closest mine and mineral fixed effects. In Panel B we also show that the results hold for clustering at the regional level, at the closest mine level, as well as multi-way clustering on both the closest mine and the DHS cluster.

Artisanal and small-scale mining

To investigate the relationship between employment and a broader set of mines, we use the USGS and CSCW datasets. The results show that being within

20 kilometers from an USGS mine is associated with roughly a one percentage point increase in the probability of working in sales or services and a 2.6 percentage point decrease in working in agriculture (see Panel A of Table A.13 in the Appendix). For diamond mines we find that the probability of being in agriculture is 5.3 percentage points lower, the probability of working in sales is 2.8 percentage points higher, and the probability of working in services is 0.6 percentage points higher if the woman lives within 20 km of a diamond mine (Panel B of Table A.13 in the Appendix). Hence, the results using these other datasets are consistent with the findings using the main dataset, which makes us confident that the results can be generalized also to non-industrial mining.

6.2 Heterogeneous effects

Who benefits from the mine expansion?

We have seen that mining may indirectly create non-agricultural job opportunities, allowing women to earn more cash and work outside the traditional and dominating agricultural sector. The uptake of jobs for women will likely depend on income (making her household richer) and substitution effects. The income effect is linked to the supply side argument in Ross (2008, 2012), where women's employment is modeled to decrease as their husbands earn more money. If this channel is correctly hypothesized, the effects will differ depending on a woman's marital status. In order to test whether there are heterogeneous effects, we include interaction terms between our treatment variables and marital status (being married or having a partner, divorced or separated, widow, and single and never married) in Table 9. The baseline category is being single and the other marital statuses are being divorced or separated (*divsep*), being a widow (*widow*), or being married or having a partner (*partner*). Divorced or separated women are affected the most by mine openings, as they increase their probability of working by 9 percentage points and their probability of working in the service sector by 8.8 percentage points. The results points toward increasing opportunities for women to find a job outside the agricultural sector and that these opportunities are exploited the most by divorced and separated women out of necessity and/or possibility.

We must be careful in interpreting these results as supporting the income effects story since marital status is a choice implying that married or divorced women are different from never married women in any case and because mari-

Table 9: Heterogeneous effects of mining by marital status.

VARIABLES	(1) Working	(2) Service	(3) Sales	(4) Agriculture
active (20 km)	0.016	0.013**	-0.010	-0.004
	(0.013)	(0.006)	(0.008)	(0.014)
inactive (20 km)	0.071***	0.002	0.006	0.056*
	(0.025)	(0.007)	(0.020)	(0.032)
partner	0.137***	0.005***	0.043***	0.085***
	(0.002)	(0.001)	(0.002)	(0.002)
actinve*partner	0.007	0.007	0.015*	-0.010
	(0.011)	(0.006)	(0.009)	(0.012)
inactive*partner	0.017	-0.000	-0.031	0.015
	(0.022)	(0.006)	(0.021)	(0.036)
divsep	0.196***	0.030***	0.077***	0.045***
	(0.003)	(0.002)	(0.003)	(0.003)
active*divsep	0.036**	0.037**	0.020	-0.004
	(0.017)	(0.015)	(0.017)	(0.015)
inactive*divsep	-0.054	-0.051***	-0.027	-0.033
	(0.038)	(0.013)	(0.045)	(0.045)
widow	0.142***	0.008***	0.056***	0.060***
	(0.004)	(0.002)	(0.004)	(0.004)
active*widow	0.044**	0.027*	0.031	-0.033*
	(0.021)	(0.015)	(0.020)	(0.018)
inactive*widow	-0.007	0.003	0.004	-0.038
	(0.043)	(0.021)	(0.047)	(0.053)
Observations	509,344	509,344	509,344	509,344
R-squared	0.209	0.092	0.144	0.355
F test: active-inactive=0	4.116	1.368	0.590	3.017
p value	0.0425	0.242	0.443	0.0824
F test: act__partner-inact__partner=0	0.176	0.848	4.033	0.406
p value	0.675	0.357	0.0446	0.524
F test: act__divsep-inact__divsep=0	4.731	20.18	0.957	0.371
p value	0.0296	7.07e-06	0.328	0.542
F test: act__widow-inact__widow =0	1.158	0.854	0.271	0.00978
p value	0.282	0.356	0.602	0.921

