WPS7251





Policy Research Working Paper 7251

# African Mining, Gender, and Local Employment

*Andreas Kotsadam*
*Anja Tolonen*

WORLD BANK GROUP
Development Research Group
Trade and International Integration Team
April 2015

Policy Research Working Paper 7251

## Abstract

It is a contentious issue whether large scale mining creates local employment, and the sector has been accused of hurting women's labor supply and economic opportunities. This paper uses the rapid expansion of mining in Sub-Saharan Africa to analyze local structural shifts. It matches 109 openings and 84 closings of industrial mines to survey data for 800,000 individuals and exploits the spatial-temporal variation. With mine opening, women living within 20 km of a mine switch from self-employment in agriculture to working in services or they leave the work force. Men switch from agriculture to skilled manual labor. Effects are stronger in years of high world prices. Mining creates local boom-bust economies in Africa, with permanent effects on women's labor market participation.

This paper is a product of the Trade and International Integration Team, Development Research Group. It is part of a larger effort by the World Bank to provide open access to its research and make a contribution to development policy discussions around the world. Policy Research Working Papers are also posted on the Web at http://econ.worldbank.org. The authors may be contacted at anja.tolonen@economics.gu.se.

# African Mining, Gender, and Local Employment

Andreas Kotsadam* and Anja Tolonen†‡

*Department of Economics, University of Oslo. andreas.kotsadam@econ.uio.no

†Department of Economics, University of Gothenburg. anja.tolonen@economics.gu.se

‡Acknowledgments: First version of this paper was circulated under the name 'Mineral Mining and Female Employment', OxCarre Working Papers 114, June 2013. We are thankful to James Fenske, Edward Miguel, Andreea Mitruut, Måns Söderbom and Francis Teal for insights and support. We thank Christa Brunnschweiler, James Cust, Henning Finseraas, Niklas Jakobsson, Amir Jina, Jo Thori Lind, Deirdre McCloskey, Halvor Mehlum, Dale Mortensen, Hanna Mühlrad and Juan Pablo Rud for helpful comments. The paper has benefited from comments by seminar and conference participants at UC Berkeley, Gothenburg University, Oxford University, the Norwegian University of Science and Technology in Trondheim and the Institute for Social Research in Oslo, and conference participants at the 8th Annual Conference on Economic Growth and Development 2012, CSAE 2013, the Annual World Bank conference on Land and Poverty, 2013, NEUDC 2013, WGAPE fall 2013, PacDev 2014 and 9th IZA/WB conference on Development and Labor. The project is part of research activities at the ESOP center at University of Oslo. ESOP is supported by The Research Council of Norway. Anja Tolonen is thankful for project funding from Lars Hjerta Research Support. We thank OxCarre for hospitality and access to RMD data. We also thank Frikk Nesje for excellent research assistance. A significant part of the research for this paper was conducted while Anja Tolonen was visiting the Trade and International Integration team of DECRG, The World Bank.

# 1 Introduction

Africa's opportunities are being transformed by new discoveries of natural resources and their rising prices (Collier, 2010), and the mining sector is 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]

While the country-level economic and political effects of extractive industries are well explored, the research on their local economic effects is nascent. The present paper adds to recent literature on local effects of natural resources (e.g. Allcott and Keniston 2014; Aragon and Rud, 2013b; Berman et al., 2014; Caselli and Michaels, 2013; Michaels, 2011; Wilson, 2012), by investigating the effects of large-scale mineral mining on local labor markets. We use the best available survey data for Africa, Demographic and Health Surveys (DHS).[2] The main focus is on women's labor market opportunities, and we contrast our findings with the effects for men. 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).

It is theoretically ambiguous whether industrial mining increases or decreases female employment. 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 that extractive industries may consolidate gender disparities in economic opportunities, with losses to women as a by-product of such 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 manufacturing 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 is also valid 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

[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).

[2] DHS focuses predominantly on women but we add information on partners' employment as well as employment for a smaller sample of men.

Bigsten and Söderbom, 2006 or Isham et al., 2005 for an overview).[3] Second, if women have the opportunity to 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 (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 few or no linkages to the local community. This "enclave" theory was first hypothesized by Hirschman (1958) and became a stylized fact in the second part of the last century (UNECA, 2011). There is limited empirical evidence for this theory. The coal mining boom of the 70's in the US resulted in modest local employment spillovers but increasing wage rates (Black et al., 2005), and contemporary oil and gas booms in the US has increased district employment levels (Allcott and Keniston, 2014). A study of local welfare effects around the world's second largest gold mine in Peru found support for the enclave 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 male and female labor force participation with female employment concentrated in services and sales and male employment concentrated in manual labor, reflecting the gender segregation in the Sub-Sahara African labor markets. Qualitative studies have 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.[4] Spillover effects on the tradable sector are less likely to substantially affect the demand for female labor because women are not strongly represented in the tradable sector, including manufacturing and construction.

The effect on 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.

A novelty of the present paper is that it connects production data on 874 industrial mines

[3] 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.

[4] 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).

starting in 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 and almost 300,000 partners in 29 countries enables us to investigate local spillover effects on employment by a difference-in-difference method. By exploiting the spatial and temporal variation in the data, we compare people living close to a mine with those living further away, and individuals 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 on 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, or out of the labor force. The effect on services is substantial; it is estimated at a more than 50% increase from the sample mean. The results are robust to a wide battery of robustness checks, such as using different measures of distance and excluding migrants. Our results of a shift toward service sector employment are supported by findings that women are more likely to earn cash and women who work are less likely to work seasonally after a mine has started producing. A back-of-the-envelope calculation estimates that more than 90,000 women get service sector jobs as a result of industrial mining in their communities, and more than 280,000 women leave the labor force. The effects of mine openings wear off with distance and are no longer statistically significant at 50 kilometers from a mine, and mine closing causes the service sector to contract. The partners of the surveyed women shift away from agriculture into skilled manual work with mine opening; this effect reverses once a mine closes. The overall decrease in work force participation induced by mine opening is gender-specific; work participation for women decreases by 5.4 percentage points with mine opening (equivalent to 8.1% change), whereas the corresponding effect for men is a decrease of 3.2 percentage points (equivalent to a 3.3% change). Using changes in world prices for ten minerals we further show that the effects are stronger in years when prices are higher.

There are large and persistent differences in value added per worker in agriculture and non-agriculture sectors in developing countries (Gollin et al., 2012). This difference indicates misallocation of workers, with too many workers in low yielding agriculture. In this paper, we show that mine opening can pull people from low value added sectors to higher value added sectors, such as services and skilled manual labor. We conclude that mining has the power to stimulate non-agricultural sectors, and provide cash earning opportunities. However, mining creates a boom-bust economy on the local level in Africa, as the newly stimulated sectors contract with mine closing.

In the next section we present the data. In Section 3, we lay out the empirical strategy. In Section 4, we present the empirical results and in Section 5, we show robustness tests and heterogeneous effects, and in Section 6, we make concluding remarks.

# 2 Data

We use a novel longitudinal data set on large-scale mineral mines in Africa, from InterraRMG. We link the resource data to survey data for women and their partners 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 individuals 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 person. These are concentric circles with radii of 5, 10, 15, 20, 25 km and so on, up to 200 kilometers and beyond 200 km.

We construct an indicator variable that answers the questions: Is there at least one active mine within x kilometers from the household? If not, is there at least one future mine (coded as inactive), or one past mine (coded as suspended) within x kilometers? If still no, the person 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 was producing in the year she was sampled. We assume that individuals seek employment around any mine situated within x kilometers from the home location and that benefits from an active mine dominate those from an inactive mine. A future mine is assumed to have little effect on the local economy, even if there may be economic activity associated with the pre-production stages. Thus, a person close to an active mine as well as an inactive mine will be assigned active=1 and inactive=0, since the categories are mutually exclusive. When we look at mine opening effects, all women close to suspended mines are excluded from the analysis.

Beyond the cut-off distance of x kilometers, transportation costs are assumed to be higher than benefits accruing from employment opportunities. Behind this assumption lie two 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. 8,195 women (1.6% of the sample) live within 20 kilometers of at least one active mine, 2,334 (0.5%) live within 20 kilometers of at least one inactive mine (but no active and no suspended mines), and 6,812 (1.3%) live close to a suspended mine.

