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Spillovers from extractive industries

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Abstract: Extractive industries form an important part of the economy for many developing countries, but their impact on growth and welfare remains understudied. With global efforts to transition to net-zero carbon emissions in the coming decades, understanding the local impacts of the extractives sector is crucially important for regional economic development policy in the management of this transition. In this paper we use tax administrative data from South Africa to examine the local spillovers from mining activities, focusing on wages, firm profitability, and job creation. Utilizing exogenous changes in international mineral and metals prices, which had a heterogeneous impact across different local areas depending on the main minerals and metals being extracted, we find that, in the short term, a general contraction in the mining sector reduces the number of jobs in related service industries, as well as the wages received by local workers in those sectors. We also find evidence that a negative shock to the mining sector through vertical integration will have negative productivity impacts on the tradable sectors (especially manufacturing).

Key words: mining, South Africa, local spillovers, firms, profitability

JEL classification: L72, O13, Q32, R11

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1 Introduction

Extractive industries play a dominant role in the economies of many developing countries.[1] While an abundance of natural resources represents a clear economic opportunity for nations, a large body of evidence supports the existence of the natural resource curse that suggests that resource abundance often fails to have the expected positive impact on welfare (Mehlum et al. 2006; Sachs and Warner 1999, 2001).[2] The impact of extractive industries on growth at a local level is, however, understudied. This is a notable gap given the current context of decarbonization and global efforts to transition to net-zero carbon emissions in the coming decades. The green transition will inevitably force certain extractive sectors to contract, but it will also present opportunities in others necessary for the development of clean technologies.[3] Understanding the local impacts of the contraction and expansion of these sectors is crucially important for regional economic development policy focused on the localized management of this net-zero transition.

In this paper we study the localized economic impact of mining activities. We estimate the impact of the expansion/contraction of extractive industries on local economies (defined at the postal code level) in South Africa in terms of wages, firm profitability, and job creation. We use a large employer–employee matched tax administrative data set for South Africa for the period 2011–16, which allows us to identify all mines, firms, and workers operating in the formal economy. We use an identification strategy in which we instrument for expansions and contractions in mining at the local level with shocks to international mineral and metal prices for the main resource produced locally. We find a positive effect of mining on the local wages in virtually every sector as well as on the productivity of firms in both tradable and non-tradable sectors. This is consistent with a scenario in which mines source at least part of their inputs from local manufacturing firms (representing the vast majority of the tradable sector) and as such indirectly benefit them rather than crowding them out.

Importantly, we also find that mining is linked to local job creation in the non-tradable sector and especially in services, while it has no impact (positive or negative) on manufacturing and agriculture. This is in line with a number of other studies finding a strong interdependence between local service and construction sectors and mining activities (see Marchand and Weber (2018) for a comprehensive summary of the existing literature). More specifically, we find that for each job created or lost in the mining sector, one to two additional jobs in the service sector are created/lost. Interestingly, unlike most of the existing literature, these findings generally reflect the impact of a contraction in mining activities following a reduction in international prices, and as such have important policy implications, particularly in light of the current context of the global decarbonization effort.

The existing empirical literature examining the local impact of mining has produced mixed findings. While there is some evidence for positive employment multiplier effects (Michaels 2011; Toews and Vezina 2020),[4] others suggest that mining activity creates local boom–bust economies with only tran-

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[1] See https://www.worldbank.org/en/topic/extractiveindustries/overview#1 for an overview of the role of extractive industries in developing country economies.

[2] This narrative has, however, been questioned both on theoretical and empirical grounds (Van Der Ploeg and Poelhekke 2010). In particular, there is a consensus that the use of aggregate data and the cross-country framework typically applied to this kind of analysis is poorly suited to empirically capturing the localized economic impact of mining activities (Marchand and Weber 2018).

[3] For example, lithium, graphite, manganese, and cobalt. See United Nations (2021) for a discussion on the sustainable transition of the extractives sector.

[4] Michaels (2011) was one of the first papers to use within-country variation in resource abundance to identify the local impact, and found positive effects on employment generation. Toews and Vezina (2020) explored the impact of foreign direct investment resulting from unexpected oil and gas discoveries on local jobs and found evidence of a large jobs multiplier through

sient effects on employment (Kotsadam and Tolonen 2016).[5] The evidence on the local effects of mining on income and living standards is also mixed. For example, Caselli and Michaels (2013) find no effect of a fiscal windfall from oil royalties on living standards in Brazilian municipalities. In contrast, Lippert (2014) and Loayza and Rigolini (2016) find positive effects of mining on living standards in Zambia and Peru. Similarly, Aragon and Rud (2013) find positive effects of the opening of a new gold mine in Peru on income and consumption and a reduction in poverty through backward spillovers. Other studies have explored related outcomes such as the business environment (De Haas and Poelhekke 2019)[6] and occupational outcomes (Fafchamps et al. 2017),[7] and other outcomes such as migration (Ticci and Escobal 2015), inequality (Loayza and Rigolini 2016), violence (Berman et al. 2017), crime (Axbard et al. 2019), health (Tolonen 2018a; Von der Goltz and Barnwell 2019), and gender norms (Tolonen 2018a,b).

