Local Effects of Artisanal Mining: Empirical Evidence from Ghana

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Abstract

I estimate local economic and environmental effects of artisanal and small-scale gold mining (ASM) in Ghana. For that purpose I use a novel dataset on the geolocation of artisanal gold mines based on machine learning techniques and satellite imagery. ASM is an informal, low-tech, but highly labour-intensive form of resource extraction that is typically associated with environmental and health damages, social problems and poverty. In contrast to common perception, I find that one additional artisanal mine increases nearby household per-capita income by 0.2 percent, which is driven by non-agricultural income sources. Other indicators of economic development point in the same direction: In artisanal mining areas more households have access to electricity, more individuals are literate and fewer people work in agriculture. On the other hand, conventional large-scale mining does not show any local economic impacts. From an environmental perspective, both small- and large-scale mining contribute to forest cover loss. In a context where reliable data is scarce, the evidence shown here thus provides a more nuanced view on local effects of artisanal mining.

Keywords: Poverty, artisanal mining, extractive industries, gold, Ghana
JEL codes: C81, O13, O55, Q32, Q33, Q56, R11

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1 Introduction

Many developing countries with high poverty rates are also blessed with abundant mineral resources. This mineral wealth is typically extracted through large-scale mines, which are highly capital intensive and thus provide very few employment opportunities for local populations. In contrast, over the last ten years much smaller mining operations have become increasingly common, particularly in the gold mining sectors of Ghana, Tanzania, Indonesia and Latin America. While these artisanal or small-scale mining operations employ millions of workers, they are also linked to environmental damages, health hazards, social costs, poverty and even political tensions (times (2017) and National Geographic (2017). Because most artisanal mines in Ghana operate without a license, data and thereby empirical evidence on this industry is extremely scarce (Cust and Poelhekke (2015) and World Bank (2015)).

I estimate local economic effects of small-scale mining on nearby households in Ghana by making use of novel data on the geolocation of these mining operations. This data is generated in collaboration with Microsoft by training a machine learning model to detect artisanal mining sites from satellite images. As a result I am able to map the distribution of a large share of visible artisanal mines in Ghana. These mines are then connected with data on household outcomes and forest cover loss.

Using household survey data from 1998/99, 2005/06 and 2012/13, I find that per-capita income is 0.2 percent higher for each additional small-scale mine within 10 kilometres of households. This result is robust to controlling for large-scale gold production, a number of individual and household controls and unobserved heterogeneity at the district level. The income gain is driving by higher non-agricultural incomes in small-scale mining areas. In contrast, large-scale mining, often taking place near artisanal mining, does not affect income or expenditure of nearby households. This result thereby supports the enclave hypothesis of large-scale industrial mining.

These positive economic effects do however come at the cost of environmental degradation. Using high-resolution forest cover loss data, I find that deforestation is almost 42 percent higher in areas with many small-scale mines than in those without. This seems to be caused by both small- and large-scale mining.

This paper is structured as follows. Chapter 2 provides institutional background on artisanal mining in Ghana. Chapter 3 introduces the different data sources used for the empirical analysis, which is carried out in chapter 4. Chapter 5 concludes.

2 Background: Artisanal mining in Ghana

Mining is a major industry in Ghana, contributing 8 percent to GDP and 16 percent to fiscal revenue. Gold accounts for 97 percent of this revenue and makes up 23 percent of all exports (US Geological Service (2014), GHEITI (2015), Simoes and Hidalgo (2011)). These macro figures relate to both large-scale mining (LSM) and artisanal and small-scale mining (ASM). It is important to distinguish between these two industries, as they differ greatly in organisation, technology and labour used. Especially local economic outcomes are therefore likely to be different. Large-scale mining is mostly operated by large international mining companies, with the Ghanaian government required to hold at least 10 percent of shares (GHEITI, 2015). It is highly capital-intensive, therefore generating only very few local employment opportunities (Aryeetey et al., 2007). As of 2014 approximately 12,300 workers, out of a labour force of 11 million people in Ghana, are employed in the large-scale mining sector (US Geological Service, 2014).

Local effects of large-scale mining, using the GPS location and production of large industrial mines, have been found in terms of decreased agricultural productivity (Aragón and Rud, 2016), higher local corruption (Knutsen et al., 2017) and more conflicts (Berman et al., 2017).[1] Some studies also use remote sensing to observe environmental damages in the form of forest loss around large mines (Schueler et al., 2011). The seemingly negligible local economic impact of large-scale mining is in sharp contrast to the artisanal and small-scale mining sector, which in Ghana alone is estimated to employ 1.1 million workers directly (Hilson and McQuilken, 2014).

Artisanal gold mining in Ghana traces back to the 15th century, when it was known as the Gold Coast under Portuguese and later British colonial rule (Crawford et al., 2015). Looking at more recent data, figure 1 shows that until roughly 2006, most of Ghana's gold production originated from large-scale producers (blue bars). It was only after 2006 that small-scale mining started to play a major role in Ghana's overall gold production, accounting for 36 percent in 2014 (green bars). This is consistent with the increased mechanisation of ASM that is reported for this time, partly caused by an influx of foreign

[1] For a recent survey of local effects of (large-scale) mineral extraction see Cust and Poelhekke (2015) and Chuhan-Pole et al. (2017).

capital, technology and labour (Mantey et al. (2016), Crawford et al. (2015)). The other common explanation for the increase in ASM activity is the hike of the gold price, which can also be observed in figure 1 (black line). In addition to this, the first major government crackdown on illegal ASM activity was conducted in summer 2013, which slowed down its expansion afterwards (Crawford et al., 2015). This observation on the timing of ASM is important to the following analysis because it enables me to use ASM locations from 2014, the only date available for satellite images, in connection with household data from 2012/13 (based on the Ghana Living Standards Survey). I thereby assume that the ASM locations detected for 2014 are also valid for 2012/13. The second identification assumption comes from the observation that artisanal mining was of negligible economic importance until roughly 2006. This allows me to make a comparison over time, assuming zero ASM activity for all survey observations until 2006. This approach will be further explained in section 4.2.

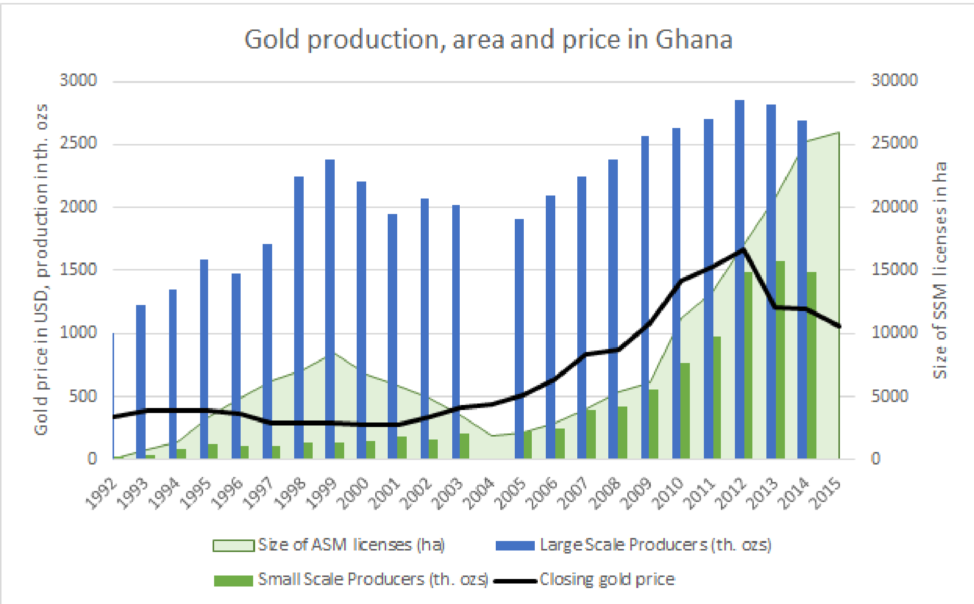

Figure 1: Gold production, area and price in Ghana

There is a sharp contrast between how ASM is perceived both in public and in the academic literature. Public perception is largely driven by reports on environmental damages, such as mercury contamination of soil and water (Mantey et al. (2016), Van Straaten (2000)) and deforestation (Hirons (2011), Rahm et al. (2015) and Schueler et al. (2011)), as well as health hazards and numerous social problems, like child labour, prostitution, drug abuse, corruption and violence (Knutsen et al., 2017). As a result, ASM operations are often blamed to cause extreme poverty (Mantey et al. (2016), Hilson and McQuilken (2014)). Opponents of this negative characterisation argue that many of the detrimental outcomes result from the illegality of most ASM operations but are not inherent to ASM itself. Thereby, formalisation of ASM and harmonisation with large-scale activities would mitigate many negative effects. Proponents of ASM claim that instead of causing poverty ASM has developed into a major industry in many developing countries, accounting for more than one million jobs in Ghana directly, and over four million indirectly through downstream industries (Hilson, 2016).