## 2.1 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 yearly 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

Table 1: Descriptive statistics for women.

| 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 $<$ 20 km. | 0.016 | 0.125 |
| inactive (20 km) | At least 1 inactive mine $<$ 20 km, no active/suspended. | 0.005 | 0.067 |
| suspended (20 km) | At least one suspended mine $<$ 20 km, no active. | 0.013 | 0.113 |
| *Main dependent variables* | | | |
| Working | 1 if respondent is currently working. | 0.659 | 0.474 |
| Services | 1 if respondent is working in the service sector. | 0.036 | 0.187 |
| Profess. | 1 if respondent is a professional. | 0.027 | 0.161 |
| Sales | 1 if respondent is working with sales. | 0.168 | 0.374 |
| Agric. (self) | 1 if respondent is self-employed in agriculture. | 0.276 | 0.447 |
| Agric. (emp) | 1 if respondent is employed in agriculture. | 0.054 | 0.023 |
| Domestic | 1 if respondent is employed as a domestic worker. | 0.010 | 0.101 |
| Clerical | 1 if respondent is employed as a clerk. | 0.010 | 0.097 |
| Skilled manual | 1 if respondent is employed in skilled manual labor. | 0.046 | 0.209 |
| Unskilled manual | 1 if respondent is employed in unskilled manual labor. | 0.030 | 0.172 |
| *Other dependent variables* | | | |
| Cash | 1 if respondent is paid in cash. | 0.462 | 0.499 |
| Cash & Kind | 1 if respondent is paid both in cash and in kind. | 0.167 | 0.373 |
| Kind | 1 if respondent is paid in kind. | 0.083 | 0.275 |
| Not paid | 1 if respondent is not paid. | 0.289 | 0.453 |
| Seasonally | 1 if respondent is working seasonally. | 0.320 | 0.467 |
| All year | 1 if respondent is working all year. | 0.569 | 0.495 |
| Occasionally | 1 if respondent is working occasionally. | 0.111 | 0.314 |
| *Control variables* | | | |
| urban | 1 if respondent is living in an urban area. | 0.327 | 0.469 |
| age | Age in years. | 28.400 | 9.560 |
| schoolyears | Years of education. | 4.200 | 4.344 |
| christian | 1 if respondent is Christian. | 0.591 | 0.492 |
| muslim | 1 if respondent is Muslim. | 0.338 | 0.473 |
| *Migration* | | | |
| non mover | 1 if respondent always lived in the same place. | 0.457 | 0.498 |
| *Marital status* | | | |
| partner | 1 if respondent has a partner. | 0.671 | 0.470 |
| N | | 512,922 | |

from 1984 to 2010.

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 densely 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 knowledge, the only existing mine production panel dataset. While the quality with respect to the exact levels of production is uncertain, the state of the mine (inactive, active, or suspended) is reliable. The metric used in reporting production volumes differs between companies producing the same mineral. Comparisons of production volumes are thus not possible.

The RMD data focuses on mines of industrial size and production methods, often with foreign or government ownership. Most mines are owned by Canadian, Australian or UK listed firms. 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). The industrial mine industry is heavy in capital and firms are often large and multinational. There are several production stages: exploration, feasibility, construction, operation and closure. In contrast to the later stages, the exploration phase is often undertaken by smaller firms who obtain a three year exploration license. Large mining firms enter mostly in the post-exploration phase. In the feasibility phase, the company determines if the deposit is viable for commercial exploration. If it is deemed so, the company will apply for a mining license. The average length of such a license is 23 years in Africa, and can be renewed upon termination. The licenses are obtained from the government and the application process takes on average 2 to 3 years (Gajigo et al., 2012). The mine life, i.e., the length of the production phase, depends on the ore deposits and the world price, among other things. In our data set, the average life length of a mine is ten years. After production, there is a reclamation process (Gajigo et al., 2012). Focusing on industrial scale production, the mines in the dataset 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 operations that are labor

[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 the ILO (1999). A more recent report from the UN and African Union (UNECA, 2011) estimates that 8.1 million people are engaged in ASM.

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 beyond those of industrial size, but has the drawback of not including time-varying production levels. Similarly, the CSCW data includes all diamond mines, but no production levels.

## 2.2 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. We combine the women's questionnaires from all 67 surveys in Sub-Saharan Africa that contain information on employment and GPS coordinates. The total dataset includes 525,180 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]

In Figure 1 we show the distribution of the mines and the DHS surveys used across Africa. 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 in Table 1. Note that a woman can only belong to one sector, which she states as her main occupation. The main focus of this paper is three occupational categories, given their relative importance. These are agriculture (total 33%), sales (16.8%) and services (3.6%). However, all categories are reported in Table 2 and the results for all categories are also presented for the baseline regressions. The surveys include 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.[7] Table 2 shows labor market outcomes

[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 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. 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 30 to 22,966 sampled women. The average sample size of a region is 1,769 and the median is 1,201.

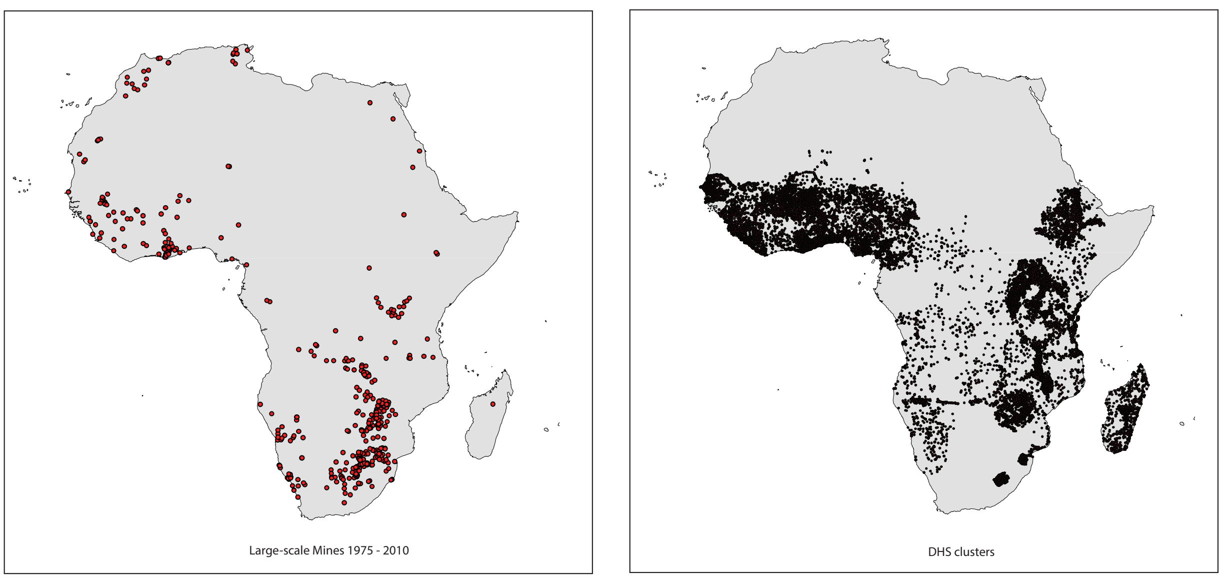
[7]Not all survey rounds include information on migration. In the sample, the year of the last move is available

Table 2: Descriptive statistics: Occupational outcomes for partners.

| Variable | Definition | Mean | St. dev. |
|---|---|---|---|
| Working | 1 if partner is currently working. | 0.966 | 0.474 |
| Services | 1 if partner is working in the service sector. | 0.054 | 0.187 |
| Profess. | 1 if partner is a professional. | 0.073 | 0.161 |
| Sales | 1 if partner is working in sales. | 0.110 | 0.374 |
| Agric. (self) | 1 if partner is self-employed in agriculture. | 0.409 | 0.447 |
| Agric. (emp) | 1 if partner is employed in agriculture. | 0.113 | 0.226 |
| Domestic | 1 if partner is employed as a domestic worker. | 0.008 | 0.100 |
| Clerical | 1 if partner is employed as a clerk. | 0.020 | 0.097 |
| Skilled manual | 1 if partner is employed in skilled manual labor. | 0.137 | 0.209 |
| Unskilled manual | 1 if partner is employed in unskilled manual labor. | 0.044 | 0.172 |
| N (partner) | | 277,722 | |

for the women's partners for all occupational categories. Partner's labor force participation is near universal at 96.6% and many (40.9%) are self-employed in agriculture. In addition, 11.3% are employed as agricultural workers and 13.7% are skilled manual workers.[8]

Figure 1: Mines and DHS clusters




for 428,735 women.

[8]Examples of skilled manual jobs are bakers, electricians, well drillers, plumbers, blacksmiths, shoe makers, tailors, tanners, precious metal workers, brick layers, printers, and painters.

# 3 Empirical Strategy

With several waves of survey data combined with detailed information on mines, the estimation relies on a spatial-temporal estimation strategy, using multiple definitions of the mine footprint area based on different proximity measures and alternative definitions of the control group.

Assuming that people 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 a mine that is not yet active), but not close to any active mines or suspended mines, and (3) more than 20 kilometers from any mine. The baseline regressions are of the form:

$$Y_{ivt} = \beta_1 \cdot active + \beta_2 \cdot inactive + \alpha_r + g_t + \delta_{r*time} + \lambda X_i + \varepsilon_{ivt}$$

where the outcome $Y$ of an individual $i$, cluster $v$, and for year $t$ is regressed on a dummy *(active)* for whether the person lives within 20 kilometers of at least one active mine, a dummy *(inactive)* for whether the person lives close to a mine that has not started 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.

Interpreting the coefficient only 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 potentially strong assumption because wage labor and population density may influence mining companies' investment decisions or could jointly vary with a third factor such as accessibility or infrastructure. Including 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 to 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.

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). With region fixed effects, we expect that only time-variant differences within regions are a threat 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. 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 that discovery depends 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 control for such factors. We control for region fixed effects and region specific time trends and thereby allow for different time trends across sub-national regions.

The interpretation of the coefficients from our estimation strategy relies on the population being the same before and after mine opening. We are using a repeated cross-sectional dataset, and we discuss in the robustness section how we deal with this issue by using the available information on migration. Additionally, we worry that the control group in the baseline definition is 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. Furthermore, the estimation strategy could capture other changes that happen parallel to and irrespective of the mine opening. Mine industrialization and employment changes could be driven by improvements in infrastructure. We use the best available data on road networks in Africa and explore whether the results are stable. Different fixed effects, for the closest mines and for different types of minerals, are also included to verify the robustness of the results. 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.