Robust standard errors clustered at the DHS cluster level in parentheses. All regressions control for year and region fixed effects, regional time trends, living in an urban area, age, years of education, and religious beliefs.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

tal status may be endogenous to the mine activities. Mining communities are characterized by a high ratio of men to women and a transient labor force (see work by Campbell, 1997 on gold mines in South Africa, and Moodie and Ndatshe, 1994 for a historic analysis), aspects that can change the marriage market and relationship formation. We do not find any evidence that mining changes relationship formation, however (see Table A.7 in the Appendix). By restricting the sample to women who married for the first time before the mine closest to them opened, we explore heterogeneous effects with less worry of marital status being endogenous to mine activity and we find that they are also more likely to be working in services (Appendix Table A.8). Columns 4-8 of Table A.8 in the Appendix further show the effects of mine openings for the sample of 4,628 women whose husbands we know are miners. Interestingly, we note a negative effect on employment for these women, a substantial decrease in service employment although only statistically significant at the 12 percent level, a large increase in sales employment, and a decline in agriculture.

The youngest population, i.e., young women aged 15-20, may face different choices when growing up in mining areas. We therefore analyze them separately (see Appendix Table A.9). We find that these women are less likely to work and less likely to work in agriculture. Looking at schooling for these young women, we find that they have more education and that the difference from before the mine opens is highly statistically significant and amounts to over half a year more of schooling on average.

Employment opportunities matter for women. For welfare, it also matters what types of jobs are offered. We try to rule out that the increase in female employment in the service sector is driven by engagement in the sex industry. Using lifetime number of sexual partners we find no indication of more risky behavior or sex trade among women in active mining areas (Table 10). In fact, there is a clear negative effect of mine openings on the number of sexual partners. Considering groups that may be at more risk, such as young women (aged under 25), women working in the service sector, and women without a partner, there is also a decrease in the number of sexual partners.

Table 10: Effects of mining on women's lifetime number of sexual partners.

VARIABLES	(1) All	(2) Under 25	(3) In services	(4) No partner
active (20 km)	-0.106*	-0.107**	-0.726***	-0.223
	(0.055)	(0.051)	(0.151)	(0.142)
inactive (20 km)	0.771***	0.708***	0.492**	0.691***
	(0.172)	(0.175)	(0.224)	(0.156)
Observations	210,456	64,672	12,049	49,128
R-squared	0.093	0.087	0.076	0.079
F test: active-inactive=0	23.61	20.02	20.15	19.17
p value	1.20e-06	7.76e-06	7.36e-06	1.21e-05

Robust standard errors clustered at the DHS cluster level in parentheses
All regressions control for year and region fixed effects, regional time trends, living in an urban area, age, years of education and religious beliefs.
*** p<0.01, ** p<0.05, * p<0.1

We have seen that the partners and husbands of the sampled women benefit to a larger extent from directly generated employment in mining operations. Looking at husbands' employment patterns, we find that there is an increase in the probability of working and in skilled manual work and a decrease in the probability of working in agriculture (Panel B of Table A.10 in the Appendix). In panel A of Table A.10, we consider all occupational categories also for women and find no significant effects beyond the ones we have investigated more fully in this paper except for a small and marginally statistically significant increase in working in the domestic sector. We also note that the decrease in agriculture is driven by agricultural self-employment rather than agricultural employment.

Gender segregation

Is it the case that the effect of getting a mine differs between societies with high and low participation of women in the service sector? In order to test this, we use data from the ILO on share of women in the service sector (ILO, 2011) and interact an indicator variable for being in a country with a high share of women working in services (above the median is defined as high). The results are shown in Table A.12 in the Appendix. We confirm that women are more likely to work in service sector jobs in these countries, but the interaction effect of being in a high female service country and in an active mining area does not increase the effect further. On the contrary, there seems to be less of an effect in countries with high participation of women in the service sector. This indicates that women in countries where the service sector is not female dominated benefit even more from mine openings, which is in contrast to a hypothesis that areas where women work more in services should enable women to capture the increased opportunities.