Our paper contributes to this literature in several ways. First, we simultaneously consider both firm and individual outcomes providing a richer picture of the mechanisms through which mining activities affect local economies. Our analysis is based on data of unprecedented scale: we observe more than 35 million worker–year data points, and nearly 1.5 million firm–year entries, enabling us to jointly look at both worker and firm outcomes. This represents a marked advantage with respect to the existing studies using micro-data to examine the localized impact of mining activity. The literature to date has focused on a specific set of outcomes usually relating to either the firm, individuals, or jobs. For example, Michaels (2011) focused only on local employment generation while De Haas and Poelhekke (2019) focused only on firm-level outcomes and Fafchamps et al. (2017) focused on occupational outcomes. None of these studies examined the effect on individual outcomes. On the other hand, Aragon and Rud (2013) focused on the impact on local wages and prices of non-tradable goods. They could not measure the effect on firm profitability or the local jobs multiplier.

By examining the impact on wages, firm profitability, and employment creation we can explore in greater detail the mechanisms through which mining impacts on the local economy. To guide our empirical analysis we develop a stylized set of hypotheses, based on the general equilibrium framework proposed by Moretti (2010) to model the effects of local labour demand shocks. According to this model, local and sector-specific shocks in labour demand can propagate to other industries. Indeed, as long as the workforce is not perfectly geographically mobile, an increase in local labour demand pushes up nominal wages, which increases local demand for goods and services. In turn, this also increases prices, especially in non-tradable goods and services sectors, which should expand as a result. Our rich data set allows us to validate this theory as we can test all intermediate steps and measure precisely the size of the impact and the predicted differences along the tradable/non-tradable dimension.

Second, we provide new evidence for South Africa, a unique case of a growing economy with a mature mining sector that has been heavily affected by the history, demography, and economy of the country. The legacy of the mining sector in South Africa is a complex one. For nearly a century it has embodied the racial and social disparities brought about by colonial rule and apartheid (Macmillan 2017). The sector has experienced a steady decline in the last few decades, after reaching a peak in the late 1980s. In 1986, extractive activities accounted for more than 12 per cent of GDP and employed more than 750,000 workers (Fedderke and Pirouz 2002; Macmillan 2017). While the sector has contracted, it still plays a

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this channel for the case of Mozambique. Other studies finding evidence of local jobs multipliers for the mining sector are Black et al. (2005), Fetzer (2014), Feyrer et al. (2017), Lee (2015), Tsvetkova and Partridge (2016), and Weber (2014).

[5] Kotsadam and Tolonen (2016) found that mining leads to women shifting employment from agricultural self-employment to the services sector and male partners shifting to skilled manual labour. They found that the overall effect on female employment was negative.

[6] De Haas and Poelhekke (2019) found that mining had a negative effect on the business environment for firms in the tradable goods sector using data on new mines from nine developing countries.

[7] Fafchamps et al. (2017) estimated the impact of gold mines on occupational outcomes in rural Ghana and found that gold mines led to increased specialization in non-farm activities.

key role in the South African economy and is a fundamental component of the country's economic framework. In 2011 (the starting year of our empirical analysis), extraction industries represented 6 per cent of GDP and accounted for 40 per cent of total exports and 15 per cent of corporate tax revenue (Minerals Council South Africa 2012). These aggregate statistics overlook a great deal of heterogeneity in the trajectory of different sub-sectors within the mining industry in South Africa. Gold, diamonds, and coal were historically at the core of the South African mineral industry, but it has diversified significantly over time. Indeed, the sizeable decline in gold production over the last few decades was coupled with an increase in the extraction of platinum, titanium, and manganese, of which South Africa is currently one of the world's leading producers (Minerals Council South Africa 2012).

In spite of the historical relevance of mining activities in South Africa, the recent economic literature has virtually overlooked it. With the exception of Axbard et al. (2019) mentioned above, to the best of our knowledge the only study that analysed the impact of the mining sector on the South African economy is Stilwell et al. (2000). Using an input–output matrix approach and data on mining activities between 1971 and 1997, they questioned the common conception that extractive industries are the engine of the South African economy. In particular, they found that the multipliers of the mining sector are, if anything, lower than the ones found in the services and manufacturing sectors. Their results suggest that the government should make an active effort to integrate mining activities with the local economy. While this study is informative, it overlooked the general equilibrium employment effects of localized labour market shocks (Moretti 2010).

Third, while most studies to date examine the impact of new mines, our analysis uses the population of mines in South Africa, where extractive industries have generally been shrinking. In the period under analysis (2011–16) the total number of workers in mining dropped by more than 5 per cent. Our study therefore provides important insights on the economic impact of a contraction in the mining sector, which is particularly relevant considering the decarbonization targets set by several countries to tackle climate change.

The rest of our paper is structured as follows. Section 2 describes the data, while the empirical approach is outlined in Section 3. The results are presented in Section 4. Section 5 concludes.