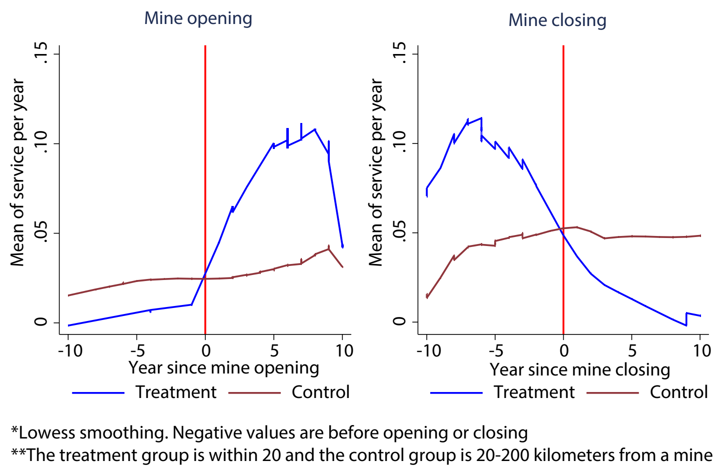
# 4 Results

We start by exploring the evolution of employment over time. Figure 2 shows the trends in service level employment for those within 20 kilometers and those between 20 and 200 kilometers from a mine. The treatment group follows a similar trend as the control group in service sector employment until mine opening, but at a lower level. Service employment increases sharply once the mine opens[9]. The levels equalize somewhat at the tenth year, which, in part could be due to a geographic dispersion of the effects with time (the control group is limited to within 200 km). Such a dispersion effect would explain the increase in service employment in the control group. The decline in the treatment group close to the tenth year may be a result of mine closings since mine length in our sample is, on average 10 years. This hypothesis is supported by the right-side figure showing 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 decreases as the date of closing appears and reverses once the mine closes. Similar trends are obtained if we have the residuals after controlled regressions instead of levels (figures are available upon request).

[9]An increase in service sector employment is noted shortly before mine opening, which corresponds to the investment phase of the mine.

Appendix figures A.2 and A.3 show these trends for our four main outcomes of interest.

Figure 2: Trends in service sector employment before and after openings and closings for those close to and further away from mines




The main results following the empirical strategy previously outlined are reported in Table 3, with Panel A showing women's outcomes and Panel B the outcomes for these women's partners. The first variable, *active (20 km)*, captures the difference in outcomes between individuals living close to a producing mine and those living farther away. In Panel A, we see that the coefficient is positive and statistically significantly correlated with the woman working, working in the service sector, and working with unskilled manual work (significant only at the 10 percent level). The second variable, *inactive (20 km),* shows the difference between women living close to future mines and women living further away. We see that women in mining areas before the mine starts producing are more likely to work, especially as self-employed agricultural workers.

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)*. Test results are presented for this difference ($\beta_1 - \beta_2 = 0$) henceforth. This difference shows that there is a decline of 5.4 percentage points in the probability that a woman is working when a mine opens in the area (which is calculated by the difference between *active* and *inactive*: 2.6 - 8.0 = 5.4). Investigating the sectoral composition of the effect, it emerges that the decline in overall employment is driven by a decline in agricultural self-employment, an effect which is partly offset by an increase in service sector employment. The increase in the likelihood of working in the service sector is substantial at 2 percentage points. The sample mean of engaging in service sector jobs is 3.6 %, so the increase in the likelihood is over 50 %. Trying to quantify the effect of mine opening on female service sector employment, we make a back-of-the-envelope calculation and estimate that 94,402 women have benefited from service sector jobs generated by the industrial mining sector, while 283,206 women left the labor market.[10]

[10]According to the World Bank Indicators for 2011, the Sub-Saharan African female population aged 15-65

With respect to selection, it is also interesting to interpret the coefficient for *inactive* as the correlation between living in 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 an 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 artisanal and small scale mining activities that may employ women directly, in addition to indirectly generating employment. The first hypothesis is supported by the baseline results, where a large share of the population engages in subsistence farming. We explore the second hypothesis by looking at trends in employment (Figure 2 and Figure A.2). According to the visual evidence, there is an increase in service sector employment and a decrease in agricultural employment during the pre-production phase, but the effects are small in magnitude and confined to the last years before mine opening. Regarding the third hypothesis, we explore direct employment in mining, and see that mining employment for women does not change with mine opening (see Table 5).

For partners, there is a decreased probability of working, driven by a drop in agricultural employment. A substantial and positive effect of mine opening on men's employment in skilled manufacturing is identified.

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 whereby small distance spans introduce more noise; (2) the geocoordinates in the mining data reflect the centroid of the mining area. With too small an area, we are likely to capture the actual mining site rather than the surrounding communities; (3) the sample size increases rapidly with distance, which increases the robustness of the results; and (4) using distances longer than 20 kilometers, we fail to capture the mine footprint. In Section A.2 in the Appendix we discuss this extensively and we show different results based on other cutoffs and specifications.

We next examine the effects of a mine closing on employment. The results are shown in Table 4. The effects are not entirely symmetrical to the effects of mine openings. Initially, mine openings induced an increase in the likelihood of service sector employment for women, an effect that is offset by the time of mine suspension. Agricultural self-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 for women; i.e., women are inhibited from going back to

is estimated to 236,241,202 people. In our sample, approximately 1.6 % percent live within 20 kilometers of an active mine. Our baseline estimates indicate that 2 % of the women close to mines benefit from service sector employment, amounting to 73,727 women, and that 202,749 women left the labor market. Using a 25 kilometer distance span from an active mine, we estimate that 94,402 women gained employment in the service sector, and 283,206 women left the labor market.

Table 3: Effects of mine opening 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 | Agriculture self-employment | Agriculture employment | Domestic | Clerical | Skilled manual | Unskilled manual |
| Panel A : Woman | | | | | | | | | | |
| active (20 km) | 0.026*** | 0.020*** | 0.000 | 0.000 | -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) | 0.080*** | -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 | 512,922 | 512,922 | 512,922 | 512,922 | 512,922 | 512,922 | 512,922 | 512,922 | 512,922 | 512,922 |
| sample mean | 0.659 | 0.036 | 0.027 | 0.168 | 0.276 | 0.054 | 0.010 | 0.010 | 0.046 | 0.030 |
| active-inactive=0 | 6.164 | 7.147 | 1.065 | 0.745 | 7.087 | 0.138 | 2.821 | 1.837 | 0.728 | 1.338 |
| p value (F-test) | 0.013 | 0.008 | 0.302 | 0.388 | 0.008 | 0.710 | 0.093 | 0.175 | 0.394 | 0.247 |
| Panel B : Husband or partner | | | | | | | | | | |
| active (20 km) | 0.003 | 0.013** | 0.008 | 0.005 | -0.039** | -0.021 | -0.002 | -0.005* | 0.034*** | 0.011* |
| | (0.005) | (0.006) | (0.006) | (0.008) | (0.016) | (0.013) | (0.002) | (0.003) | (0.012) | (0.006) |
| inactive (20 km) | 0.034*** | 0.002 | 0.020* | 0.008 | -0.013 | 0.015 | -0.001 | -0.003 | -0.002 | 0.007 |
| | (0.010) | (0.014) | (0.011) | (0.011) | (0.030) | (0.018) | (0.005) | (0.008) | (0.010) | (0.012) |
| observations | 277,722 | 277,722 | 277,722 | 277,722 | 277,722 | 277,722 | 277,722 | 277,722 | 277,722 | 277,722 |
| sample mean | 0.966 | 0.054 | 0.073 | 0.110 | 0.409 | 0.113 | 0.008 | 0.020 | 0.137 | 0.044 |
| active-inactive=0 | 8.075 | 0.502 | 0.990 | 0.054 | 0.587 | 2.521 | 0.121 | 0.104 | 5.229 | 0.081 |
| p value (F-test) | 0.004 | 0.479 | 0.320 | 0.816 | 0.444 | 0.112 | 0.728 | 0.747 | 0.022 | 0.775 |

Robust standard errors clustered at the DHS cluster level in parentheses. All regressions control for year and region fixed effects, regional time trends, urban dummy, age, years of education, and religious beliefs. The coefficients of interest are active (20 km) and the difference between active (20 km) and inactive (20 km) capturingthe shift that happens with mine opening. The p-values presented show if this difference is significantly different from zero. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

agricultural production after a mine closing. In contrast, male partners increase agricultural self-employment after mine closings, but experience a contraction in skilled manual and agricultural employment. There is a small increase in clerical jobs and a small decrease in professional work, but the magnitudes are negligible.

We further explore whether jobs are created in mining per se. A subset of the surveys includes information on whether a woman or her partner work 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.[11] We run regressions on whether a woman or her partner is engaged in mining using three different mine datasets (RMG, USGS or the CSCW diamond dataset). Table 5 shows that industrial scale mining has no effect on employment in mining for women, as there is no statistically significant difference between active and inactive in Column 1. 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. Using the diamond dataset from CSCW, no correlation is found for women. In contrast, being within 20 kilometers 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 4.1 percentage points, which is a large increase relative to the sample mean of 2.6%.