7 Conclusion

The discovery of natural resources across the African continent brings hope for millions of poor people, but there are also fears that the resources will be a curse rather than a blessing (e.g., Collier 2010; Frankel 2010; van der Ploeg 2011). In particular, one fear spelled out in The Africa Mining Vision is that gender inequality in economic opportunities may increase with mining. Using detailed data on industrial mining in Sub-Saharan Africa, we explore whether mining generates local employment opportunities for women. Based on GPS coordinates, we merge individual level data with mining data, which enables a highly localized analysis of spillover effects. We then employ a difference-in-difference estimation strategy to compare areas that are close to mines before and after the production has started with areas further away.

The results show a localized structural shift where a mine opening offers new employment opportunities for women. There is a decrease in agricultural employment and an increase in service sector employment. The changing local economy also brings secondary effects for women with more cash employment and non-seasonal work. The effects are locally concentrated and wear off with distance from mine. Using multiple definitions of mining areas by changing the proximity measures and control group definitions, we show that these results of structural change are robust. The effects of mine closing are not symmetrical; mine suspension leads to reduced service sector employment, yet women do not shift back to agricultural production to the same extent as they left it when the mines opened. Instead, the employment rate decreases, perhaps indicating that these localized structural shifts are not reversible. Allowing for heterogeneity, we find that marital status is an important mediator for the employment outcomes, whereby divorced women experience the most pronounced positive effect of mining activity on their employment.

The results are robust to a wide battery of robustness checks such as using different distance cut-offs, different classifications of the control group, including different types of fixed effects and exluding migrants. The results are also quantitatively important. For example, we calculate that more than 90,000 women may have gained a service sector job as a result of mine openings. Female employment is likely to foster female agency and is also argued to be important for child health, schooling, and survival (see Duflo, 2012 for an overview). Future studies should investigate the impacts of mining on these aspects as well. The results of this paper are in sharp contrast to the bleak picture painted by previous literature, i.e., that female employment is harmed by the existence of natural resources (Ross 2008, 2012).

Nonetheless, we have not assessed the quality of these work opportunities or whether women are facing decent and productive employment as a result of the mining. Whether women are winners in the scramble for Africa's resources can only be concluded via a full welfare analysis. Such a welfare analysis must explore effects on agricultural productivity (see Aragón and Rud 2013a regarding pollution effects from gold mines in Ghana) and access to land, which could induce the push of women from agriculture to service sector jobs. Furthermore, to assess the welfare effects from mining, commonly reported environmental and social concerns associated with the mining industry should be explored.[11]

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[11] Such as deforestation, land degradation, pollution of air and water sources, as well as social issues such as displacement, inequality and tension between miners and non-miners, intra household economic inequality, the spread of HIV/AIDS, and boom and bust economies (UNECA, 2011).

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A Appendix

The Appendix presents results that are not central to the understanding of the paper but that can be used for extra information. It also shows a wide battery of robustness checks. The Appendix presents extra summary statistics in Section A.1 and further robustness checks, treatment heterogeneity, and effects on other outcome variables in Section A.2. Finally, we present analyses based on other mining data sets in Section A.3.

A.1 Descriptive statistics

Table A.1: Distribution of the sample by country.

Country	Number of women
Benin	11,633
Burkina Faso	22,489
Burundi	9,329
Cameroon	29,785
Central African Republic	5,877
Congo DR	9,717
Cote d'Ivoire	11,103
Ethiopia	29,216
Ghana	14,918
Guinea	14,389
Kenya	16,493
Lesotho	3,311
Liberia	3,981
Madagascar	24,047
Malawi	47,306
Mali	36,453
Mozambique	4,912
Namibia	15,783
Niger	14,024
Nigeria	49,125
Rwanda	24,756
Senegal	29,677
Sierra Leone	7,186
Swaziland	4,879
Tanzania	10,792
Togo	8,500
Uganda	34,899
Zambia	7,107
Zimbabwe	23,493
Total	525,180

Table A.2: Distribution of the sample by year.

Year	Number of women
1990	8,738
1991	3,867
1992	6,472
1993	8,171
1994	13,956
1995	9,685
1996	5,446
1997	7,023
1998	25,502
1999	16,424
2000	41,693
2001	18,847
2003	40,615
2004	22,249
2005	55,878
2006	35,799
2007	20,805
2008	70,136
2009	8,223
2010	81,749
2011	23,902
Total	525,180

Table A.3: Closest mines opening and closing 1975-2010.