This article adds to the discussion by providing evidence on ASM's local economic and environmental effects for a large sample. The major obstacle for this analysis is that due to its illegality, data on ASM is extremely scarce. For the relatively few legal ASM operations some licensing data is available (see section 3.3). However, this data cannot be exactly geolocated to measure local effects and is further substantially underrepresenting the size of illegal ASM activities, which are assumed to make up most of Ghana's small-scale mining (Hilson and McQuilken, 2014). Many studies have looked at interview and case-study evidence to measure the effects of ASM, but lack consistent measures and the scope to draw inferences for a large scale (Fisher et al. (2009), Kitula (2006)). Only recently credible attempts that employ low-level ASM data have been made. Asner et al. (2013) identify forest loss through satellite images that is caused by both industrial and artisanal mining in the Amazon region. Bazillier and Girard (2017) combine official ASM registers and geological data to infer the location of small mines and infer the effect of small-scale mining. They find positive effects of ASM on the wealth of nearby households. The most similar attempt to this article is conducted by Saavedra and Romero (2017). They generate a panel of ASM locations in Colombia using satellite images and machine learning techniques to show how a reform on tax revenue distribution from local to central governments increases illegal mining activity.

3 Data

3.1 Artisanal mining data

The main small-scale mining data for this article is generated by Microsoft in a joint project with Royal Holloway, University of London. A machine learning model based on a convolutional neural network is trained to identify mines on satellite images from Ghana.[2] These identified mines can then be mapped against other georeferenced data to draw inferences about the effects of ASM. The latest release of Bing Maps for Ghana from 2014 is used for this project. Satellite images for previous years are not available from Bing Maps, so it is unfortunately impossible to construct a panel that way.

One of the most common forms of ASM, alluvial or surface mining, can be spotted by the human eye on high-resolution satellite images (see figure 2). The distinctive visual features of surface ASM sites are described in Mantey et al. (2016), Rahm et al. (2015) and Unitar (2016). These are water pits of unnatural shape, often found next to rivers, which have changed to a light-brown colour. Other forms of artisanal mining not covered in this analysis include underground mining, mill-house operation and pilfering mining. Note that there are many different forms of surface mining, which cannot be distinguished by the approach in this article.

Starting from known ASM centres such as Dunkwa-on-Offin and Obuasi, satellite images are then labelled as either mine, no mine, or cloud by trained users. The validity of this labelling process is verified afterwards by comparing the results to a smaller sample of georeferenced ASM data by Mantey et al. (2016). Most of the Southern half of Ghana is included in this approach. Other regions are excluded because of high computational costs and because we can not visually identify any small-scale surface mining sites in the Northern half. This results in roughly four million satellite image tiles at a resolution of 0.6 metres per pixel, with each tile spanning 152.9 by 152.9 metres (equalling 0.02 square kilometres of surface). The area covered by the detection model is depicted in figure 3. The initial training data set consisted of roughly 4,000 images with 1,000 labelled as mine, 2,000 as not mine and another 1,000 as cloud. The

[2] A More technical background on the data generation methodology can be found soon at https://www.microsoft.com/en-us/research/academic-program/microsoft-azure-for-research/. The image recognition model is designed in Python using Keras with a Tensorflow model. For an intuitive introduction on convolutional neural networks see https://ujjwalkarn.me/2016/08/11/intuitive-explanation-convnets/, for more details see https://www.deeplearning.ai/. For Keras see https://keras.io/.

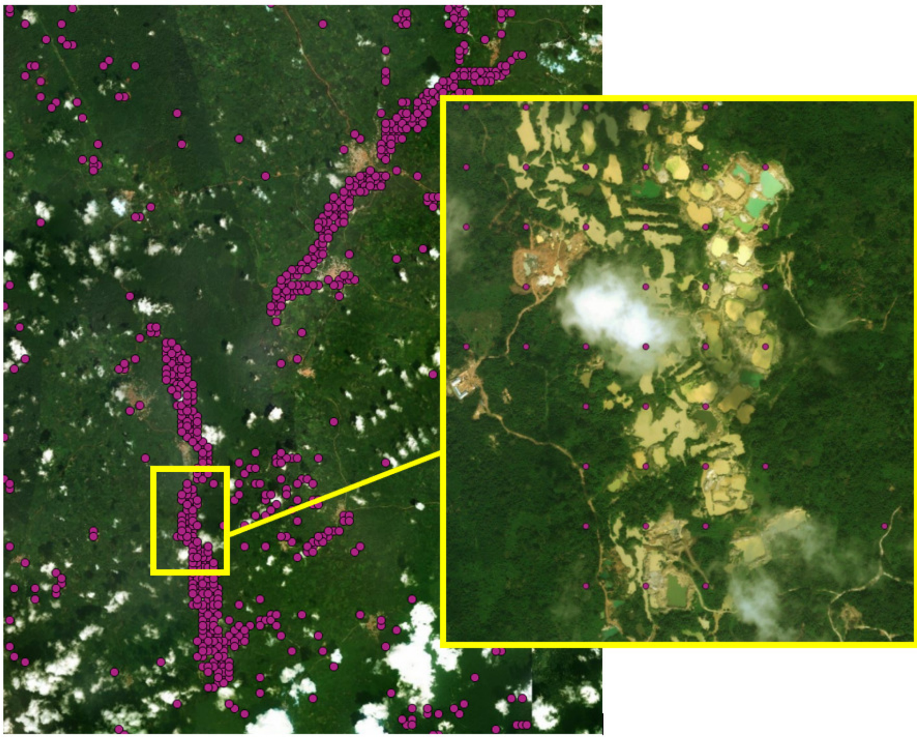

Figure 2: Detected ASM sites in Ghana

training set is then divided into 70 percent model training, 20 percent testing and 10 percent validation. Because this set overpredicted mines the training set was later increased to 1,330 mine, 27,750 not mine and 1,020 cloud labels to improve the accuracy of predicting mines. Figure 4 shows the confusion matrix for the initial training set, a metric for the accuracy of the model, based on the validation part of the training data. Elements on the diagonal from top left to bottom right indicate images that are correctly detected by the model. Elements off the diagonal are mispredictions.

In total, 3,967 images are detected to contain as mine as depicted in figure 3. As anticipated, the small-scale mines form different clusters either in bulks or following rivers. Most detected mines lie in the Ashanti region, with some clusters also being in the Central, Eastern and Western regions. These are also the main large-scale mining areas.

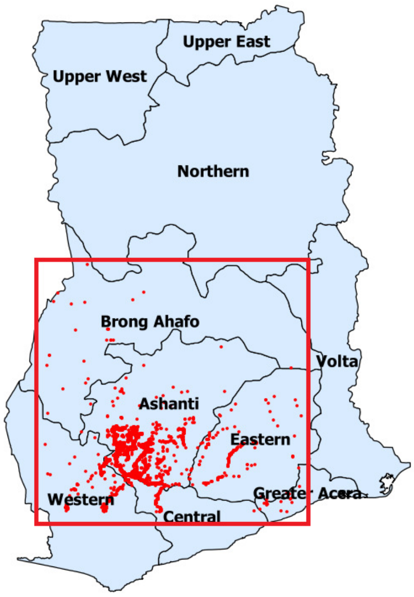

Figure 3: Overview of detected mines in Ghana

Notes: Detected artisanal mines in red. The red box shows the covered area by the machine learning prediction. Source: Microsoft, author's visualisation.