Despite women seldom taking part in the large-scale mining, their labor market outcomes are substantially affected by industrial mining. The sectoral composition of the labor market effects for women is different from that of their partners. We continue by further assessing the robustness of the findings for women because we do not have all the necessary variables for the partners. In Section 5.2, however, we will conduct some extra analysis for a smaller sample of men for whom we have information on cash earnings and seasonality of work. We furthermore choose to restrict the focus to our four main outcome variables due to their relative importance. Results for all other variables are available upon request.

## 4.1 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 women are paid for work outside the household and whether they work all year, seasonally, or occasionally. The sample is smaller because the question is not asked in all DHS survey rounds. Being close to an inactive mine is associated with a higher probability of earning in-kind only and negatively correlated with earning cash (Panel A of Table 6), and women are less likely to work seasonally after mine opening,

[11] 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 workers; mining and quarrying workers; and laborers in mining, construction and manufacturing.

Table 4: The effect of mine suspension 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 | Agriculture self-employment | Agriculture employment | Domestic | Clerical | Skilled manual | Unskilled manual |
| Panel A : Woman | | | | | | | | | | |
| suspended (20 km) | 0.026* | 0.002 | -0.004 | 0.007 | 0.016 | -0.003 | 0.004 | -0.001 | -0.001 | 0.007 |
| | (0.014) | (0.006) | (0.003) | (0.009) | (0.017) | (0.006) | (0.003) | (0.002) | (0.004) | (0.006) |
| active (20 km) | 0.024** | 0.020*** | -0.000 | 0.001 | -0.011 | 0.001 | 0.002 | 0.003 | 0.005 | 0.004* |
| | (0.010) | (0.005) | (0.003) | (0.008) | (0.012) | (0.007) | (0.002) | (0.002) | (0.004) | (0.002) |
| observations | 519,734 | 519,734 | 519,734 | 519,734 | 519,734 | 519,734 | 519,734 | 519,734 | 519,734 | 519,734 |
| sample mean | 0.659 | 0.036 | 0.027 | 0.168 | 0.276 | 0.054 | 0.010 | 0.010 | 0.046 | 0.030 |
| suspended-active=0 | 0.00945 | 5.358 | 0.714 | 0.290 | 1.813 | 0.186 | 0.365 | 1.907 | 1.219 | 0.141 |
| p value | 0.923 | 0.021 | 0.398 | 0.590 | 0.178 | 0.666 | 0.545 | 0.167 | 0.270 | 0.707 |
| Panel B : Husband or partner | | | | | | | | | | |
| suspended (20 km) | 0.012** | -0.001 | -0.008 | 0.014 | 0.004 | -0.023** | 0.001 | 0.006 | -0.005 | 0.023** |
| | (0.006) | (0.005) | (0.006) | (0.011) | (0.018) | (0.011) | (0.004) | (0.005) | (0.010) | (0.011) |
| active (20 km) | 0.001 | 0.003 | 0.007 | 0.007 | -0.059*** | 0.005 | -0.003* | -0.007** | 0.036*** | 0.013** |
| | (0.005) | (0.006) | (0.006) | (0.008) | (0.014) | (0.008) | (0.002) | (0.003) | (0.012) | (0.006) |
| observations | 281,021 | 281,021 | 281,021 | 281,021 | 281,021 | 281,021 | 281,021 | 281,021 | 281,021 | 281,021 |
| sample mean | 0.966 | 0.054 | 0.073 | 0.110 | 0.409 | 0.113 | 0.008 | 0.020 | 0.137 | 0.044 |
| suspended-active=0 | 2.100 | 0.185 | 3.029 | 0.252 | 8.247 | 4.161 | 0.879 | 6.021 | 7.395 | 0.659 |
| p value (F-test) | 0.147 | 0.667 | 0.082 | 0.616 | 0.004 | 0.041 | 0.349 | 0.014 | 0.007 | 0.417 |

Robust standard errors clustered at the DHS cluster level in parentheses. All regressions control for year and region fixed effects, regional time trends, urban dummy, age, years of education, and religious beliefs. Please see Table 3 for more information about coefficients of interest.
*** p<0.01, ** p<0.05, * p<0.1

Table 5: 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 is miner | Husband is miner | Woman is miner | Husband is miner | Woman is miner | Husband is miner |
| active (20 km) | 0.004* | 0.046*** | | | | |
| | (0.003) | (0.011) | | | | |
| inactive (20 km) | 0.011 | 0.005 | | | | |
| | (0.009) | (0.021) | | | | |
| usgs mine (20 km) | | | 0.001 | 0.008*** | | |
| | | | (0.001) | (0.003) | | |
| diamond mine (20 km) | | | | | -0.000 | 0.037*** |
| | | | | | (0.002) | (0.012) |
| Observations | 259,114 | 149,692 | 264,695 | 152,228 | 264,695 | 152,228 |
| R-squared | 0.026 | 0.071 | 0.026 | 0.069 | 0.026 | 0.070 |
| F test: active-inactive=0 | 0.406 | 2.913 | | | | |
| p value | 0.524 | 0.0879 | | | | |

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. Please see Table 3 for more information about coefficients of interest. *** p<0.01, ** p<0.05, * p<0.1

and more likely to work occasionally (Panel B). This is a finding in line with previous results, signaling that mining areas have a higher share of agricultural workers prior to production. The probability of earning cash increases by 7.4 percentage points (0.014 - (-0.060)) with mine opening and this effect is statistically significant. We also see a statistically significant reduced probability of being paid in-kind only or being paid both cash and in-kind. The effects indicate that the labor market opportunities for women change with mining. Mine opening induces a shift from more traditional sources of livelihoods, such as subsistence farming which is seasonal by nature and oftentimes paid in kind, to more cash-based, all year or occasional sectors such as services.

In more recent years, DHS has surveyed men based on the same questionnaire used for women's labor market outcomes. The male sample is, however, much smaller. This sample of 128,135 men (Table 6) indicate that men have higher cash earning opportunities (Panel C) and are less likely to work seasonally after mine openings (Panel D), in line with the results for women. The surveys of men produce very similar results to the partner regressions for the main occupational outcomes (results are available upon request).

## 4.2 Migration

Inward migration can be spurred by natural resource and mining booms and there is evidence of the creation of mining cities (Lange, 2006 in Tanzania), urban-rural migration (around small-scale mines; Hilson, 2009) as well as work-migration (Corno and de Walque, 2012). Such migration patterns can cause a selection issue where women and their partners have moved to mining areas for work. While urbanization and inward migration are possible channels through which the multipliers work, we are also interested in knowing if the original population benefited from the expansion. The data is repeated cross-sectional data. By restricting the sample to women who have never moved, we try to show that our effects are not driven by women who have migrated inward. The results can be seen in Table 7 and resemble the baseline results both in terms of direction of effects and statistical significance.

We conduct several other robustness tests of our baseline results and these are extensively discussed in Appendix Section A.3. Most importantly, the results are qualitatively unchanged if we restrict the sample to only having control groups closer to the mines or if we control for distance to roads and add fixed effects for mineral and closest mine. The results are also robust to different clusterings and we examine the intensity of mining finding that living closer to several mines magnifies the effects.

Table 6: Effects of mining on payment and seasonality.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| *Panel A : Remuneration of work for women* | | | | |
| VARIABLES | Cash | Cash & Kind | Kind | Not Paid |
| active (20 km) | 0.014 | -0.029*** | 0.015* | -0.001 |
| | (0.015) | (0.011) | (0.008) | (0.012) |
| inactive (20 km) | -0.060** | 0.017 | 0.056*** | -0.013 |
| | (0.030) | (0.019) | (0.018) | (0.030) |
| Observations | 255,889 | 255,889 | 255,889 | 255,889 |
| F test: active-inactive=0 | 4.864 | 4.469 | 4.485 | 0.155 |
| p value | 0.0274 | 0.0345 | 0.0342 | 0.694 |
| *Panel B : Seasonality of work for women* | | | | |
| VARIABLES | Seasonal | All year | Occasional | |
| active (20 km) | -0.075*** | 0.059*** | 0.016** | |
| | (0.015) | (0.013) | (0.008) | |
| inactive (20 km) | -0.005 | 0.029 | -0.024* | |
| | (0.029) | (0.025) | (0.015) | |
| Observations | 303,291 | 303,291 | 303,291 | |
| F test: active-inactive=0 | 4.713 | 1.138 | 6.084 | |
| p value | 0.0300 | 0.286 | 0.0137 | |
| *Panel C : Remuneration of work for men* | | | | |
| VARIABLES | Cash | Cash & Kind | Kind | Not Paid |
| active (20 km) | 0.073*** | -0.013 | -0.013 | -0.047*** |
| | (0.016) | (0.013) | (0.009) | (0.013) |
| inactive (20 km) | -0.009 | -0.021 | 0.032 | -0.002 |
| | (0.037) | (0.030) | (0.034) | (0.035) |
| Observations | 128,135 | 128,135 | 128,135 | 128,135 |
| F test: active-inactive=0 | 4.056 | 0.0715 | 1.693 | 1.399 |
| p value | 0.0440 | 0.789 | 0.193 | 0.237 |
| *Panel D : Seasonality of work for men* | | | | |
| VARIABLES | Seasonal | All year | Occasional | |
| active (20 km) | -0.013 | 0.019 | -0.006 | |
| | (0.016) | (0.017) | (0.009) | |
| inactive (20 km) | 0.004 | 0.051 | -0.055*** | |
| | (0.048) | (0.051) | (0.011) | |
| Observations | 108,764 | 108,764 | 108,764 | |
| F test: active-inactive=0 | 0.102 | 0.374 | 11.81 | |
| p value | 0.750 | 0.541 | 0.001 | |

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. Please see Table 3 for more information about coefficients of interest.*** 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. Please see Table 3 for more information about coefficients of interest.*** p<0.01, ** p<0.05, * p<0.1

# 5 Heterogeneous impacts

## 5.1 Heterogenous effects by world prices

Labor market effects are likely to be stronger in years with high mineral prices, due to higher production and higher wages. We therefore interact our variables of interest, active and inactive, with yearly world prices. The world price data comes from RMG and is available for ten of the most important minerals (gold, silver, platinum, aluminum, copper, lead, nickel, tin, zinc and palladium) for the years 1992 to 2011.[12] Prices are normalized with 1992 as baseline price, set to zero. The variables active and inactive are interacted with the yearly normalized prices, and test statistics for the difference between these interaction terms are presented. This allows comparisons of the difference in the price effects for those having an active mine nearby and those having an inactive mine nearby.