2 Data

Our analysis is based on the SARS-NT/CIT-IRP5 employer–employee matched panel, which contains tax administrative data collected by the South African Revenue Service (SARS) (National Treasury and UNU-WIDER 2019a; Pieterse et al. 2018). We consider the fiscal years between 2011 and 2016. More specifically, we match the South African corporate income tax (CIT) data, which are collected annually and are based on self-reported CIT returns, to the individual-level panel (Ebrahim and Axelson 2019; National Treasury and UNU-WIDER 2019b), which includes information on workers' characteristics, employment, wages, and location. This allows us to study both worker-level and firm-level outcomes.[8]

Additionally, the data set locates all firms and workers in the formal sector across 1,530 different postal codes. This allows us to match spatially our observations with the exact location of active mines in South Africa from the metals and mining data set produced by S&P Global (2021). S&P Global (2021) also provide information on the main metals extracted by each mine (up to six), as well as the international

[8] See the data appendix (Appendix B) for more details.

prices of 16 different metals and minerals.[9] We combine the data on type of production and prices to generate a single, location-specific price index, which we use to instrument changes in the local level of mining activities. We provide more details on the construction of the instrument below. Our key outcome variables include the creation of new jobs, the wages of local workers, and firm profitability.

We define a firm as an entity that issues employers' tax certificates to its workers. Each firm is identified by a unique code and issues a certificate for each worker employed in a given financial year, indicating the total wage paid and the number of months worked. In turn, each worker is uniquely identified by a code, which allows us to observe their career path and occupational outcomes for the whole period under analysis, even when they move to a different location or change jobs. Furthermore, workers are asked to describe the main activity of their employer and to report the postal code of their workplace. We exploit this information to identify and geolocate firms and workers. It also allows us to classify firms into either tradable and non-tradable industries. In particular, we define 34 different industries, which are subsequently aggregated into five macro-categories/sectors: agriculture, mining, manufacturing, construction, and services. We consider the agriculture and manufacturing sectors as tradable sectors and the construction and services sectors as non-tradable sectors.

To geolocate firms and workers we rely on their postal code, which is the narrowest geographical unit available in our data and is reported by workers who are asked the location of the firms they are employed by. In some instances (about 20 per cent of the cases) different postal codes were reported for the same firm. When this happens we considered the modal occurrence. Unfortunately, there is no map available for the South African postal codes, so it is not immediately possible to match postal codes to coordinates. In order to address this issue, we use data from GeoNames (2021) and GeoPostcodes (2021). In particular, these data sets consist of places, their coordinates, and the postal codes they are located in. This allows us to link most postal codes to a set of coordinates. When more than one place is listed for a postal code, we take the median latitude and longitude.

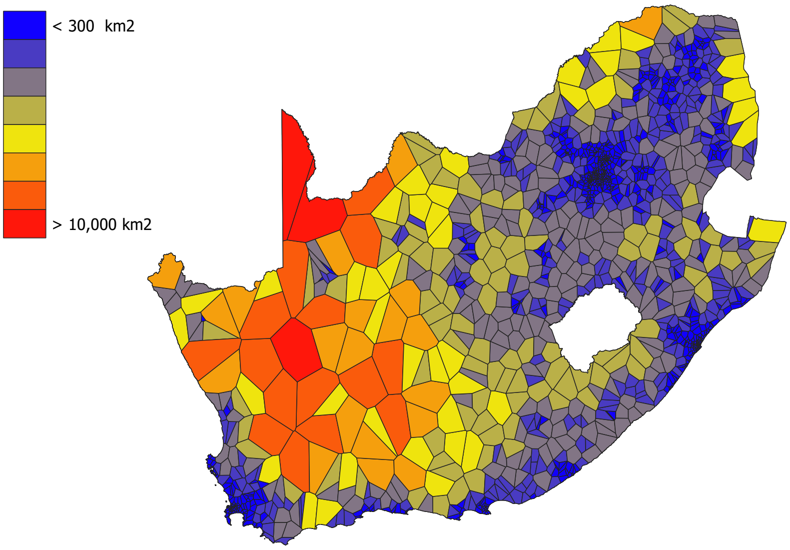
Following this procedure, we can match 82 per cent of the firms and 93 per cent of the workers in the original sample to 1,530 separate coordinates. In the remainder of the paper we will refer to this set of 1,530 different coordinate pairs as postal codes or locations interchangeably. The precision of our geolocation procedure depends crucially on the density of postal codes matched, as well as the size of the postal code areas themselves. We obtain a proxy for the accuracy of the location identified by computing the area of the Voronoi cell for each location. This is the set of all points that are closer to the coordinates of that location than to any other location. Low values indicate better accuracy in the geolocation procedure. Figure 1 shows the Voronoi cells and a colour scale of their size.

By matching the firm and worker data to the postal codes, it is possible to obtain an accurate description of the economic activities taking place in South Africa at a very narrow level, and to study their evolution over time. For the purpose of our paper, it is particularly interesting to examine the spatial distribution of mining activities and their contraction/expansion over the five years under analysis. Figure 2 shows the locations and intensities of extraction activities in South Africa and the local changes in mining employment that occurred between 2011 and 2016 in each location.