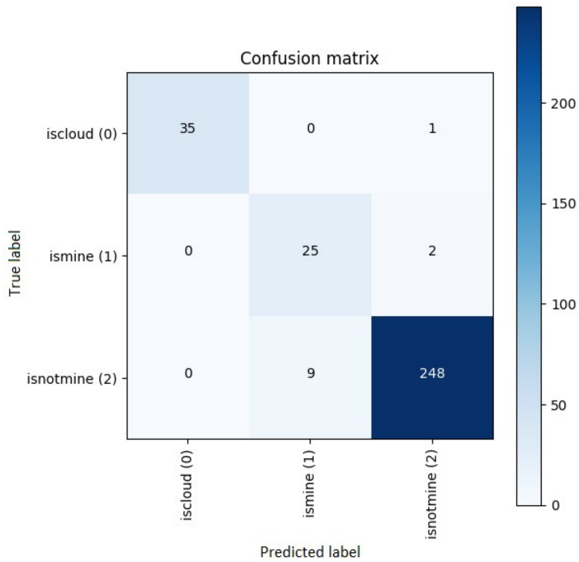

Figure 4: Confusion matrix for validation set

Source: Microsoft

3.2 Socio-economic and environmental data

In addition to the ASM data, two different main data sources are used to estimate effects of ASM on economic and environmental outcomes. The Ghana Living Standards Survey (GLSS) provides data on economic development. To represent environmental effects I use forest cover loss data from Hansen et al. (2013). These data sources are described in more detail below.

The regionally representative Ghana Living Standards Survey (GLSS), produced by the Ghana Statistical Service (GSS), provides three waves that are suitable for this analysis: GLSS 4 (1998/99), GLSS 5 (2005/06) and GLSS 6 (2012/13). Together they sum to a total of 29,459 households and 124,170 individuals. The clusters in GLSS are drawn randomly within the ten regions of Ghana for each survey year. This means that the clusters do not necessarily overlap between survey years but only provide a repeated cross-section. The GLSS provides a rich set of questions at the individual, household and community level (one cluster can have multiple communities). Amongst these are detailed questions on types of income and expenditure, assets, employment, education and health. Price levels at the cluster level allow for a precise comparison of living standards between households in different regions. In addition, the community questionnaire of GLSS provides information on each community's major economic activities, infrastructure (roads, hospitals, electricity, piped water etc.), migration and average wages.

Table 1 shows the number of individual-level observations for each GLSS wave and region covered in the image detection introduced in the previous section. The total number of observations in this table is lower than outlined in the previous paragraph for two main reasons. First, the area covered by the satellite image predictions only spans six out of Ghana's ten regions. Second, GPS coordinates are not available for all GLLS observations, in particular not for GLSS 6 (2012/13).[3] Figure 5 shows the combined data from GLSS and the machine learning predictions.

[3]Unfortunately, most GPS coordinates for Ghana's Central region, which contains many small- and large-scale mines, are missing.

	4	5	6	Total
Ashanti	4865	6529	4874	16268
Brong Ahafo	1871	2729	5125	9725
Central	585	726	0	1311
Eastern	3398	3210	6155	12763
Greater Accra	490	1118	1137	2745
Western	1114	963	2012	4089
Total	12323	15275	19303	46901

Table 1: Number of individual observations per region and GLSS wave

Source: Ghana Statistical Service (1998), Ghana Statistical Service (2008), Ghana Statistical Service (2012).

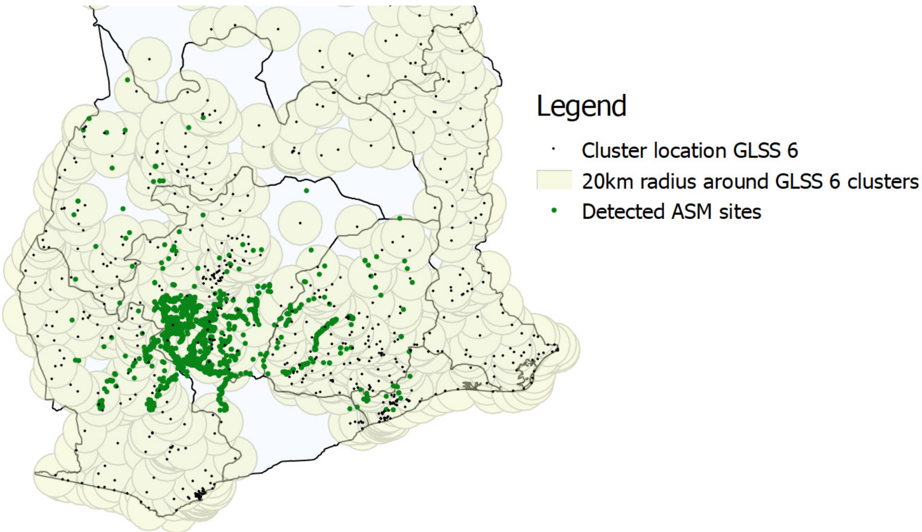

Figure 5: Small-scale mines and household location

Source: author's visualisation of Ghana Statistical Service (2012), Microsoft.

To measure environmental effects of ASM, I use data on forest cover loss (FCL) from Hansen et al. (2013). The FCL data shows areas where canopy cover above 5 metres height was lost between 2001 and 2016 at a resolution of 30 by 30 metres. As data on other environmental outcomes such as soil and water quality is not available at this scale for Ghana, the FCL data might be a suitable proxy for at least this specific form of environmental degradation. FCL has been used in similar applications to show the connection between political incentives and deforestation (Burgess et al., 2012) and to identify small-scale mining in Colombia (Saavedra and Romero, 2017).

3.3 Other sources

In addition to the machine learning based data introduced in section 3.1, other sources on small- and large-scale mining are used in this analysis. For small-scale mining, data on official licenses issued between 1992 and 2017 from Ghana's Minerals Commission Small Scale Mining database is applied.[4] For each registered ASM operation the database contains name, location (given by the nearest village/town plus district and post address of the company), issue and expiry date as well as size in hectares. Note that the issue and expiry date is only provided for licenses that expired before April 25th 2017, the date the data was released to me. Licenses are granted for five years. Therefore,

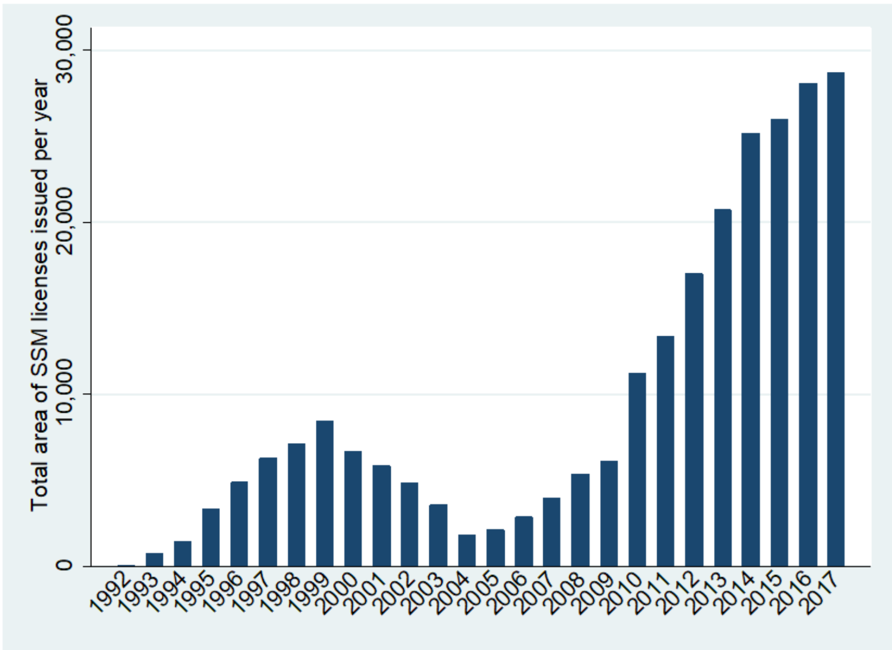

Figure 6: Area of small-scale mining licenses by year issued in ha

Source: Authors calculation based on data from the Ghanaian Minerals Commission Small Scale Mining Database, April 25th, 2017. This graph combines the data sets "Expired licenses" (incl. year issued, year expired) and "Valid licenses" (year issued, expired not available). For the valid licenses the year issued is assigned uniformly between 2012 and 2017.