Table 8, Panel A presents the results for women's employment. The baseline coefficients for active (20 km) and inactive (20 km) are now interpreted as the relation between closeness to a mine and employment when the normalized prices are zero, i.e. when the prices are at their 1992 level. We see that while the difference between active and inactive points in the same direction as in the baseline regressions, the effects are generally not as large. The price interaction terms indicate that higher prices lead to stronger labor market effects. In particular, higher prices lead to larger negative effects of mine openings on working, driven by less self-employment in agriculture but partly offset by a larger increase in service work. Higher prices also intensify the effects for men (Table 8, Panel B). High prices lead to a larger decrease in self-employment in

[12] This restricts the sample to 266,020 women and 138,483 husbands. The sample is nonetheless generalizable to the wider sample as indicated by similar descriptive statistics and baseline results (results are available upon request).

agriculture, and increase in service sector, sales, and manual employment.[13]

World prices are arguably exogenous to local labor conditions and this robustness exercise thereby strengtens our confidence in our main empirical strategy. Effects are, as expected, stronger in times of high prices. The results are indicative that women are more likely to leave the labor market in times of higher prices, possibly due to a household income effect spurred by higher male incomes, although we can only speculate so. However, in such times women are more likely to benefit from a service sector expansion.

## 5.2 Other heterogeneous effects

**Which women benefit from the mine expansion?**

Mining can 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. Interacting the treatment variables with marital status (1 if being married or having a partner, 0 otherwise) we find little difference in the effects between the two groups (Table 9).

Columns 4-8 of Table A.12 in the Appendix further show the effects of mine openings for the sample of 4,628 women whose husbands we know are miners. We note a negative effect on employment for these women, a large increase in sales employment, and a decline in agriculture and, although only statistically significant at the 12 percent level, a substantial decrease in service employment.

We must be careful in interpreting the results as supporting or rejecting the income effects story because marital status is a choice, implying that married women are different from non-married women, and because marital status may be endogenous to 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. However, we do not find any evidence that mining changes relationship formation (see Table A.11 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 concern that marital status may be endogenous to mine activity. We find that they are also more likely to be working in services (Appendix Table A.12).

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.13).

[13] For men we note some statistically significant correlations between prices and living close to an inactive mine. This may be due to increased investments in mining in those periods or increased intensity of small scale mining.

Table 8: Interactions with world market prices

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| | Working | Service | Profess. | Sales | Agric | Agric | Domestic | Clerical | Skilled | Unskilled |
| VARIABLES | | | | | self-emp. | emp. | | | manual | manual |
| Panel A : Woman | | | | | | | | | | |
| active (20 km) | 0.073*** | 0.017** | 0.000 | 0.011 | 0.042*** | -0.015 | 0.005 | 0.003 | 0.010 | 0.000 |
| | (0.015) | (0.009) | (0.004) | (0.012) | (0.016) | (0.014) | (0.004) | (0.003) | (0.006) | (0.004) |
| inactive (20 km) | 0.082*** | 0.001 | 0.003 | -0.016 | 0.061** | 0.003 | -0.003 | 0.007 | -0.008 | 0.035 |
| | (0.022) | (0.005) | (0.005) | (0.019) | (0.029) | (0.010) | (0.002) | (0.005) | (0.013) | (0.022) |
| active * price | -0.051*** | 0.011 | -0.004 | 0.000 | -0.070*** | 0.017* | -0.004** | -0.003 | 0.000 | 0.002 |
| | (0.015) | (0.008) | (0.004) | (0.009) | (0.016) | (0.009) | (0.002) | (0.002) | (0.004) | (0.003) |
| inactive * price | 0.021 | -0.017 | 0.002 | 0.013 | 0.023 | 0.005 | -0.006*** | 0.014 | 0.014 | -0.028 |
| | (0.040) | (0.014) | (0.014) | (0.022) | (0.023) | (0.006) | (0.002) | (0.010) | (0.009) | (0.020) |
| price | -0.017 | -0.004 | 0.005* | -0.012* | 0.023* | -0.021*** | -0.002* | -0.002 | 0.001 | -0.002 |
| | (0.012) | (0.004) | (0.003) | (0.006) | (0.013) | (0.005) | (0.001) | (0.002) | (0.002) | (0.002) |
| p values | | | | | | | | | | |
| active-inactive | 0.722 | 0.097 | 0.680 | 0.205 | 0.548 | 0.300 | 0.051 | 0.532 | 0.199 | 0.111 |
| active*price-inactive*price | 0.091 | 0.084 | 0.695 | 0.583 | 0.001 | 0.262 | 0.335 | 0.117 | 0.163 | 0.137 |
| Panel B : Husband or partner | | | | | | | | | | |
| active (20 km) | 0.021** | 0.010 | 0.011 | 0.012 | 0.001 | -0.039 | -0.002 | -0.008* | 0.044** | -0.008 |
| | (0.009) | (0.010) | (0.008) | (0.013) | (0.025) | (0.027) | (0.003) | (0.004) | (0.018) | (0.009) |
| inactive (20 km) | 0.005 | 0.009 | 0.014 | 0.003 | -0.046 | 0.015 | -0.000 | -0.002 | -0.005 | 0.015 |
| | (0.005) | (0.016) | (0.012) | (0.012) | (0.032) | (0.022) | (0.006) | (0.009) | (0.011) | (0.014) |
| active*price | -0.015* | -0.002 | -0.016** | -0.001 | -0.072*** | 0.031 | -0.001 | 0.003 | 0.019 | 0.023*** |
| | (0.008) | (0.012) | (0.007) | (0.008) | (0.019) | (0.019) | (0.002) | (0.004) | (0.016) | (0.008) |
| inactive*price | 0.036*** | -0.037** | 0.010 | -0.031* | 0.103*** | 0.000 | -0.008* | -0.007 | 0.019 | -0.014 |
| | (0.007) | (0.017) | (0.021) | (0.016) | (0.023) | (0.021) | (0.005) | (0.008) | (0.029) | (0.016) |
| price | -0.001 | -0.026*** | -0.003 | 0.034*** | -0.051*** | 0.048*** | 0.004*** | -0.007** | -0.005 | 0.003 |
| | (0.005) | (0.005) | (0.005) | (0.006) | (0.011) | (0.006) | (0.002) | (0.003) | (0.007) | (0.004) |
| p values | | | | | | | | | | |
| active-inactive | 0.130 | 0.963 | 0.818 | 0.619 | 0.244 | 0.123 | 0.840 | 0.538 | 0.020 | 0.138 |
| active*price-inactive*price | 0.000 | 0.096 | 0.236 | 0.096 | 0.000 | 0.286 | 0.155 | 0.238 | 0.986 | 0.031 |

Robust standard errors clustered at the DHS cluster level in parentheses. All regressions control for year and region fixed effects, regional time trends, urban dummy, age, years of education, and religious beliefs. Please see Table 3 for more information about coefficients of interest. P-value active-inactive refers to a F-test of the difference active-inactive, p value active*price-inactive*pricerefers to a F-test of the difference of the interaction effects. *** p<0.01, ** p<0.05, * p<0.1. Panel A has 266,020 observations, and Panel B 138,483 observations.

Table 9: Heterogeneous effects of mining by marital status.

| VARIABLES | (1) Working | (2) Service | (3) Sales | (4) Agriculture |
|---|---|---|---|---|
| active (20 km) | 0.021* | 0.015** | -0.012 | 0.001 |
| | (0.013) | (0.007) | (0.008) | (0.012) |
| inactive (20 km) | 0.067** | -0.007 | 0.012 | 0.045* |
| | (0.028) | (0.009) | (0.016) | (0.026) |
| partner | 0.070*** | -0.004*** | 0.015*** | 0.066*** |
| | (0.002) | (0.001) | (0.001) | (0.002) |
| active*partner | 0.019 | 0.010 | -0.038* | 0.029 |
| | (0.029) | (0.009) | (0.021) | (0.034) |
| inactive*partner | 0.007 | 0.009 | 0.020* | -0.015 |
| | (0.013) | (0.008) | (0.010) | (0.012) |
| Observations | 507,088 | 507,088 | 507,088 | 507,088 |
| R-squared | 0.200 | 0.091 | 0.136 | 0.356 |
| F test: active-inactive=0 | 2.237 | 3.760 | 1.877 | 2.283 |
| p value | 0.135 | 0.0525 | 0.171 | 0.131 |
| F test: act*partner-inact*partner=0 | 0.140 | 0.00798 | 5.955 | 1.548 |
| p value | 0.708 | 0.929 | 0.0147 | 0.214 |

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. Please see Table 3 for more information about coefficients of interest.*** p<0.01, ** p<0.05, * p<0.1

We find that these women are less likely to work and less likely to work in agriculture. We also test if it the case that the effect of mines differs between societies with high and low participation of women in the service sector. To this end 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 in the ILO data is defined as a high share). The results are shown in Table A.14 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. If anything, there seems to be less of an effect in countries with high participation of women in the service sector.