Year	Mines opening	Mines closing
Between 1975 and 1984	51	6
1984	9	1
1985	1	2
1986	1	0
1988	7	1
1989	1	3
1990	5	0
1991	3	2
1992	4	2
1993	3	1
1994	2	1
1995	3	1
1996	3	2
1997	9	4
1998	6	4
1999	4	8
2000	4	5
2001	5	7
2002	6	2
2003	4	4
2004	2	7
2005	6	2
2006	7	2
2007	4	9
2008	4	9
2009	3	5
2010	3	0
Not closing		70
Total	160	160

Table A.4: Sample size by treatment variables.

At least one	...active mine	...inactive mine	...suspended mine
within 5 km	905	519	1 029
within 10 km	2 651	739	3 895
within 15 km	5 573	1 131	5 338
within 20 km	8 195	2 334	6 812
within 25 km	11 647	3 202	9 859
within 30 km	15 697	3 970	12 431
within 50 km	30 209	7 719	26 233
within 75 km	50 871	14 207	34 476
within 100 km	67 845	23 528	48 289

Table A.5: Effects of mining intensity on our main outcomes.

VARIABLES	(1) Working	(2) Service	(3) Sales	(4) Agriculture
active (20 km)	0.018*	0.015***	0.007	-0.019
	(0.010)	(0.005)	(0.008)	(0.013)
inactive (20 km)	0.080***	-0.000	-0.014	0.065***
	(0.020)	(0.006)	(0.015)	(0.024)
intensity	0.009**	0.006***	-0.007***	0.012***
	(0.004)	(0.001)	(0.002)	(0.004)
Observations	518,368	518,368	518,368	518,368
R-squared	0.198	0.092	0.142	0.354
F test: active+2*intensity-inactive=0	3.800	11.83	0.143	4.714
p value	0.0513	0.000583	0.706	0.0299

Robust standard errors clustered at the DHS cluster level in parentheses.
All regressions control for year and region fixed effects, regional time trends, living in an urban area, age, years of education, and religious beliefs.
*** p<0.01, ** p<0.05, * p<0.1

A.2 Additional heterogeneity, robustness, and outcomes.

This section presents results discussed in the paper. In particular, we present results with additional control variables and clusterings of the standard errors, results for different sub-samples, and results on related outcomes of interest.

Table A.6: Additional fixed effects and alternative clusterings of the standard errors.

VARIABLES	(1) Working	(2) Service	(3) Sales	(4) Agriculture	(5) Working	(6) Service	(7) Sales	(8) Agriculture
Panel A. Mineral and mine fixed effects.								
active (20 km)	0.029***	0.019***	-0.002	-0.001	0.035***	0.012**	-0.004	0.011
	(0.010)	(0.005)	(0.008)	(0.013)	(0.010)	(0.005)	(0.009)	(0.014)
inactive (20 km)	0.081***	0.001	-0.017	0.069***	0.073***	-0.000	-0.022	0.067**
	(0.020)	(0.005)	(0.016)	(0.025)	(0.020)	(0.005)	(0.015)	(0.027)
Observations	478,288	478,288	478,288	478,288	518,368	518,368	518,368	518,368
Mineral FE	YES	YES	YES	YES	NO	NO	NO	NO
Mine FE	NO	NO	NO	NO	YES	YES	YES	YES
F test: active-inactive=0	5.627	6.399	0.829	6.609	3.038	2.769	1.112	3.509
p value	0.0177	0.0114	0.362	0.0102	0.0814	0.0961	0.292	0.0611
Panel B. Clustering of standard errors at the regional, the closest mine, and closest mine as well as DHS cluster level.								
active (20 km)	0.026	0.020**	0.001	-0.009				
	(0.016)	(0.010)	(0.012)	(0.020)				
	(0.015)	(0.008)	(0.012)	(0.018)				
	[0.015]	[0.008]	[0.012]	[0.018]				
inactive (20 km)	0.081**	0.000	-0.014	0.065**				
	(0.033)	(0.007)	(0.025)	(0.022)				
	(0.034)	(0.006)	(0.026)	(0.032)				
	[0..034]	[0.006]	[0.026]	[0.032]				
Observations	518,368	518,368	518,368	518,368				
p value region	0.0923	0.0618	0.481	0.0128				
p value (mine level)	0.0973	0.0359	0.518	0.0205				
p value [mine and DHS cluster]	0.0962	0.0350	0.518	0.0198				

Panel A: robust standard errors clustered at the DHS cluster level in parentheses.
Panel B: robust standard errors clustered at the mine cluster level in parentheses and at the mine and year level in brackets.
All regressions control for year and region fixed effects, regional time trends, living in an urban area, age, years of education, and religious beliefs. *** p<0.01, ** p<0.05, * p<0.1

Table A.7: Effects of mining on marital status.