the licenses currently valid, issued between the years 2012 to 2017, cannot be dated precisely. To get some idea about the magnitude of how many licenses

[4] Official data on SSM licenses is available from 1992 onwards, following the legalisation of this industry. The legalisation of SSM was part of the Minerals and Mining Law 1986 (PNDCL 153) and further implemented in Mercury Law (PNDCL 217), Small-Scale Gold Mining Law (PNDCL 218), and Precious Minerals and Marketing Law (PNDCL 219) in 1989, see Hilson and Potter (2005).

were issued from 2012 onwards and how much area they covered, I assume that the year of issuance is distributed uniformly between 2012 and 2017. The resulting development of area covered by official ASM operations is shown in figure 6. This data can be geo-located at the district level and can thus be used to distinguish effects between legal (this data) and illegal (satellite image based data) ASM.

To account for large-scale gold mining, combined data on the GPS location and annual production of these mines is obtained for years between 1992 and 2013 from Aragón and Rud (2016) and GHEITI (2017). The validity of the GPS location provided in these sources is double-checked by satellite-imaged based observation and information from the respective mining company websites.

4 Empirical Analysis

This section presents the empirical analysis of the effect of artisanal mining on socio-economic and environmental outcomes.

4.1 Descriptive Statistics

The geographic distribution between small-scale mining, large-scale mining and per-capita expenditure, divided by quintiles, is depicted in figure 7.[5] It shows that large industrial mines and small artisanal mines often coincide. More specifically, large mines almost always have some amount of small mines nearby, but not necessarily vice versa (see for example Eastern and Western region). At first glance, per-capita expenditure in Ghanaian cedis (GHC) appears higher in districts with mining activity. It is not clear however, whether this is due to small- or large-scale mining, or other omitted factors.

[5]The same figure is presented for income in the appendix (see figure A.2).

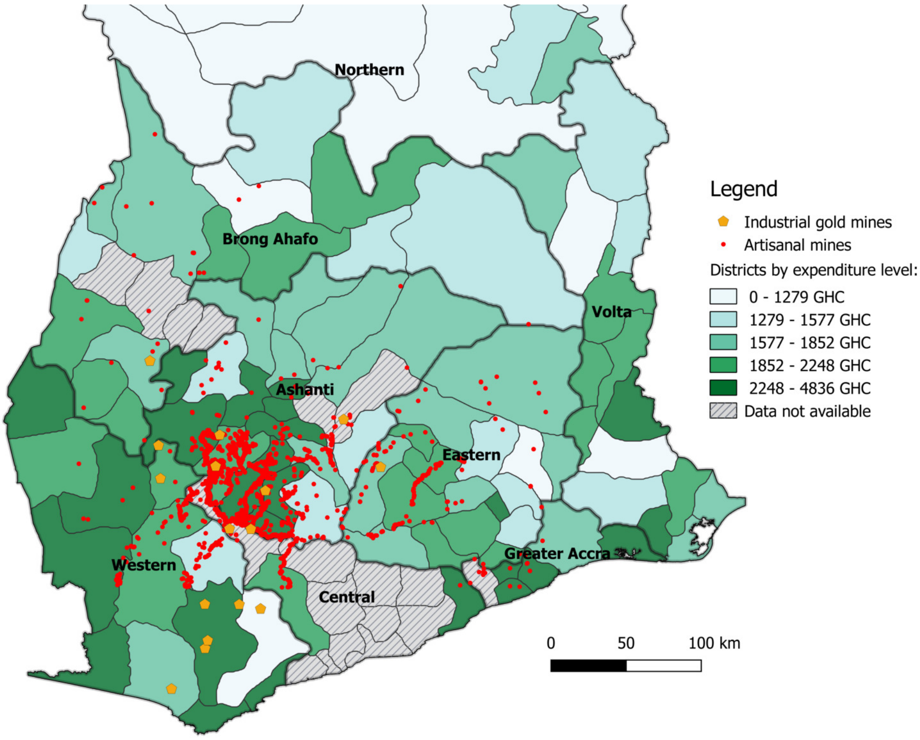

Figure 7: Small- and large-scale mining and expenditure in Ghana

Source: Author's visualisation based on data from Ghana Statistical Service (2012), Microsoft, Aragón and Rud (2016), GHEITI (2015).

To get a more nuanced view on the differences between areas with and without ASM, table 2 presents summary statistics for the main variables for the GLSS survey year 2012/13. I define an ASM area as the 10 kilometre radius around household location with at least 4 detected small-scale mines, which corresponds to the 90th percentile of the overall ASM distribution. The table presents the figures only for the sample area, so only the Southern regions and households with full observations are included. By construction the number of ASM sites is much higher in ASM areas. As predicted, the production of nearby industrial large-scale gold mines is also significantly higher in ASM areas. On average 1.4 tonnes of gold are produced in areas with at least 4 small-scale mines and 0.3 tonnes in areas with less than 4 small-scale mines. More importantly still, log expenditure is 1.7 percent higher ASM areas, while income is not significantly different. Many other variables point to higher economic development in areas with a lot of small-scale mines: Less households are engaged in agriculture, education and literacy are higher and more households have electricity in ASM- vs. non-ASM areas.

Table 2: Summary statistics on main variables by ASM frequency in 2012/13

	(1)	(2)	(3)	
	ASM area	Non-ASM area	Diff.	s.e.
Number ASM sites within 10 km	39.56	0.61	38.95***	(1.20)
Large-scale gold prod. within 10 km	1.40	0.34	1.07***	(0.08)
Ln real income per-capita	7.31	7.27	0.04	(0.02)
Ln real consumption per-capita	7.28	7.16	0.13***	(0.01)
Share male	0.48	0.48	0.00	(0.01)
Share HH head in agriculture	0.49	0.60	-0.11***	(0.01)
Age	32.63	32.58	0.05	(0.36)
Educational attainment on scale 1-5	2.40	2.09	0.31***	(0.03)
Share literate	0.63	0.56	0.08***	(0.01)
Share urban	0.42	0.40	0.02	(0.01)
Share with electricity	0.77	0.58	0.18***	(0.01)
Cluster population	1720.18	1862.35	-142.17	(107.46)
Price index	0.98	0.99	-0.01***	(0.00)
N	3289	9915	13204	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Based on GLSS data from 2012/13. ASM area is defined as an area with at least four detected artisanal mines within 10 kilometres of the household, which corresponds to the 90th percentile of the ASM distribution.

4.2 Effects of ASM on socio-economic outcomes

The previous section shows how mining areas differ from non-mining areas. At this stage it is unclear however whether this is due to small-scale mining, large-scale mining, or other factors. This will be investigated here. The main shortcoming of the machine learning based ASM data is that satellite images, which are required to detect small-scale mines, are only available for 2014. I will therefore start by analysing the cross-section of the ASM data in relation to household survey data from 2012/13 in section 4.2.1. Using the fact that ASM did not become a major industry in Ghana before 2006 (see section 2), I assign zero ASM locations for the years until 2006. This allows me to add a time dimension, the results of which are shown in section 4.2.2 below.