Employment opportunities matter for women. For welfare, it also matters what types of jobs are offered. We try to rule out the possibility that the increase in female employment in the service sector is driven by engagement in the sex industry. Using lifetime number of sexual partners, which should increase with sex trade activity, we find no indication of 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. Finally, we find no statistically significant difference in the likelihood of the woman never having sexual intercourse, and no change in the use of a condom in the last intercourse.

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

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Lifetime number of sexual partners | | | | Never sex | Used condom |
| Sample | All | Under 25 | In services | No partner | All | All |
| VARIABLES | | | | | | |
| active (20 km) | -0.106* | -0.107** | -0.726*** | -0.223 | 0.011** | -0.006 |
| | (0.055) | (0.051) | (0.151) | (0.142) | (0.005) | (0.005) |
| inactive (20 km) | 0.771*** | 0.708*** | 0.492** | 0.691*** | 0.001 | -0.014* |
| | (0.172) | (0.175) | (0.224) | (0.156) | (0.009) | (0.008) |
| Observations | 210,456 | 64,672 | 12,049 | 49,128 | 512,922 | 350,797 |
| R-squared | 0.093 | 0.087 | 0.076 | 0.079 | 0.252 | 0.142 |
| F test: active-inactive=0 | 23.61 | 20.02 | 20.15 | 19.17 | 1.145 | 0.749 |
| p value | 1.20e-06 | 7.76e-06 | 7.36e-06 | 1.21e-05 | 0.285 | 0.387 |

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. Please see Table 3 for more information about coefficients of interest. *** p<0.01, ** p<0.05, * p<0.1

### 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 living 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 the probability of working in agriculture (see Panel A of Table A.15 in the Appendix). For diamond mines, we find that the probability of working 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.15 in the Appendix). The results using these other datasets are in line with the findings using the main dataset.

## 6 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 and men. 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 with areas farther away, before and after the production has started.

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, and an overall drop in labor force participation. The changing local economy brings secondary effects for women with more cash employment and non-seasonal work. For men, we see a structural shift focused on increasing work in skilled manual jobs and decreasing self-employment in farming.

The effects of mine closing are not symmetrical for women; 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 remains low, indicating that the localized structural shifts are not reversible. For men, the effects of closing are almost symmetrical. This indicates that mining works as a boom-bust economy on the local level in Africa, but with permanent effects of women's labor market participation.

The results are robust to a wide battery of checks, such as using different distance cut-offs and different classifications of the control group, including different types of fixed effects and exlusion of migrants. The results are quantitatively important. We calculate that more than 90,000 women may have gained a service sector job as a result of mine openings, but, in parallel, more than 280,000 women left the labor market. Female employment is likely to foster female agency and is also argued to be important for child health, schooling, and child survival (see Duflo, 2012 for an overview). Future studies should investigate the impacts of mining on these aspects as well. Using world market prices for ten different minerals we also find that the effects are strongest in periods when prices are higher.

We have not assessed the quality of the new work opportunities and whether women are facing decent and productive employment as a result of mining. Value added per worker differs between sectors in developing countries. The gap between agriculture and non-agriculture sectors has been found to be large (on average four times higher) and persistent according to national accounts. The difference remains after considering human capital and work hours differentials using micro-data (Gollin et al., 2012). The productivity difference is indicative of a misallocation of workers, with too many workers in agriculture. In this paper, we have shown that mine opening can pull people from low value added sectors to higher value added sectors, such as services and skilled manual labor. We also see that the probability of earning cash incomes increases for both men and women. Using data from the World Bank Living Standard Surveys, we explore wage rates further. The workers earning cash in the agricultural sector do not earn more than workers earning cash in the service sector (results are available upon request). This is not necessarily the interesting metric of remuneration to evaluate the effects of the mining industry; we have noticed an important shift from in kind to cash remuneration for work.

Our results are broadly consistent with the U-shaped development of female labor force participation with development as outlined by Goldin (1995). She shows that participation is initially reduced as women move from the farm but eventually increases as women enter the more advanced segments of the labor market. 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, further analysis of income and substitutions effects driving women's shifts on the labor market, exploration of secondary effects such as women's bargaining power, and other environmental and social concerns associated with the large-scale mining industry.[14]

# References

Allcott, H. and D. Keniston (2014): "Dutch Disease or Agglomeration? The Local Economic Effects of Natural Resource Booms in Modern America," *NBER Working Paper 20508.*

Angrist, J. and A. Kugler (2008): "Rural Windfall or a New Resource Curse? Cocoa,

[14] These include deforestation, land degradation, and 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).

Income, and Civil Conflict in Colombia," *The Review of Economics and Statistics*, 90(2), 191–215.

Aragón, F. M. and J. P. Rud (2013a): "Modern Industries, Pollution and Agricultural Productivity: Evidence from Mining in Ghana," *International Growth Center Working Paper*.

Aragón, F. M. and J. P. Rud (2013b): "Natural Resources and Local Communities: Evidence from a Peruvian Gold Mine," *American Economic Journal: Economic Policy*, 5(2), 1–25.

Auty, R. (2001): "The political economy of resource-driven growth," *European Economic Review*, 45(4), 839–846.

——— (2007): "Natural resources, capital accumulation and the resource curse," *Ecological Economics*, 61(4), 627–634.

Barro, R. (2000): "Democracy and the Rule of Law," in *Governing for prosperity*, ed. by B. B. de Mesquita and H. Root, pp. 209–231. Yale University Press, New Haven, CT.

Berman, N., M. Couttenier, D. Rohner and M. Thoenig (2014): "This Mine is Mine! How minerals fuel conflicts in Africa," *CEPR Discussion Paper No. DP10089*.

Bigsten, A. and M. Söderbom (2006): "What Have We Learned from a Decade of Manufacturing Enterprise Surveys in Africa?," *World Bank Research Observer*, 21, 241–265.

Black, D., T. McKinnish and S. Sanders (2005): "The Economic Impact Of The Coal Boom And Bust," *The Economic Journal*, 115, 449–476.

Brückner, M. and A. Ciccone (2010): "International Commodity Prices, Growth and the Outbreak of Civil War in Sub-Saharan Africa," *The Economic Journal*, 120(544), 519–534.

Brunnschweiler, C. and E. Bulte (2008a): "Linking Natural Resources to Slow Growth and More Conflict," *Science*, 320, 616–617.

——— (2008b): "The Resource Curse Revisited and Revised: A Tale of Paradoxes and Red Herrings," *Journal of Environmental Economics and Management*, 55(3), 248–264.

——— (2009): "Natural Resources and Violent Conflict: Resource Abundance, Dependence, and the Onset of Civil Wars," *Oxford Economic Papers*, 61(4), 651–674.

Buhaug, H. and J. Rød (2006): "Local determinants of African civil wars, 1970-2001," *Political Geography*, 25(3), 315–335.

Campbell, C. (1997): "Migrancy, Masculine Identities and AIDS: The Psychosocial Context of HIV Transmission on the South African Gold Mines," *Social Science & Medicine*, 45(2), 273–281.

Caselli, F. and G. Michaels (2013): "Do Oil Windfalls Improve Living Standards? Evidence from Brazil," *American Economic Journal: Applied Economics*, 5(1), 208–238.

Collier, P. (2010): *The Plundered Planet*. Allen Lane, London.

Collier, P. and A. Hoeffler (2004): "Greed and grievances in civil war," *Oxford Economic Papers*, 56(4), 563–595.

——— (2005): "Resource Rents, Governance and Conflict," *Journal of Conflict Resolution*, 49, 625–633.

Corno, L. and D. de Walque (2012): "Mines, Migration and HIV/Aids in Southern Africa," *Journal of African Economies*, 21(3), 465–498.

Dube, O. and J. Vargas (2013): "Commodity Price Shocks and Civil Conflict: Evidence from Colombia," *Review of Economic Studies*, 80(4), 1384–1421.

Duflo, E. (2012): "Women's Empowerment and Economic Development," *Journal of Economic Literature*, 50(4), 1051–1079.

Eggert, R. (2002): "Mining and Economic Sustainability: National Economies and Local Communities," *Mining, Minerals and Sustainable Development*, 19.

Fafchamps, M. and M. Söderbom (2006): "Wages and Labor Management in African Manufacturing," *Journal of Human Resources*, 41(2), 346–379.

Frankel, J. (2010): "The Natural Resource Curse: A survey," *NBER Working Paper 15836*.