It is apparent that mining activities are mostly clustered in the north-eastern area of the country, particularly in the Gauteng, Limpopo, Mpuma-Langa, and North West provinces. However, there are also some relevant extractive sites in the central region of the country, between the provinces of Northern Cape and Free State, as well as along the coast. Interestingly, there has been a general reduction in the number of workers in the sector between 2011 and 2016. However, there is some heterogeneity across postal codes and the number of jobs in mining has increased in a non-trivial share of the areas under analysis.

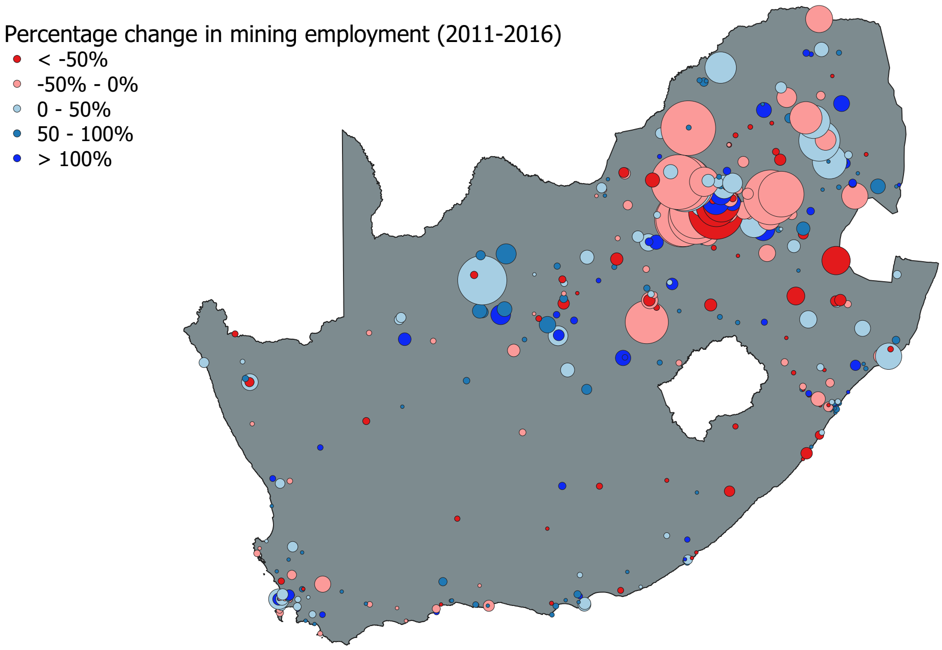
[9] The minerals and metals for which price data are available include chromite, coal, copper, diamonds, gold, iron, lead, manganese, nickel, palladium, platinum, silver, tin, titanium, uranium, and zinc.

Figure 1: Postal codes and Voronoi cells



Source: authors' elaboration based on data from GeoNames and GeoPostcodes.

Figure 2: Mining activities in South Africa



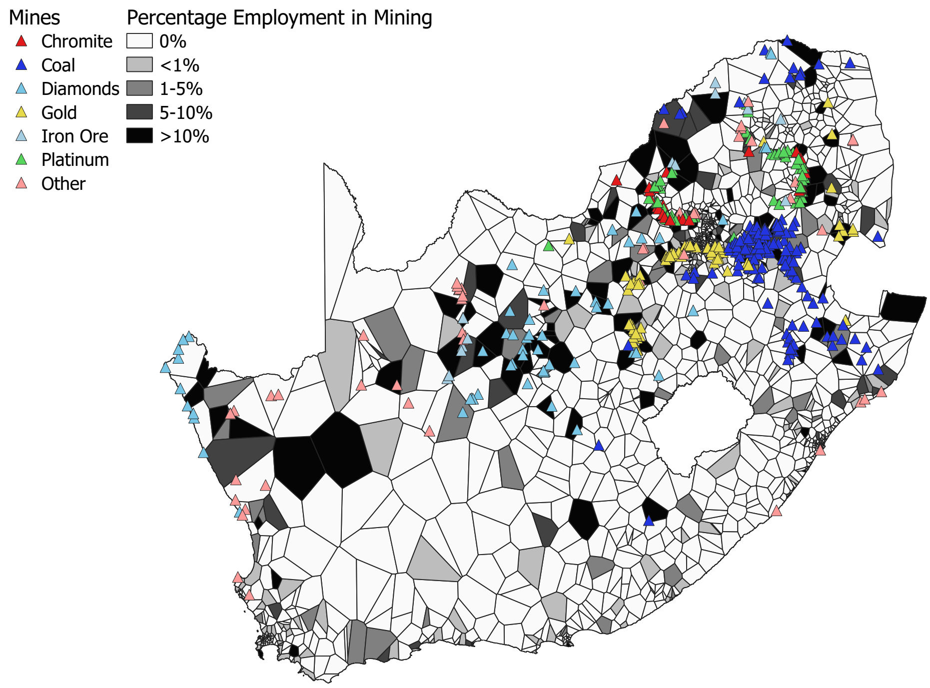
Note: the circles are proportional to the average number of workers in mining over 2011–16.