4.2.1 Cross-sectional results

To estimate the effect of small-scale gold mines on economic outcomes I start from cross-sectional analysis, that makes use of the last GLSS survey wave 6 from 2012/13 and the ASM data from 2014. The estimation is done by using OLS of the form:

$$Outcome_i = \beta_0 + \beta_1 ASM_i + \beta_2 LSM_i + \beta_3\text{'}\mathbf{X}_i + \gamma_d + \epsilon_i, \tag{1}$$

where $Outcome_i$ is, depending on the specification used, either the natural logarithm of individual i's household income or expenditure per-capita. ASM_i is the treatment variable representing the number of artisanal small-scale mines within 10 kilometres of the household cluster. $\mathbf{X}_i$ is a set of control variables at the individual level, such as gender, age, educational attainment, religion, literacy and migration status. LSM_i is the production of large-scale gold mines in tonnes within 10 kilometres of the household cluster. γ_d accounts for district-level fixed effects. The error term ϵ_i is clustered at the GLSS cluster level.

The results for this cross-sectional specification are displayed in table 3. The number of detected artisanal mines within 10 kilometres of the household location is positive and significant at the one percent confidence level for real per-capita income. One additional small-scale mine in the proximity of a household increases real per-capita income by 0.2 percent, but has no effect on expenditure. At the same time, the production of large mines within 10 kilometres does not significantly affect economic well-being. This supports the enclave theory of large-scale mining, which states that these mines operate independently from local communities, by hiring very little local labour.

Over which distance does ASM affect households' economic well-being? Figure 8 shows the results of the above specification for different household radiuses between 5 and 50 km. The trend is clear: the closer ASM mines are to the household location, the stronger is their effect on income. The magnitude ranges from 5 percent for the 5 kilometre radius to under 1 percent for the 50 kilometre radius. At the same time, narrower treatment areas exhibit bigger confidence intervals, which points to sizeable unobserved heterogeneity between different ASM areas. This will be further explored in section 4.4.

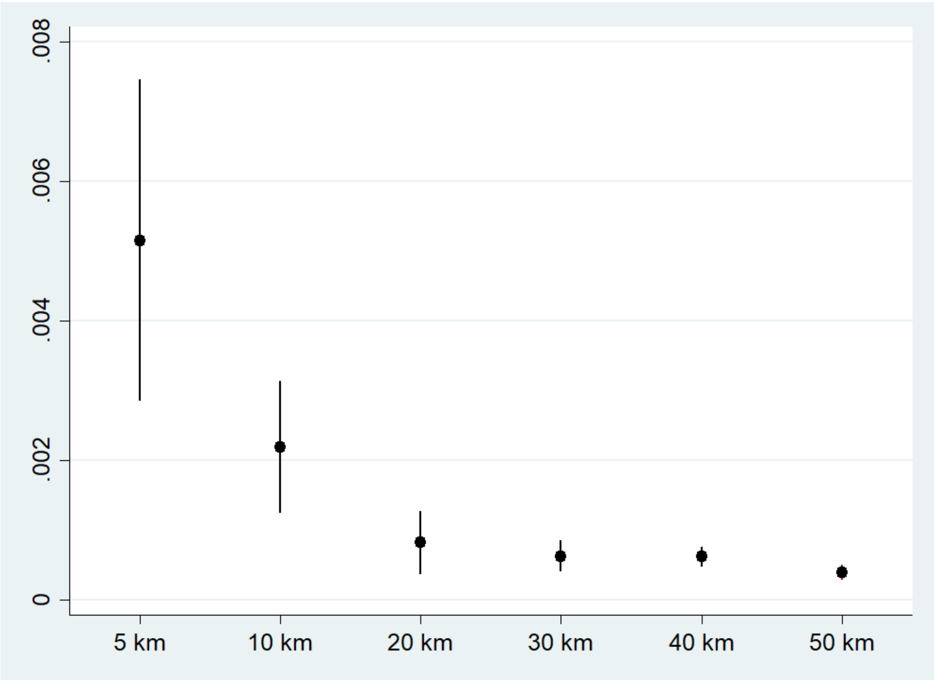

Figure 8: Effect of ASM on log real per-capita income, by distance

Source: Author's calculation, based on Ghana Statistical Service (2012), Microsoft.

Table 3: Effect of artisanal mining on income and expenditure

	(1) LN real income per-capita	(2) LN real expenditure per-capita
Number of ASM sites within 10 km	0.0021**	0.0002
	(0.0009)	(0.0005)
LSM gold production within 10 km	0.0122*	−0.0097*
	(0.0073)	(0.0058)
Male	0.0652***	0.0192*
	(0.0191)	(0.0101)
Age	0.0199***	0.0102***
	(0.0024)	(0.0013)
Age squared	−0.0002***	−0.0001***
	(0.0000)	(0.0000)
Never in school	0.0000	0.0000
	(.)	(.)
Less than primary education	0.1150***	0.0756***
	(0.0388)	(0.0232)
Completed primary but less than MSLC	−0.0432	0.0900
	(0.1441)	(0.0707)
MSLC or vocational	0.1705***	0.1527***
	(0.0405)	(0.0240)
Secondary or higher	0.4303***	0.4335***
	(0.0587)	(0.0345)
Literacy	0.1732***	0.1069***
	(0.0323)	(0.0174)
Born here	−0.0705**	−0.0720***
	(0.0338)	(0.0194)
Urban	0.2879***	0.3197***
	(0.0592)	(0.0384)
Constant	6.0599***	7.0106***
	(0.3386)	(0.1714)
Observations	13204	13204
R^2	0.142	0.334

Clustered standard errors at GLSS cluster level in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Both regressions include district fixed effects and control for religion.

4.2.2 Repeated cross-sectional results

The main drawback of the cross-sectional specification is that it does not provide time variation. To overcome this, I define the treatment variable of detected small-scale mines as zero for all observations in the first two survey waves of GLSS (1998/99 and 2005/06). This is motivated by the evidence presented in section 2. Official ASM production volumes, the number of ASM licenses, gold price and evidence from other articles (Crawford et al. (2015), Aragón and Rud (2016)) all point to very little artisanal gold mining activity until 2006. To check whether this is robust, I will only assign the values from 1998/99 as zero and omit observations from 2005/06.
With the updated ASM treatment variable I then run OLS with year and district fixed effects of the form:

$$Outcome_{idt} = \beta_0 + \beta_1 ASM_{idt} + \beta_2 LSM_{idt} + \beta_3\text{'}\mathbf{X}_{idt} + \gamma_d + \delta_t + \epsilon_{idt}, \qquad (2)$$

Where $Outcome_{idt}$ is now the logarithm of per-capita income or expenditure of individual i in district d in year t. ASM_{idt} indicates the number of detected small-scale mines within 10 kilometres of the household location in 2014. For the first two survey waves (1998/99 and 2005/06), ASM_{idt} is set to zero for all observations. LSM_{idt} is large-scale mine production within 10 kilometres of the household. $\mathbf{X}_i$ is a set of individual controls as in the previous specification. γ_d and δ_t are district and time fixed effects. The error term ϵ_{idt} is clustered at the GLSS cluster level.
The results of the above specification are presented in table 4. The coefficient on ASM is similar to the one estimated in the cross-sectional part, with one additional artisanal small-scale mine adding 0.16 percent to real per-capita income. The effect on expenditure is again insignificant. Further, large-scale gold mining does not have an effect on either of the two outcome variables. These results are in line with the cross-sectional evidence presented in the previous section.

Table 4: Effect of artisanal mining on income and expenditure with time effects

	(1) LN real income per-capita	(2) LN real expenditure per-capita
Number of ASM sites within 10 km	0.0016** (0.0007)	0.0007 (0.0004)
LSM gold production within 10 km	0.0076 (0.0049)	0.0028 (0.0037)
Male	0.0213* (0.0125)	0.0016 (0.0067)
Age	0.0110*** (0.0015)	0.0068*** (0.0008)
Age squared	−0.0001*** (0.0000)	−0.0000*** (0.0000)
Never in school	0.0000 (.)	0.0000 (.)
Less than primary education	0.0891*** (0.0264)	0.0741*** (0.0157)
Completed primary but less than MSLC	0.1351*** (0.0372)	0.1198*** (0.0206)
MSLC or vocational education	0.1839*** (0.0297)	0.1644*** (0.0170)
Secondary or higher	0.5329*** (0.0419)	0.4578*** (0.0250)
Literacy	0.1271*** (0.0214)	0.0975*** (0.0120)
Born here	−0.0652*** (0.0229)	−0.0746*** (0.0132)
Urban	0.1836*** (0.0459)	0.3120*** (0.0310)
Constant	4.9278*** (0.2135)	6.0127*** (0.1132)
Observations	30518	30518
R^2	0.381	0.440

Standard errors in parentheses, clustered at GLSS cluster level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Both specifications include district and year fixed effects and control for religion.