Gajigo, O., E. Mutambatsere and G. Ndiaye (2012): "Mining in Africa: Maximizing EEconomic Returns for Countries," *African Development Bank Group Working Paper 147*.

Goldin, C. (1995): "The U-Shaped Female Labor Force Function in Economic Development and Economic History," in *Investment in Women's Human Capital*, ed. by T. P. Schultz, pp. 61–90. University of Chicago Press.

Gollin, D., D. Lagakos and M. Waugh (2012): "The agricultural productivity gap in developing countries," *Mimeo*.

Hilson, G. (2009): "Small-scale mining, poverty and economic development in sub-Saharan Africa: An overview," *Resources Policy*, 34(1), 1–5.

Hinton, J. (2006): "Communities and Small Scale Mining: an Integrated Review for Development Planning," *World Bank Publication*.

Hirschman, A. O. (1958): *The Strategy of Economic Development*. New Haven: Yale University Press.

ILO (1999): *Social and Labour Issues in Small-scale Mines: Report for Discussion at the Tripartite Meeting on Social and Labour Issues in Small-scale Mines*. International Labour Organization, Geneva.

——— (2011): *Key Indicators of the Labour Market*. International Labour Organization, Geneva.

InterraRMG (2013): http://www.rmg.se/Products/RawMaterialsData.aspx.

Isard, W., I. Azis, M. Drennan, R. Miller, S. Saltzman and E. Thorbecke (1998): *Methods of Interregional and Regional Analysis*. Ashgate, Aldershot.

Isham, J., M. Woolcock, L. Pritchett and G. Busby (2005): "The Varieties of Resource Experience: Natural Resource Export Structures and the Political Economy of Economic Growth," *The World Bank Economic Review*, 19(2), 141–174.

Jensen, N. and L. Wantchekon (2004): "Resource Wealth and Political Regimes in Africa," *Comparative Political Studies*, 37(7), 816–841.

Krugman, P. (1991): "Increasing Returns and Economic Geography," *Journal of Political Economy*, 99(3), 483–499.

KUDAMATSU, M. (2012): "Has Democratization Reduced Infant Mortality in Sub-Saharan Africa? Evidence from Micro Data," *Journal of the European Economic Association*, 10(6), 1294–1317.

LANGE, S. (2006): *Benefit Streams from Mining in Tanzania: Case Studies from Geita and Mererani*. CMI Report.

LAW, G. (1999): *Administrative Subdivisions of Countries: A Comprehensive World Reference, 1900 through 1998*. McFarland & Co Inc Pub, Jefferson, N.C.

——— (2012): "Administrative Divisions of Countries ("statoids")," .

LEITE, C. AND J. WEIDMANN (2002): "Does mother nature corrupt? Natural resources, corruption, and economic growth," in *Governance, Corruption and Economic Performance Investment in Women's Human Capital*, ed. by G. T. Abed and S. Gupta, pp. 71–99. International Monetary Fund.

MAYSTADT, J.-F., G. DE LUCA, P. SEKERIS AND J. ULIMWENGU (2013): "Mineral resources and conflicts in the Democratic Republic of Congo: A case of ecological fallacy," *Oxford Economic Papers*.

MEHLUM, H., K. MOENE AND R. TORVIK (2006a): "Cursed by Resources or Institutions?," *The World Economy*, 29(8), 1117–1131.

——— (2006b): "Institutions and the Resource Curse," *The Economic Journal*, 116(508), 1–20.

MICHAELS, G. (2011): "The Long Tem Consequences of Resource-Based Specialisation," *The Economic Journal*, 121, 31–57.

MOODIE, T. D. AND V. NDATSHE (1994): *Going for Gold: Men, Mines and Migration*. University of California Press.

MORETTI, E. (2010): "Local Multipliers," *American Economic Review. Papers and Proceedings*, 100, 1–7.

MORETTI, E. AND P. THULIN (2013): "Local multipliers and human capital in the United States and Sweden," *Industrial and Corporate Change*, 22, 339–362.

MRDS (2005): "Mineral Resources Data System: U.S. Geologival Survey," Reston, Virginia.

NORMAN, C. (2009): "Rule of Law and the Resource Curse: Abundance Versus Intensity," *Environmental and Resource Economics*, 43(2), 183–207.

ROSS, M. (2008): "Oil, Islam, and women," *American Political Science Review*, 102(1), 107–123.

ROSS, M. (2012): *The Oil Curse: How Petroleum Wealth Shapes the Development of Nations*. Princeton University Press, Princeton.

TORVIK, R. (2001): "Learning by doing and the Dutch disease," *European Economic Review*, 45(2), 285–306.

UNECA (ed.) (2011): *Minerals and Africa's Development : The International Study Group Report on Africa's Mineral Regimes*. United Nations Economic Commission for Africa, Addis Ababa, Ethiopia.

VAN DER PLOEG, F. (2011): "Natural Resources: Curse or Blessing?," *Journal of Economic Literature*, 49(2), 366–420.

Wilson, N. (2012): "Economic Booms and Risky Sexual Behavior: Evidence from Zambian Copper Mining Cities," *Journal of Health Economics*, 31(6), 797–812.

World Bank (2011): *Global Economic Prospects June 2011: Regional Annex.* World Bank Group.

WORLD BANK (2012): *World Development Report 2012.* World Bank Group.

Wright, G. and J. Czelusta (2003): "Mineral resources and economic development.," in *Paper prepared for the Conference on Sector Reform in Latin America (Nov 13-15), Stanford Center for International Development.*

# 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 Sections A.2-A.5. Finally, we present analyses based on other mining data sets in Section A.6.

## A.1 Descriptive statistics

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

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

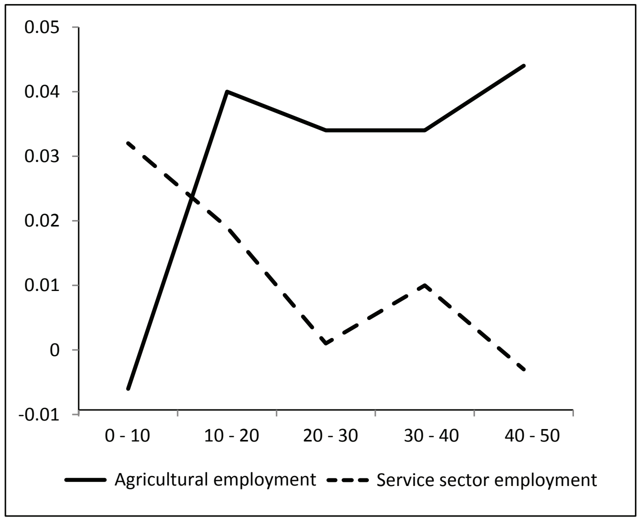
Table A.3: Closest mines opening and closing 1975-2010.

| 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 |
| Total | 160 | 90 |

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

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

Figure A.1: Spatial Lag Model: Distance from mine and agricultural and service sector employment




* Figure A.1 shows the result from Table A.6 Panel E. The x-axis measures distance from an active mine and the y-axis the coefficients for the 10km distance bins. The control group if further away than 50km, but within 200km.

## A.2 Heterogeneous effects by distance

The empirical strategy relies on a decreasing footprint with distance from a mine. As seen in Table A.5, 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 or to leaving the work force. The largest effects are found using a cut-off of 5 kilometers and the most statistically significant effects are for distances up until 15 kilometers. The probability of having a service sector job within 10 kilometers of 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 of an active mine is 4.9 percentage points less (*active*) and the effect of mine opening at this distance is a reduction of 16.2 (*active* – *inactive*) percentage points. At 50 kilometers away from the mine center point, we no longer find significant difference in outcomes comparing active and inactive mining communities. Women living within 50 kilometers of a mine are more likely to work, to work in agriculture, and less likely to work in sales, but there is no extra effect of the mine opening. Table A.4 shows the sample sizes broken down by treatment status (*active*, *inactive* and *suspended*) for the different distances.

As shown in Table A.6, 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 agricultural work for women. We also do a horse race with the logged distance to the closest mine regardless of activity (*distance to closest mine*) and do the same with the logged distance to the closest active mine. In accordance with previous results, we find that 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

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 |

distance to any mine is negative.

Table A.6 Panel E, we show results from a spatial lag model indicating that the strongest effects for services are found within 10 km of an active mine. The probability of working in services is 3.2 percentage points higher for women living within 10 kilometers of an active mine, whereas the likelihood of an agricultural job is 3.8 percentage points lower. The results are illustrated in Figure A.1, showing that agricultural employment is much lower close to an active mine, and increases with distance from an active mine, while the service sector employment decreases with distance from mine. The strongest effects are found very close, within 10km and 20km.