Source: authors' elaboration based on data from the SARS-NT/CIT-IRP5 panel.

The administrative data do not include any additional information on the firms that operate in the mining sector and more specifically on the minerals or metals extracted or the exact location of the mining sites within the postal codes. For this reason we complement this data set with the S&P Global data which offer the exact coordinates of 443 active mining sites in South Africa, as well as up to six of the most important minerals and metals produced in each mine. We use these data to create a postal-code-specific price index based on the minerals and metals produced by all the mines located within the postal code Voronoi cell and/or within 30 km of its centroid.[10]

Figure 3 shows the spatial distribution and the main production of the mines as identified by the S&P Global data set and the postal-code-specific share of employment in mining computed from the administrative data. Reassuringly, the two data sets seem to provide a consistent picture of the spatial distribution of mining activities in South Africa as the share of employment in mining is systematically higher in areas with higher densities of mines.

Figure 3: Mine locations and employment in the extractive industries



Source: authors' elaboration based on data from the SARS-NT/CIT-IRP5 panel (percentage employment) and S&P Global (mine location and production).

The price index is based on the median price observed for each financial year (March to February) of the 16 minerals and metals in our sample, normalized to 100 in 2010. For each postal code and year we calculate the index as the average normalized price across all the minerals and metals produced by mines in the postal code and/or within 30 km of its centroid, counting all the occurrences of each metal. The latter ensures that minerals and metals produced in more sites are given a larger weight. We also compute an alternative index considering only the main mineral or metal extracted in each mine.[11]

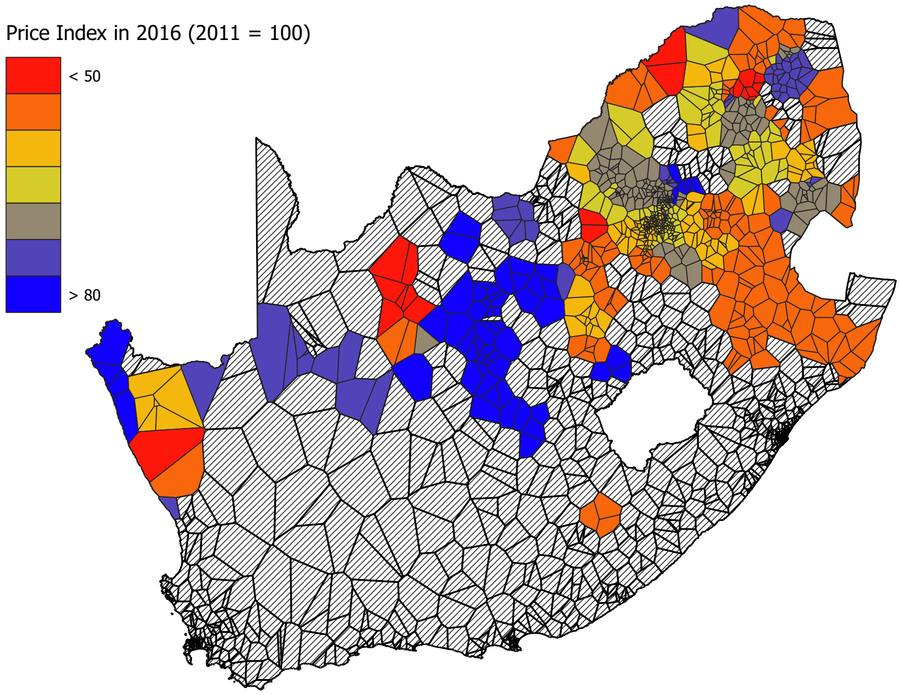
It is clear that there is some heterogeneity in production across different regions. This fact plays a key role in our identification strategy, which is based on differences in prices shocks experienced by different areas. In particular, Figure 4 shows that although all prices have generally gone down between 2011 and 2016, there is marked heterogeneity in the extent to which different locations experienced these shocks.

[10] Including also mines within 30 km of the centroid allows to include in the price index very close mines located in other postal codes. This is especially meaningful in the north-eastern part of the country, where postal codes are smaller (see Figure 1) and where most mining activities are concentrated (see Figures 2 and 3).