VARIABLES	(1) Divorced/separated	(2) Partner	(3) Single	(4) Widow
active (20 km)	0.002	-0.002	-0.006	0.006**
	(0.003)	(0.007)	(0.006)	(0.002)
inactive (20 km)	-0.004	0.004	0.000	-0.001
	(0.004)	(0.013)	(0.012)	(0.004)
Observations	512,534	512,534	512,534	512,534
R-squared	0.032	0.219	0.359	0.058
F test: active-inactive=0	1.236	0.149	0.242	2.073
p value	0.266	0.699	0.623	0.150

Robust standard errors clustered at the DHS cluster level in parentheses
All regressions control for year and region fixed effects, regional time trends, living in an urban area, age, years of education, and religious beliefs.
*** p<0.01, ** p<0.05, * p<0.1

Table A.9: Effects of mining for young women (15-20 years old).

VARIABLES	(1) Working	(2) Service	(3) Sales	(4) Agriculture	(5) Schoolyears
active (20 km)	0.004	0.007	-0.014*	-0.008	0.271***
	(0.014)	(0.007)	(0.009)	(0.013)	(0.103)
inactive (20 km)	0.056**	-0.006	-0.012	0.057**	-0.269*
	(0.027)	(0.005)	(0.017)	(0.028)	(0.158)
Observations	138,606	138,606	138,606	138,606	138,606
R-squared	0.194	0.070	0.109	0.290	0.488
F test: active-inactive=0	3.069	2.085	0.0149	4.463	8.288
p value	0.0798	0.149	0.903	0.0346	0.00400

Robust standard errors clustered at the DHS cluster level in parentheses
All regressions control for year and region fixed effects, regional time trends, living in an urban area, age, years of education, and religious beliefs.
*** p<0.01, ** p<0.05, * p<0.1

Table A.8: Effects of mining for those married before any mine within 20 km opened and for those married to miners.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Married before mine opening				Married to a miner			
VARIABLES	Working	Service	Sales	Agriculture	Working	Service	Sales	Agriculture
active (20 km)	0.003	0.029***	-0.008	-0.023	-0.075**	-0.029	0.027	-0.069***
	(0.015)	(0.009)	(0.013)	(0.018)	(0.035)	(0.020)	(0.028)	(0.024)
inactive (20 km)	0.033	-0.035***	0.022	0.101	0.185**	0.080	-0.164***	0.073
	(0.110)	(0.012)	(0.039)	(0.094)	(0.086)	(0.067)	(0.050)	(0.080)
Observations	291,395	291,395	291,395	291,395	4,628	4,628	4,628	4,628
R-squared	0.201	0.094	0.165	0.347	0.172	0.133	0.191	0.319
F test: active-inactive=0	0.0742	20.25	0.554	1.719	7.951	2.425	11.74	2.943
p value	0.785	6.83e-06	0.457	0.190	0.00485	0.120	0.000623	0.0864