4.3 Effects of ASM on forest cover loss

While income is higher in areas with small-scale mining, the environmental effects have not been taken into account yet. Here I test whether ASM affects forest cover loss, a measure for deforestation. Table 5 reports the differences between ASM- and non-ASM areas from GLSS survey 6 (2012/13) in terms of forest cover loss. The units are in percentage points. Overall, deforestation is significantly higher in ASM- than non-ASM areas. In 2012/13 the difference amounts to half a percentage point, which equals nearly 42 percent (compare columns 1 and 2). Particularly high levels of forest cover loss are reported for the years 2013, 2014 and 2015.

Table 5: Forest cover loss by year and ASM-/ non-ASM area

	(1)	(2)	(3)	
	ASM area	Non-ASM area	Diff.	s.e.
Number ASM	39.56	0.61	38.95***	(1.20)
LSM production	1.40	0.34	1.07***	(0.08)
Forest loss 2012/13	1.66	1.17	0.48***	(0.02)
Forest loss 2012-15	4.29	2.73	1.56***	(0.04)
Forest loss 2001	0.48	0.27	0.21***	(0.01)
Forest loss 2002	0.23	0.23	0.00	(0.01)
Forest loss 2003	0.59	0.32	0.27***	(0.01)
Forest loss 2004	0.41	0.48	-0.07***	(0.01)
Forest loss 2005	0.48	0.27	0.21***	(0.01)
Forest loss 2006	0.23	0.23	0.00	(0.01)
Forest loss 2007	0.59	0.32	0.27***	(0.01)
Forest loss 2008	0.41	0.48	-0.07***	(0.01)
Forest loss 2009	0.46	0.22	0.24***	(0.00)
Forest loss 2010	0.25	0.21	0.04***	(0.00)
Forest loss 2011	0.46	0.33	0.13***	(0.01)
Forest loss 2012	0.34	0.27	0.07***	(0.01)
Forest loss 2013	1.32	0.91	0.41***	(0.02)
Forest loss 2014	1.87	1.10	0.76***	(0.02)
Forest loss 2015	0.76	0.45	0.31***	(0.01)
N	3289	9915	13204	

Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: Hansen et al. (2013), Ghana Statistical Service (2012).

Only observations from GLSS 6 - 2012/13 are used.

To check whether the forest cover loss is driven by ASM or LSM I run a short regression of the logarithm of forest cover loss during the GLSS survey years (column 1) on the number of detected ASM sites and the gold production of LSM within 10 kilometres of the household location. The results are shown in table 6. The effect of ASM is economically small at 0.07 percent, but statistically significant. Using forest cover loss during survey years and the following two years (column 2) as the dependent variable, the effect of ASM increases to 0.2 percent for each additional small-scale mine within 10 kilometres of the household location.

Table 6: Effect of artisanal mining on income and expenditure, incl. time effects

	(1) Forest cover loss during survey years	(2) Forest cover loss during survey years + two years
Number of ASM sites	0.0007^{***}	0.0021^{***}
	(0.0003)	(0.0002)
LSM gold production	0.0014	0.0025
	(0.0015)	(0.0020)
	30,518	30,518
R^2	0.734	0.765

Standard errors in parentheses, clustered at GLSS cluster level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Both specifications include district and year fixed effects.

4.4 Channels and Robustness Checks

The results so far suggest that artisanal and small-scale mining is associated with lower income and increased forest cover loss. In this section, I test provide alternative specifications, distinguish between legal and illegal ASM and dissect the income effects further.

First, I test whether part of the heterogeneity between different treatment areas can be explained by legal versus illegal artisanal mining. For this, I use official ASM license data from Ghana's Minerals Commission Small Scale Mining database, which includes years 1992-2017. Because the exact GPS location for these licensed operations is not available, I match them with the household data by district. This is not ideal, since districts in Ghana have different sizes, meaning that some households can be far away from licensed ASM sites within a district. This limitation in mind, I re-estimate the previous results in table 7. Licensed ASM operations do not have a separate effect on income or expenditure. This may be due to the identification at the district level, or it can simply reflect the small importance of licensed relative to illegal ASM.

Table 7: Illegal, legal ASM and LSM with time effects

	(1) Income	(2) Income	(3) Expenditure	(4) Expenditure
Number ASM	0.0016**	0.0022***	0.0007	0.0006
	(0.0007)	(0.0007)	(0.0004)	(0.0005)
LSM production	0.0076	0.0080	0.0028	0.0028
	(0.0049)	(0.0049)	(0.0037)	(0.0037)
Licensed ASM		-0.0049		0.0006
		(0.0031)		(0.0019)
Constant	4.9278***	4.9026***	6.0127***	6.0158***
	(0.2135)	(0.2140)	(0.1132)	(0.1143)
Observations	30518	30518	30518	30518
R^2	0.381	0.382	0.440	0.440

Standard errors in parentheses, clustered at GLSS cluster level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
All specifications include district and year fixed effects and control for individual and household characteristics. Only years 1998/99 and 2012/13 are used here.

The important identifying assumption for the repeated cross-sectional results in section 4.2.2 is that small-scale mining is negligible for the years 1998/99 and 2005/06 and can thus be set to zero for the according survey observations. Table 8 shows how the effect of illegal ASM, official ASM and large-scale gold mining differs when excluding observations from years the 2005/06. The effect of illegal ASM on expenditure is still not significant. Income however remains significant, even if only at 10 percent without and 5 percent with controlling for legal ASM. The according coefficient is of similar magnitude as before, one additional ASM site leading to 1.4 or 1.6 percent more per-capita income. Again, large-scale mining and licensed artisanal mining have no significant effect on income.

In a next step, I want to test whether the effect on income depends on the source of income. Specifically, I am interested in the difference between agricultural and non-agricultural incomes. With 49 percent the percentage of individuals engaged in agriculture is significantly lower in ASM areas, than the 60 percent in non-ASM areas, as the summary table 2 shows. This is confirmed in a regression context, see table A.6 in the appendix. There are

Table 8: Illegal, legal ASM and LSM with time effects, excluding 2005/06

	(1) Income	(2) Income	(3) Expenditure	(4) Expenditure
Number ASM	0.0014*	0.0016**	0.0001	0.0001
	(0.0007)	(0.0007)	(0.0004)	(0.0005)
LSM production	0.0032	0.0037	0.0012	0.0013
	(0.0059)	(0.0060)	(0.0042)	(0.0042)
Licensed ASM		-0.0039		-0.0005
		(0.0038)		(0.0020)
Constant	4.9895***	4.9544***	6.0996***	6.0955***
	(0.3138)	(0.3191)	(0.1618)	(0.1637)
Observations	19069	19069	19069	19069
R^2	0.379	0.379	0.460	0.460

Standard errors in parentheses, clustered at GLSS cluster level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

All specifications include district and year fixed effects and control for individual and household characteristics. Only years 1998/99 and 2012/13 are used here.

various reasons why agricultural income may be lower in mining areas. First, ASM and related industries can provide higher-paying jobs than, often subsistence, agriculture. On the other hand, negative environmental externalities, for example through deforestation or soil and water pollution, may decrease agricultural productivity and therefore also profitability. Finally, if these ASM areas are more developed overall, then the share of agriculture is expected to be lower.

Table 9 shows the results of the main specification with time effects for different income variables, measured as adult equivalents. Taking adult equivalents instead of per-capita measures can produce more representative income and expenditure figures if households have many children. Columns (1) and (2) repeat the main specification with the adult equivalent numbers. The effect of ASM on income is still 0.16 percent and significant. Unlike before consumption is also affected by ASM now. Columns (3) to (5) show income separated by (3) any work income (farming and non-farming), (4) only agricultural income and (5) only non-agricultural work income. The effect on any work income is of the same magnitude as the total income effect. Agricultural income however is not significantly affected by artisanal mining. Thus only the effect on income from non-agricultural sources is significant (column 6).