[11] The data do not have exhaustive information on the quantity of minerals and metals produced, which would allow for a more sophisticated weighting strategy

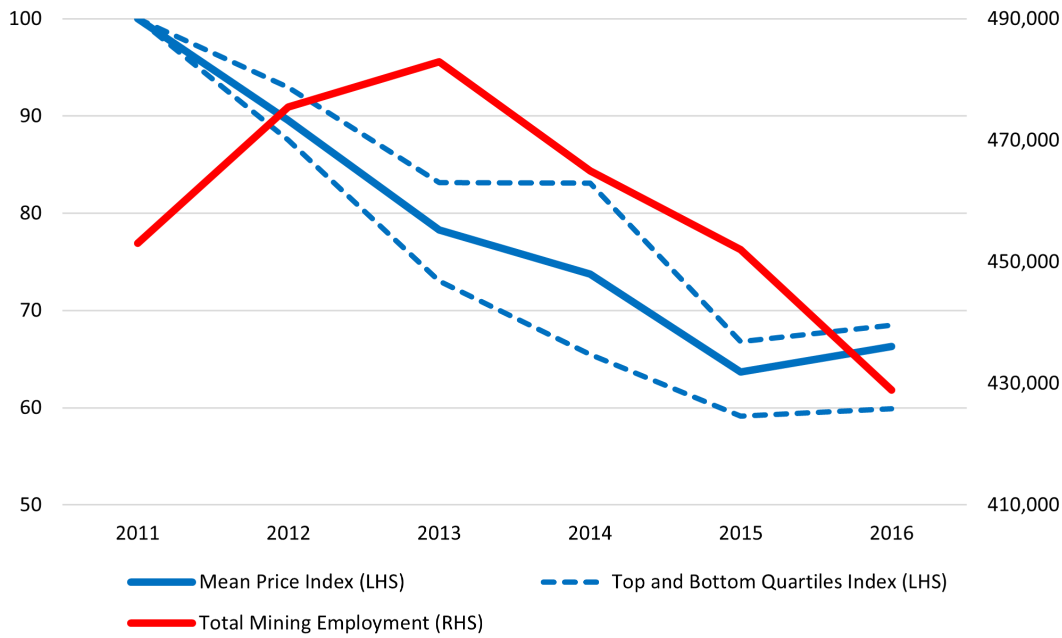
This is also reflected in Figure 5, which shows a significant reduction (although with some heterogeneity) in the local mineral/metal price index computed at the location level between 2011 and 2016 and a similarly marked contraction in employment in the extractive sector in South Africa from 2013.

Figure 4: Distribution of price index



Source: authors' computation based on data from S&P Global (mine locations and production).

Figure 5: Metal price index and total employment in mining



Source: authors' computation based on data from the SARS-NT/CIT-IRP5 panel and S&P Global.

Table 1 shows the number of workers by year and industry in the geolocated sample. In line with the insights from Figure 5, the table reveals that the share of employment in mining has been declining steadily over time, although the absolute number of workers has increased between 2011 and 2013.

Table 1: Number of workers by sector and year

	2011	2012	2013	2014	2015	2016
Agriculture	551,086	618,109	673,017	669,224	695,665	725,882
	(5.91%)	(6.20%)	(6.35%)	(6.21%)	(6.32%)	(6.59%)
Mining	453,060	475,495	482,957	465,002	452,039	428,873
	(4.86%)	(4.77%)	(4.56%)	(4.31%)	(4.11%)	(3.89%)
Manufacturing	1,430,773	1,534,006	1,637,878	1,647,661	1,654,391	1,641,456
	(15.35%)	(15.37%)	(15.46%)	(15.29%)	(15.03%)	(14.89%)
Construction	370,009	403,039	436,339	459,602	477,118	463,946
	(3.97%)	(4.04%)	(4.12%)	(4.26%)	(4.33%)	(4.21%)
Services	6,518,403	6,946,742	7,365,063	7,535,096	7,727,411	7,761,634
	(69.91%)	(69.62%)	(69.51%)	(69.92%)	(70.21%)	(70.42%)
Total	9,323,332	9,977,391	10,595,254	10,776,584	11,006,623	11,021,790

Note: the figures indicate the number of full-time worker equivalent (12 months) employed by each sector, rounded up to the closest integer. The percentages in parentheses represent the share of employment in the sector for each given year.

Source: authors' computation based on data from the SARS-NT/CIT-IRP5 panel.

The individual panel also contains detailed information on the wages received by workers, sourced directly from their tax certificates. Each worker entering the data set is uniquely identified by a code, which can be used to derive all the related tax certificates and thus all of their sources of income. Each tax certificate contains information on the period worked as well as the amount received and the employer, which can be used to compute the monthly income earned each year by each worker and the industry/sector they operated in. Since the same worker can receive income from different sources in the same year, we only consider the job paying the highest monthly wage. To eliminate outliers we trim the top and bottom 0.5 per cent of the distribution for each year–sector pair. Table 2 presents descriptive statistics on the average monthly wages (nominal) earned by workers in each sector for the time period of our study.

Table 2: Median nominal wage by sector and year

	Agriculture	Mining	Manufacturing	Construction	Services
2011	1,575	6,044	5,169	3,761	4,054
2012	1,643	6,633	5,707	4,025	4,373
2013	1,764	7,460	6,000	4,313	5,283
2014	2,316	8,323	6,419	4,596	5,700
2015	2,534	8,966	6,759	5,031	5,995
2016	2,774	10,600	7,217	5,500	6,475

Note: the figures indicate nominal wages and are expressed in ZAR. They are obtained by keeping only one observation per year–worker pair based on the length of the employment. In the case of a tie, the one paying the higher wage was chosen.

Source: authors' computation based on data from the SARS-NT/CIT-IRP5 panel.