Robust standard errors clustered at the DHS cluster level in parentheses. All regressions control for year and region fixed effects, regional time trends, living in an urban area, age, years of education, and religious beliefs.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A.10: Effects of mining on all occupational categories for women (Panel A) and men (Panel B).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	Working	Service	Profess.	Sales	Agric (self)	Agric (empl.)	Domestic	Clerical	Skilled manual	Unskilled manual
Panel A : Woman										
active (20 km)	0.026***	0.020***	0.000	0.001	-0.010	0.001	0.002	0.003	0.005	0.005*
	(0.010)	(0.005)	(0.003)	(0.008)	(0.012)	(0.007)	(0.002)	(0.002)	(0.004)	(0.002)
inactive (20 km)	0.081***	0.000	0.005	-0.014	0.060**	0.005	-0.003	0.009**	-0.005	0.023
	(0.020)	(0.005)	(0.005)	(0.015)	(0.024)	(0.008)	(0.002)	(0.004)	(0.011)	(0.016)
Observations	518,368	518,368	518,368	518,368	518,368	518,368	518,368	518,368	518,368	518,368
active-inactive=0	6.154	7.152	1.053	0.751	7.072	0.142	2.819	1.842	0.719	1.334
p value (F-test)	0.0131	0.00750	0.305	0.386	0.00783	0.706	0.0932	0.175	0.397	0.248
Panel B : Husband or partner										
active (20 km)	-0.004	-0.000	-0.004	0.004	-0.029**	-0.024**	-0.002	0.011**	0.037***	0.010*
	(0.004)	(0.006)	(0.003)	(0.007)	(0.014)	(0.012)	(0.002)	(0.006)	(0.010)	(0.005)
inactive (20 km)	-0.031***	0.014*	0.002	0.001	-0.018	0.021	-0.000	0.007	0.001	0.004
	(0.009)	(0.008)	(0.007)	(0.009)	(0.026)	(0.016)	(0.003)	(0.013)	(0.011)	(0.009)
Observations	367,822	367,822	367,822	367,822	367,822	367,822	367,822	367,822	367,822	367,822
active-inactive=0	7.540	2.046	0.761	0.101	0.132	4.956	0.116	0.113	5.812	0.367
p value (F-test)	0.00604	0.153	0.383	0.750	0.717	0.0260	0.734	0.737	0.0159	0.545

Robust standard errors clustered at the DHS cluster level in parentheses. All regressions control for year and region fixed effects, regional time trends, living in an urban area, age, years of education, and religious beliefs. *** p<0.01, ** p<0.05, * p<0.1

Table A.11: Effects of mining in a sub-sample of countries when controlling for living close to a road.

VARIABLES	(1) Working	(2) Service	(3) Sales	(4) Agriculture
active (20 km)	0.104***	0.031**	0.001	0.018
	(0.039)	(0.016)	(0.026)	(0.033)
inactive (20 km)	0.196***	0.001	-0.008	0.139***
	(0.046)	(0.019)	(0.022)	(0.022)
road within 50 km	-0.004	-0.001	-0.018***	0.025***
	(0.007)	(0.001)	(0.004)	(0.009)
Observations	151,355	151,355	151,355	151,355
R-squared	0.169	0.049	0.146	0.318
F test: active-inactive=0	2.330	1.417	0.0692	9.245
p value	0.127	0.234	0.793	0.00237

Robust standard errors clustered at the DHS cluster level in parentheses. All regressions control for year and region fixed effects, regional time trends, living in an urban area, age, years of education, and religious beliefs.
*** p<0.01, ** p<0.05, * p<0.1

Table A.12: Different effects of mining in countries with many women working in services.

VARIABLES	(1) Working	(2) Service	(3) Sales	(4) Agriculture
active (20 km)	0.023*	0.017**	0.006	-0.010
	(0.014)	(0.007)	(0.010)	(0.016)
inactive (20 km)	0.022**	0.000	-0.003	0.023**
	(0.009)	(0.003)	(0.007)	(0.011)
highservice*active (20 km)	-0.005	-0.022**	0.010	0.012
	(0.019)	(0.009)	(0.017)	(0.025)
highserv	-0.300*	0.161***	0.141	-0.174
	(0.165)	(0.055)	(0.099)	(0.154)
Observations	372,635	372,635	372,635	372,635
R-squared	0.208	0.081	0.139	0.357
F test: active-inactive=0	0.000812	4.376	0.543	2.566
p value	0.977	0.0365	0.461	0.109

Robust standard errors clustered at the DHS cluster level in parentheses All regressions control for year and region fixed effects, regional time trends, living in an urban area, age, years of education, and religious beliefs.
*** p<0.01, ** p<0.05, * p<0.1

A.3 Cross-sectional results using data from U.S. Geological Survey (USGS) and CSCW diamond data.