These findings shows that while the share of individuals in agriculture is lower

Table 9: Artisanal mining, adult-equivalent measures and income components

	(1) Income	(2) Expend.	(3) Income any work	(4) Income agric.	(5) Income non-agric.
Number ASM	0.0016**	0.0016***	0.0017**	0.0004	0.0014*
	(0.0007)	(0.0005)	(0.0007)	(0.0013)	(0.0008)
LSM production	0.0074	0.0055	0.0074	-0.0048	0.0100**
	(0.0048)	(0.0047)	(0.0058)	(0.0085)	(0.0043)
Male	-0.0364***	-0.0009	0.0082	0.0827***	-0.0312*
	(0.0124)	(0.0112)	(0.0135)	(0.0191)	(0.0167)
Age	0.0101***	0.0182***	0.0178***	0.0122***	0.0210***
	(0.0015)	(0.0013)	(0.0017)	(0.0021)	(0.0022)
Age squared	-0.0001***	-0.0001***	-0.0002***	-0.0001***	-0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Never in school	0.0000	0.0000	0.0000	0.0000	0.0000
	(.)	(.)	(.)	(.)	(.)
Less than primary	0.0999***	0.1107***	0.1077***	0.0242	0.1176***
	(0.0262)	(0.0249)	(0.0280)	(0.0374)	(0.0401)
Primary only	0.1366***	0.1910***	0.1272***	-0.0194	0.1533***
	(0.0369)	(0.0330)	(0.0399)	(0.0548)	(0.0539)
Vocational education	0.1886***	0.2855***	0.1708***	-0.0336	0.2150***
	(0.0297)	(0.0270)	(0.0311)	(0.0435)	(0.0425)
Secondary or higher	0.5231***	0.6427***	0.5242***	-0.1985***	0.6168***
	(0.0417)	(0.0384)	(0.0445)	(0.0716)	(0.0556)
Literacy	0.1106***	0.0023	0.1111***	-0.0196	0.1973***
	(0.0213)	(0.0178)	(0.0230)	(0.0343)	(0.0288)
Born here	-0.0649***	-0.1057***	-0.0773***	0.0343	-0.0967***
	(0.0228)	(0.0203)	(0.0242)	(0.0380)	(0.0293)
Urban	0.1712***	0.4055***	0.1831***	-0.6799***	0.5168***
	(0.0456)	(0.0406)	(0.0508)	(0.0924)	(0.0579)
Constant	5.1995***	4.2234***	4.9393***	4.5975***	4.3913***
	(0.2094)	(0.1457)	(0.2575)	(0.3476)	(0.1889)
N	30518	30518	29792	20312	22915
R^2	0.383	0.284	0.330	0.150	0.384

Standard errors in parentheses, clustered at GLSS cluster level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

All specifications include district and year fixed effects and control for individual and household characteristics.

in ASM areas, the according agricultural income is unchanged. This is therefore evidence against the presumed negative externalities of ASM on agricultural productivity. The small income gain that does arise from ASM is earned by non-agricultural activities, which supports the hypothesis of positive externalities, possibly through employment generation or wage and business revenue increases. The precises channels of this effect still have to be investigated.

5 Conclusion

This article is among the first to provide empirical evidence on the economic and environmental effects of artisanal small-scale mining. Using a novel data set on the exact GPS location of small-scale mines in connection with household survey data, I estimate higher per-capita income for areas with high ASM activity. Other indicators of economic development point in the same direction: more households have access to electricity, more people are literate and fewer individuals work in agriculture. However, there is also some evidence for environmental damages in the form of forest cover loss. Better data on the intensive margin of ASM, for example in the form of production volumes or number of workers, is needed to establish the precise channels through which artisanal mining affects economic outcomes. Nonetheless, the empirical evidence presented here allows for a more nuanced view on the effects of artisanal and small-scale mining in an otherwise data-sparse environment.

A Appendix

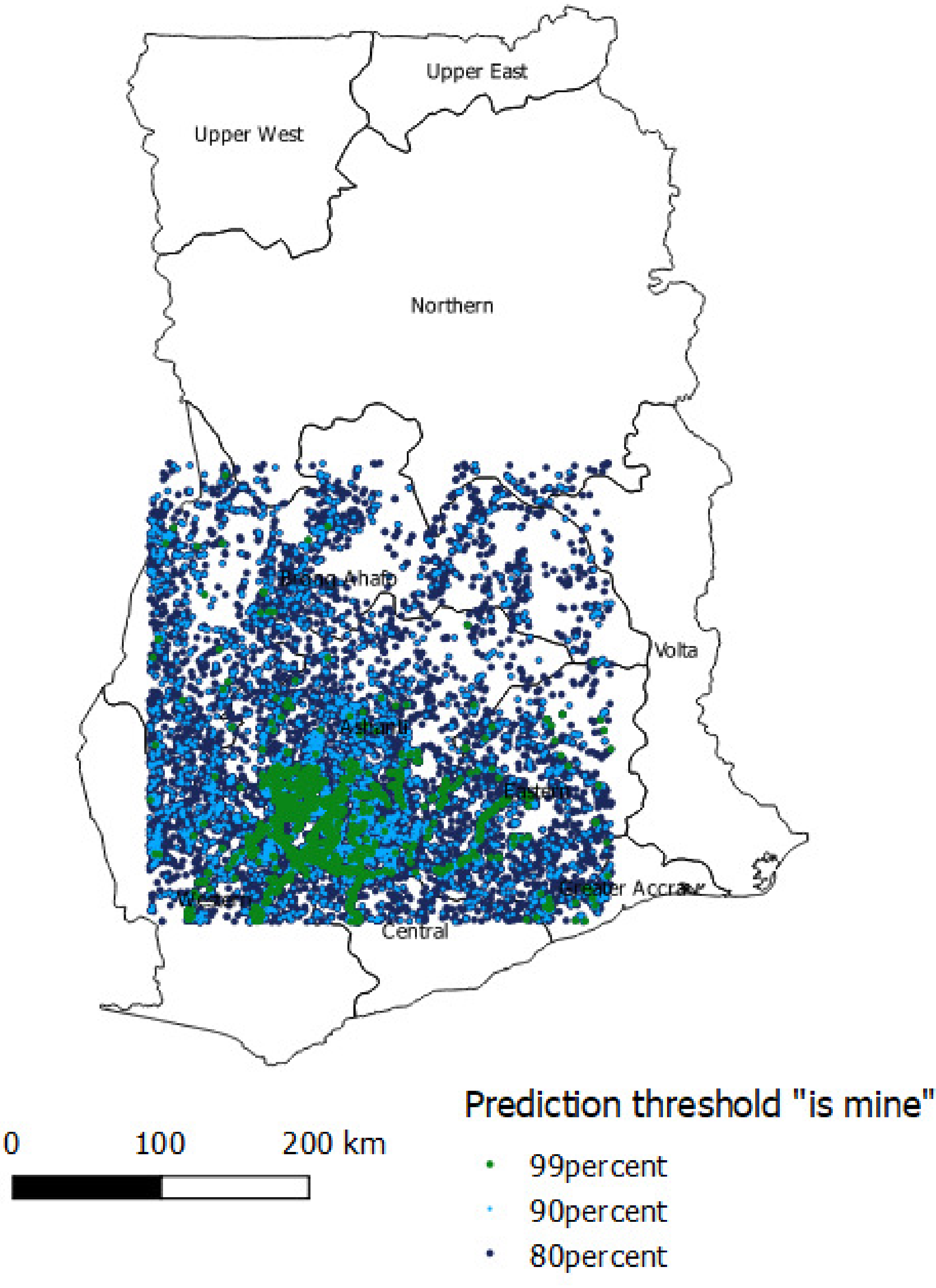

Figure A.1: Detected mines by threshold

	4	5	6	Total
Ashanti	4865	6529	4874	16268
Brong Ahafo	1818	2522	5014	9354
Central	517	658	0	1175
Eastern	3300	3210	6079	12589
Greater Accra	91	363	726	1180
Western	1021	913	1954	3888
Total	11612	14195	18647	44454

Table A.1: Number of individual observations per region and GLSS year, excluding observations 5 km from coverage border

Source: Ghana Statistical Service (1998), Ghana Statistical Service (2008), Ghana Statistical Service (2012).