Table A.5: Effects of mining on main outcomes with different cut-off distances.

| VARIABLES | (1)<br>Working | (2)<br>Service | (3)<br>Sales | (4)<br>Agriculture | Obs. |
|---|---|---|---|---|---|
| active (5 km) | 0.038 | 0.023 | -0.017 | -0.008 | |
| | (0.025) | (0.016) | (0.017) | (0.033) | |
| inactive (5 km) | 0.214*** | -0.022 | 0.034 | 0.133*** | |
| | (0.043) | (0.014) | (0.032) | (0.023) | |
| p value: active-inactive=0 | 0.000 | 0.030 | 0.157 | 0.001 | 518,705 |
| 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 | 0.015 | 0.113*** | |
| | (0.033) | (0.011) | (0.025) | (0.021) | |
| p value: active-inactive=0 | 0.000 | 0.007 | 0.845 | 0.000 | 515,839 |
| active (15 km) | 0.018 | 0.024*** | -0.000 | -0.024* | |
| | (0.012) | (0.007) | (0.009) | (0.015) | |
| inactive (15 km) | 0.136*** | -0.001 | -0.002 | 0.111*** | |
| | (0.024) | (0.009) | (0.019) | (0.023) | |
| p value: active-inactive=0 | 8.92e-06 | 0.0304 | 0.937 | 8.13e-07 | 514,396 |
| active (25 km) | 0.023*** | 0.018*** | 0.003 | 0.001 | |
| | (0.009) | (0.005) | (0.007) | (0.011) | |
| inactive (25 km) | 0.064*** | 0.000 | -0.014 | 0.045* | |
| | (0.017) | (0.004) | (0.014) | (0.023) | |
| p value: active-inactive=0 | 0.035 | 0.007 | 0.285 | 0.082 | 509,875 |
| active (50 km) | 0.039*** | 0.004 | -0.013** | 0.043*** | |
| | (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 | 0.293 | 0.304 | 0.969 | 0.382 | 493,501 |

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. Please see Table 3 for more information about coefficients of interest.*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A.6: Effects of mining using continuous distance measures and distance spline.

| VARIABLES | (1) Working | (2) Service | (3) Sales | (4) Agriculture |
|---|---|---|---|---|
| *Panel A : Continuous distance* | | | | |
| Distance to closest active mine | -0.016*** | -0.001 | -0.000 | -0.011*** |
| | (0.003) | (0.001) | (0.002) | (0.003) |
| *Panel B : Sample limit to 200km* | | | | |
| 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: Spatial lag model* | | | | |
| Distance to closest active mine | | | | |
| 0-10km | 0.027 | 0.032*** | 0.003 | -0.038* |
| | (0.018) | (0.011) | (0.013) | (0.020) |
| 10-20km | 0.028** | 0.019*** | -0.015 | 0.021 |
| | (0.012) | (0.006) | (0.010) | (0.016) |
| 20-30km | 0.022** | 0.001 | -0.008 | 0.033** |
| | (0.011) | (0.005) | (0.008) | (0.013) |
| 30-40km | 0.004 | 0.010** | -0.026*** | 0.024* |
| | (0.011) | (0.005) | (0.008) | (0.014) |
| 40-50km | 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 controlfor year and region fixed effects, regional time trends, living in an urban area, age, yearsof education, and religious beliefs. *** p<0.01, ** p<0.05, * p<0.1

## A.3 Additional robustness tests

In this section we perform a series of robustness tests for the main results. We start by limiting the range of the control group as people living in areas far away may be too different for a meaningful comparison. Reducing the sample to include a control group within 200 km, the sample is reduced to half the initial size. Nonetheless, we see in Table A.7 that all effects point in the same direction and are still statistically significant.

Another concern 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 we include proximity to roads as an extra control variable to see whether the results remain robust. Unfortunately, the road data is not time variant and is only available for a subset of countries. The results are presented in Table A.8, using data from the African Development Bank for Benin, Central African Republic, Cameroon, DRC, Mali, Niger, Senegal, and Togo. We see that

Table A.7: Effects of mining on main outcomes for women with sample restricted to those within 200 kilometers.

| VARIABLES | (1)<br>Working | (2)<br>Service | (3)<br>Sales | (4)<br>Agriculture |
|---|---|---|---|---|
| active (20 km) | 0.025** | 0.020*** | -0.002 | -0.008 |
| | (0.010) | (0.005) | (0.008) | (0.013) |
| inactive (20 km) | 0.067*** | 0.002 | -0.015 | 0.051** |
| | (0.020) | (0.005) | (0.015) | (0.025) |
| | | | | |
| Observations | 264,905 | 264,905 | 264,905 | 264,905 |
| R-squared | 0.220 | 0.095 | 0.157 | 0.395 |
| F test: active-inactive=0 | 3.635 | 5.902 | 0.631 | 4.496 |
| p value | 0.0566 | 0.0151 | 0.427 | 0.0340 |

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. Please see Table 3 for more information about coefficients of interest. *** p<0.01, ** p<0.05, * p<0.1

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. This analysis cannot ensure that road construction is not driving the results, but it shows that there is no difference in the effects of mines in areas with roads as compared to the effect in areas without large roads. We think it unlikely that time-varying road infrastructure explains the main findings in this paper.

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 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.9, 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 magnitudes of the effects 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.10, we show that our main findings are robust to the 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 and at the closest mine level, as well as multi-way clustering on both the closest mine and the DHS cluster.

## A.4 Additional heterogeneity and outcomes.

This section presents results discussed in the paper. In particular, we present results for different sub-samples, and results on related outcomes of interest.

Table A.8: 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.9: 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. Intensity is a count variable for the number of active mines that are near. *** p<0.01, ** p<0.05, * p<0.1

Table A.10: 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 region, the mine in parentheses and at the mine and cluster 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.11: 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.13: Effects of mining for young women (15-20 years old).

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

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: 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.14: Different effects of mining in countries with many women working in services.

| VARIABLES | (1)<br>Working | (2)<br>Service | (3)<br>Sales | (4)<br>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.5 Trend graphs for our four main outcomes

Figure A.2: Trends in outcomes around openings

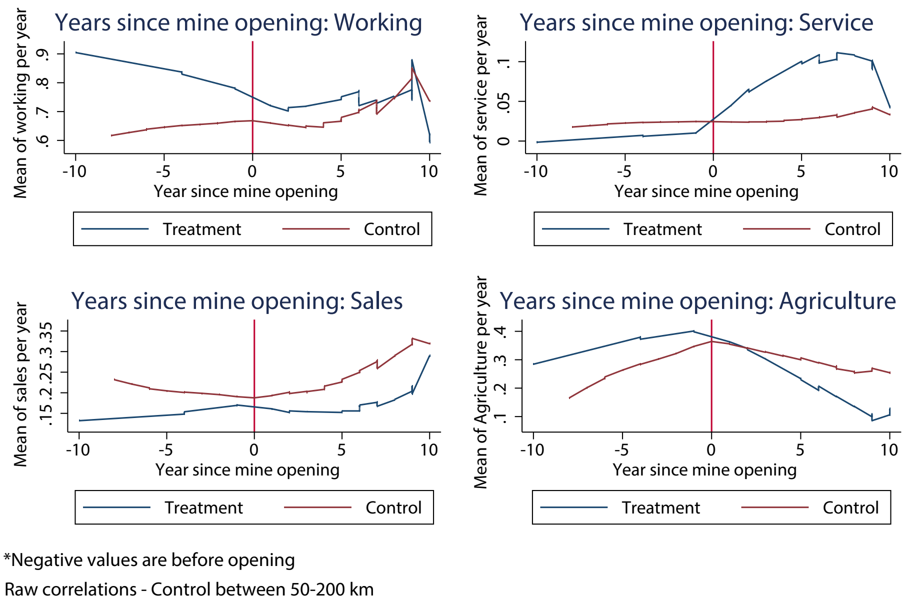
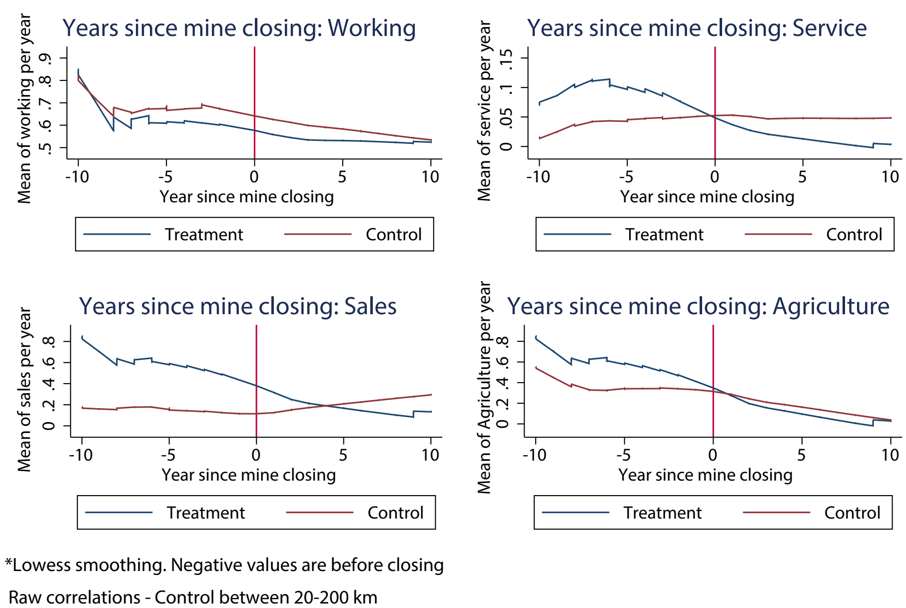



Figure A.3: Trends in outcomes around closings



## A.6 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.15. 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. There is significant diamond mining in Africa, and while the RMD includes some diamond mines, it does not 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 the same as the one for the USGS data sets. The results are presented in Panel B of Table A.15. We find that being close to a mine is associated with a higher probability of engaging in sales and a lower probability of working in agriculture.

Table A.15: 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