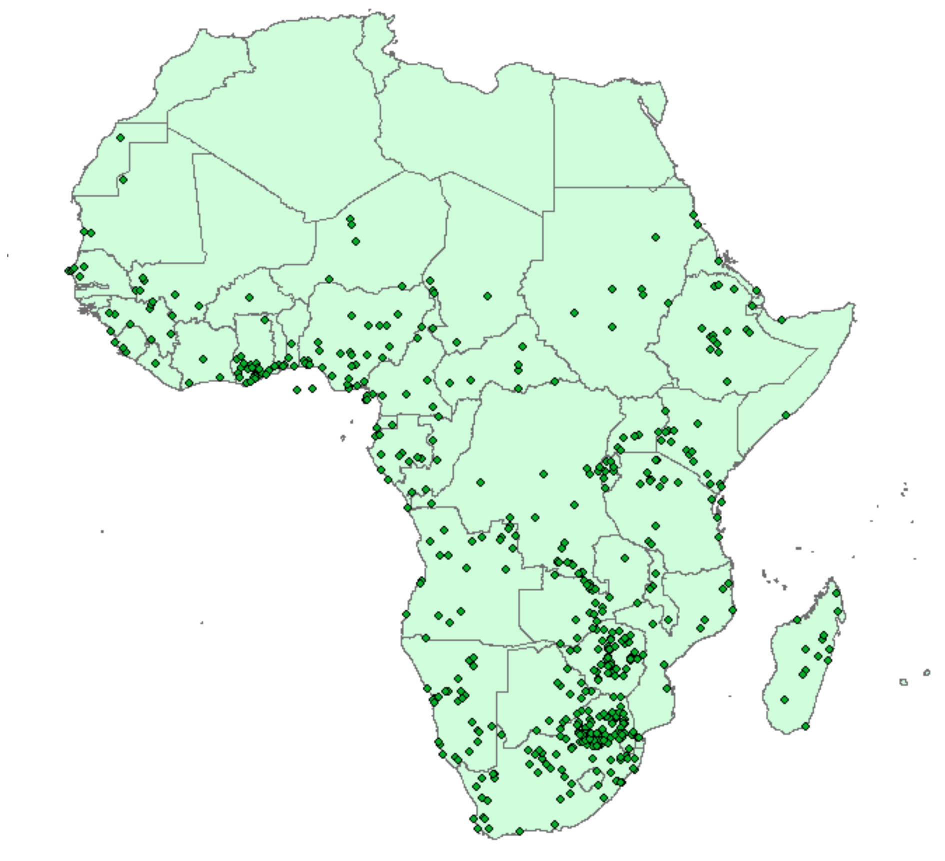
Since our empirical strategy requires data on production over time, we are not able to include all mines in the region. Hence, our results may not be generalizable to the effects of other, in particular smaller, mines. While we cannot completely overcome this problem, we show below that the cross-sectional results using all mines in the region obtained from USGS point in the same direction as our difference-in-difference results with the RMG data. The cross-sectional results are shown in Panel A of Table A.13 and the distribution of the USGS mines are shown in Figure A.1. We find that being close to a USGS mine is positively associated with being in services and sales and negatively associated with agriculture. These results are in line with anecdotal evidence pointing to female engagement in services and sales and that mining activities may compete with agriculture in terms of land use.

Table A.13: Cross-sectional correlation between being close to a USGS mine or a CSCW mine and our main outcomes.

VARIABLES	(1) Working	(2) Service	(3) Sales	(4) Agriculture
Panel A. USGS data.				
usgs (20 km)	-0.003	0.009***	0.008***	-0.026***
	(0.004)	(0.002)	(0.003)	(0.005)
Observations	525,180	525,180	525,180	525,180
R-squared	0.197	0.091	0.141	0.355
Panel B. CSCV diamond data.				
dia (20 km)	0.001	0.006*	0.028***	-0.053***
	(0.009)	(0.004)	(0.010)	(0.013)
Observations	525,180	525,180	525,180	525,180
R-squared	0.197	0.091	0.141	0.355

Robust standard errors clustered at the DHS cluster level in parentheses.
All regressions control for year and region fixed effects, regional time trends, living in an urban area, age, years of education, and religious beliefs.
*** p<0.01, ** p<0.05, * p<0.1

Figure A.1: USGS mines in Africa



There is significant diamond mining in Africa, and while the RMD includes some diamond mines it does capture all diamond mines. The RMG data set excludes all mines that produce only diamonds. To correct for this and explore the effects of diamond mining on local women's employment opportunities, we use the CSCW data set. This diamond data set has GPS coordinates for the mines, but does not contain production data. The identification strategy here is thus similar to the one for the USGS data sets. The results are presented in Panel B of Table A.13. We find that being close to a mine is associated with a higher probability of engaging in sales and lower probability for agriculture. The distribution of the diamond mines across the continent are shown in Fugure A.2.

Figure A.2: Diamond mines from CSCW