	4	5	6	Total
Ashanti	4865	6529	4874	16268
Brong Ahafo	1752	2471	4827	9050
Central	452	466	0	918
Eastern	3117	3184	5956	12257
Greater Accra	91	131	146	368
Western	931	859	1635	3425
Total	11208	13640	17438	42286

Table A.2: Number of individual observations per region and GLSS year, excluding observations 10 km from coverage border

Source: Ghana Statistical Service (1998), Ghana Statistical Service (2008), Ghana Statistical Service (2012).

	4	5	6	Total
Ashanti	4865	6529	4874	16268
Brong Ahafo	1693	2218	3939	7850
Central	262	194	0	456
Eastern	2759	2831	5055	10645
Western	726	630	1004	2360
Total	10305	12402	14872	37579

Table A.3: Number of individual observations per region and GLSS year, excluding observations 20 km from coverage border

Source: Ghana Statistical Service (1998), Ghana Statistical Service (2008), Ghana Statistical Service (2012).

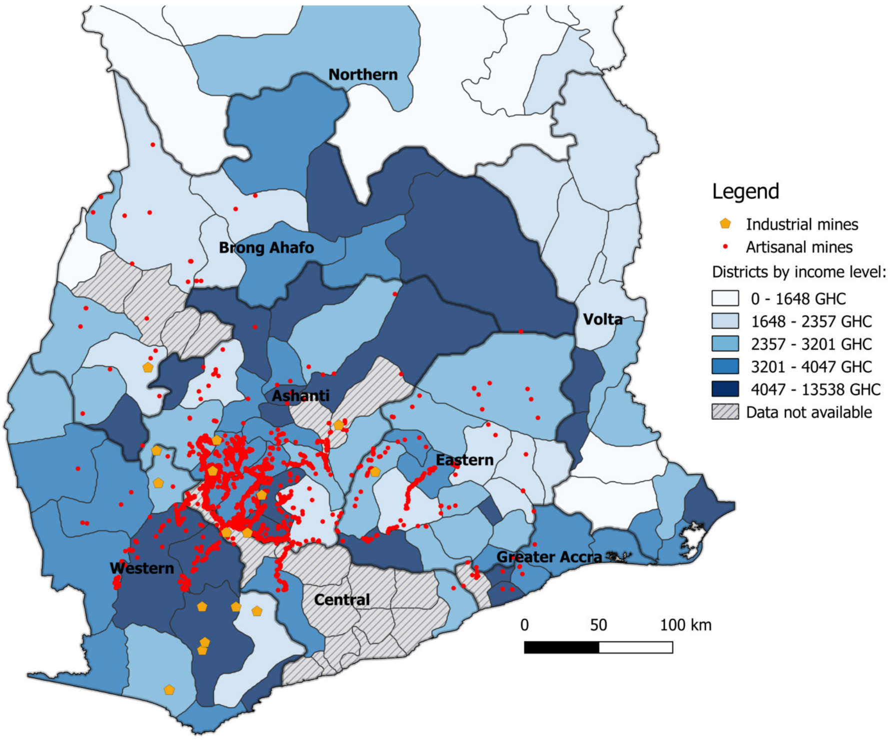

Figure A.2: Small- and large-scale mining and income in Ghana

Source: Ghana Statistical Service (2012), Microsoft, Aragón and Rud (2016), GHEITI (2015).

Table A.4: Effect of artisanal mining on income and expenditure, excluding observations 5 km from coverage border

	(1) LN real income pc	(2) LN real expenditure pc
c99p_10km	0.0021**	0.0002
	(0.0009)	(0.0005)
cumul_production_10km	0.0121*	−0.0096*
	(0.0073)	(0.0058)
male	0.0683***	0.0172*
	(0.0192)	(0.0103)
age	0.0201***	0.0103***
	(0.0025)	(0.0014)
age_sq	−0.0002***	−0.0001***
	(0.0000)	(0.0000)
0.educ_attainment	0.0000	0.0000
	(.)	(.)
1.educ_attainment	0.1297***	0.0789***
	(0.0392)	(0.0239)
2.educ_attainment	−0.0833	0.0674
	(0.1544)	(0.0716)
3.educ_attainment	0.1906***	0.1588***
	(0.0405)	(0.0247)
4.educ_attainment	0.4415***	0.4384***
	(0.0593)	(0.0355)
1.religion	0.0000	0.0000
	(.)	(.)
2.religion	0.0445	−0.0314
	(0.0647)	(0.0378)
3.religion	−0.0917*	−0.0566
	(0.0534)	(0.0375)
literacy_any	0.1687***	0.1069***
	(0.0330)	(0.0179)
born_here	−0.0665*	−0.0706***
	(0.0347)	(0.0200)
urban	0.2851***	0.3166***
	(0.0608)	(0.0395)
_cons	6.0373***	7.0089***
	(0.3378)	(0.1714)
N	12694	12694
R^2	0.139	0.315

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.5: Effect of artisanal mining on income and expenditure, excluding observations 10 km from coverage border

	(1) ln_rincpc	(2) ln_rexpenditurepc
c99p_10km	0.0021**	0.0003
	(0.0009)	(0.0005)
cumul_production_10km	0.0121	−0.0097*
	(0.0074)	(0.0058)
male	0.0752***	0.0171
	(0.0204)	(0.0108)
age	0.0194***	0.0102***
	(0.0026)	(0.0014)
age_sq	−0.0002***	−0.0001***
	(0.0000)	(0.0000)
0.educ_attainment	0.0000	0.0000
	(.)	(.)
1.educ_attainment	0.1283***	0.0805***
	(0.0405)	(0.0251)
2.educ_attainment	−0.0778	0.1086
	(0.1575)	(0.0674)
3.educ_attainment	0.1821***	0.1543***
	(0.0422)	(0.0259)
4.educ_attainment	0.4149***	0.4213***
	(0.0629)	(0.0349)
1.religion	0.0000	0.0000
	(.)	(.)
2.religion	0.0242	−0.0367
	(0.0690)	(0.0390)
3.religion	−0.0925*	−0.0709*
	(0.0560)	(0.0379)
literacy_any	0.1719***	0.1121***
	(0.0344)	(0.0186)
born_here	−0.0837**	−0.0715***
	(0.0360)	(0.0206)
urban	0.2905***	0.3144***
	(0.0632)	(0.0415)
_cons	6.0633***	7.0102***
	(0.3384)	(0.1720)
N	11759	11759
R^2	0.138	0.305

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.6: Effect of artisanal and industrial mining on industry shares

	Agriculture			Mining		
	Head	Couple	HH	Head	Couple	HH
ASM	0.9969**	0.9961***	0.9958***	1.0067***	1.0065***	1.0059***
	(0.0013)	(0.0013)	(0.0013)	(0.0020)	(0.0020)	(0.0020)
LSM	0.9771**	0.9681***	0.9663***	1.0587***	1.0627***	1.0619***
	(0.0103)	(0.0096)	(0.0112)	(0.0173)	(0.0167)	(0.0158)
N	28914	29553	30298	16173	16671	18767
Pseudo R^2	0.327	0.355	0.385	0.271	0.274	0.247

Results, shown as exponentiated coefficients, from logit regression of household head / head or spouse / any household member being in agriculture / mining on ASM and LSM variables, controlling for individual, household characteristics, district-level and year fixed effects. Standard errors are clustered at the GLSS cluster level. Source: Ghana Statistical Service (1998), Ghana Statistical Service (2008), Ghana Statistical Service (2012), Microsoft, Aragón and Rud (2016), GHEITI (2015). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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