The CIT part of the administrative data set contains information on firms' sales, cost of sales, and physical capital.[12] Using these data, we compute the revenue productivity of firms using a sector-specific production function.[13] We use the Ackerberg et al. (2015) modification of the Olley and Pakes (1996) approach and estimate productivity using the Wooldridge (2009) estimator, which addresses issues around the identification of the parameters in the first stage. When estimating the productivity, we consider the total value of production reported by the firm rather than their physical output (which incidentally is not available in the data); therefore, the resulting estimates can be interpreted as the profitability of the firms as opposed to their physical productivity. This implies that this measure also captures the changes in output prices that might occur as a result of the expansion/contraction of the local mining sector.

[12] Not all PAYE records could be merged to the CIT data. Overall, out of 681,464 PAYE–year observations, we were able to match more than two-thirds (458,836) to the CIT data. The firm-level analysis on productivity will thus be limited to that subsample since the location information come from the PAYE data set. The main explanatory variable used in the analysis (intensity of mining activities) is computed using the complete sample.

[13] Specifically, we use intermediate goods as the proxy for productivity and lagged variables of wages paid as instruments.

In the empirical analysis we examine whether and to what extent the expansion/contraction in mining impacted local wages and firm productivity/profitability in South Africa and whether this in turn had an appreciable impact on job creation/destruction across sectors.

3 Empirical approach

Moretti (2010, 2011) develops a general equilibrium framework to examine the impact of localized labour market shocks, in the form of new job creation or contraction, on the local economy. According to this framework, industry-specific labour demand shocks can impact other sectors locally. In particular, unless workers are perfectly mobile, local wages are expected to increase in all the other industries (unless there is no mobility whatsoever across industries) and as a result the local demand for goods and services also increases.

A priori, the impact on firm profitability can differ for tradable and non-tradable sectors. Generally, a positive labour demand shock is expected to have a beneficial impact on the local non-tradable industries whose prices and profitability will increase as a result of the boost in local demand. On the other hand, the same shock could potentially be detrimental to the tradable sectors where prices might not be determined locally and so the sector might be crowded out by the increasing prices of local inputs and wages brought about by the input and labour demands of the mining sector. As pointed out by Aragon and Rud (2013), this depends crucially on the extent to which mines source their inputs from the local manufacturing firms. This framework is ideal for exploring the local impact of the expansion/contraction of the mining sector in a comprehensive fashion, leveraging our firm- and worker-level data.

Finally, we will estimate the resulting local jobs multipliers, providing important insights into the potential impact of the inevitable contraction of the mining sector in the coming decades.

3.1 Wages

As mentioned above, according to Moretti (2010, 2011) an increase (decrease) in local labour demand should result in an increase (decrease) in wages as long as workers are not perfectly geographically mobile. As long as workers are at least partially mobile across sectors, the impact of increases/decreases in local demand for labour from the mining sector will also affect the wages in other industries.

We capture the intensity of mining activities in each of the 1,530 postal codes as the number of workers employed by local mines. To explore whether there is evidence of local impacts on wages, we regress the log of individual monthly wages in a particular sector k (agriculture, manufacturing, construction, and services) on the (log) number of workers in mining in their location, as shown in Equation 1:

$$\ln W^k_{isjt} = \alpha + \beta \text{ Mines Workers}_{jt} + X_{isjt}\xi' + \gamma_s + \lambda_j + \tau_t + \varepsilon_{isjt} \quad (1)$$

where $\ln W^k_{isjt}$ is the log of wages for worker i in industry s and location j at time t; Mines Workers$_{jt}$ is the (log) number of workers employed in the mining sector in the postal code j; and γ_s, λ_j, and τ_t are industry, postal code, and fiscal year fixed effects, respectively. The error term ε_{isjt} is assumed *i.i.d.*. The vector X includes a number of worker-specific controls;: gender, age (linear and square), and the number of months worked in the job in the financial year. Where workers had more than one job for the financial year, we only consider the job that paid the highest monthly salary.

The shock to mining is measured through deviations from the time average of the number of workers in the extractive industry in location j. The inclusion of location fixed effects controls non-parametrically for all unobserved time-invariant, postal-code-specific characteristics that might affect the wages earned by workers that are also correlated with the expansion/contraction in mining activities. Despite the inclusion of these controls, using ordinary least squares (OLS) to estimate this relationship will likely lead to biased estimates due to other sources of omitted variable bias and/or reverse causality. To address this we use an instrumental variables (IV) approach, where we exploit exogenous changes in the price of minerals and metals to instrument changes in the intensity of extractive activities, as proxied by the number of workers in mining in the local area. As discussed above, we combine international prices of 16 different minerals and metals to create a location-specific index based on the production of all mines located in the postal code and/or within 30 km of each postal code's centroid. Since we do not have exact information on the quantity of minerals and metals produced by each mine, but rather only on up to six of the most important minerals/metals produced, we weight each metal produced equally in computing the benchmark index and only consider the most important one as a robustness check and to estimate the over-identified specifications. Moreover, following the insight from Figure 5, we use lagged index levels to instrument the number of workers employed by mines since there appears to be a lag between the realization of the price shocks and the intensity of mining activities. This is consistent with the existence of constraints such as employment laws and/or other fixed costs which reduce the extent to which mines can react to changes in prices.

3.2 Profitability

The second outcome of interest is firm profitability. According to Moretti (2010, 2011), where there is an expansion (contraction) in mining activity due to some exogenous shock, we would expect prices in the non-tradable sector to increase (decrease) while prices in the tradable sector should not be affected as they are not sensitive to changes in local demand. This will have knock-on effects for profitability and job creation in the non-tradable sector. The overall impact on the profitability of the tradable sector is ambiguous. Indeed, the potential increase in local wages brought about by the expansion of the mining sector can have a detrimental impact on profitability of firms in the tradable sector where it is not matched by an increase in the output prices.

To identify the effect of the labour demand shock in mining on the profitability of local firms we estimate a firm-level regression very similar to Equation 1. In a similar fashion to the wage analysis, we will estimate the regression separately for the four macro-sectors as we expect the impact to differ between tradable and non-tradable industries.

The main empirical specification is given in Equation 2:

$$\ln TFPR^{k}_{isjt} = \alpha + \beta \text{ Mines Workers}_{jt} + X_{isjt}\xi' + \gamma_s + \lambda_j + \tau_t + \varepsilon_{isjt} \tag{2}$$

where $TFPR_{isjt}$ is revenue productivity for firm i in industry s and location j at time t, estimated as described in Appendix A; Mines Workers is the main explanatory variable and is the (log) number of workers in extractive industries in location j at time t. X is a vector containing firm-specific characteristics. In the main specification we include firms' total wages paid and total capital.

Our key parameter of interest is β, which represents the elasticity of firms' revenue productivity with respect to the size of the local mining sector (as proxied by the number of workers employed by local mines) and is identified through deviations from the location-specific average across the years considered.

Moretti (2010, 2011) indicates that the sign and significance of the elasticity can differ between non-tradable and tradable industries. The former are likely to be more positively affected by the increase in local prices than are the latter, and as such they will experience a boost in profits where the local mining sector expands. On the other hand, firms operating in tradable industries might be penalized by local extractive activities as they could push wages up without affecting output prices. Existing evidence in this sense is mixed. De Haas and Poelhekke (2019) find that local manufacturing firms typically experience a tightening of business constraints when new mines open as they compete in the local market for workers, credit, and other intermediate goods. On the other hand, Aragon and Rud

(2013) find that manufacturing firms close to a new Peruvian mine experienced an increase in sales and profitability once the mine was required by law to source inputs locally. In short, we expect mining to have a positive impact on the profitability of non-tradable industries while we do not have any particular prior on the direction of the relationship for the tradable firms as it crucially depends on the context and in particular on the extent to which mines source their inputs from local manufacturing firms.

3.3 Job creation

In the last part of our empirical analysis we estimate the local multiplier of mining activities, namely the number of jobs in other sectors that are created/lost for each new/lost job in the extractive sector. According to Moretti (2010), localized labour demand shocks increasing/decreasing local wages will have a more pronounced positive/negative impact on non-tradable sectors. We expect, therefore, that the multiplier takes on different values (and potentially different signs) depending on the sector considered. We estimate Equation 3 separately for the four sectors k: agriculture, manufacturing, construction, and services.

$$\Delta N^k_{jt} = \alpha + \beta_k \Delta N^M_{jt} + \tau_t + e_{jt} \tag{3}$$

where ΔN^M_{jt} represents the change in number of jobs in mining in location j, while the dependent variables ΔN^k_{jt} are the corresponding change in the number of jobs in each sector k, respectively. The parameters β_k can be directly interpreted as the number of jobs created/lost in sector k in location j for each new/lost job in mining.

We estimate Equation 3 using a simple OLS estimator and instrumenting ΔN^M_{jt} using the lagged change in the location-specific price index. Since the dependent variable is the change in the absolute value of workers in mining, we multiply the index used in this specification by the average number of workers in mining in location j between 2011 and 2016. This allows us to interpret the first-stage coefficient as the impact of a percentage change in the price index on the number of new workers in mining for each worker in the extractive industries (on average) in location j.

4 Results

Guided by Moretti (2010, 2011), the objective of this paper is to estimate the local economic impact of mining activities on other sectors, with a particular focus on local wages, profitability/productivity, and job creation.

The first step in our empirical analysis considers whether there is any evidence that changes in the numbers employed in mining affected the level of wages locally. As described in Section 3, to examine this we estimate Equation 1. The results are presented in Table 3 both for the OLS and the IV specifications. The coefficients are obtained from four separate regressions considering workers in agriculture, manufacturing, construction, and services.

Broadly speaking, we find that the expansion/contraction of mining activities at the local level impacts local wages. This is true for every sector except for agriculture, where the coefficients are positive but statistically not well determined. Interestingly, IV estimates are larger than OLS estimates, although it should be noted that standard errors are also inflated such that the full range of OLS coefficient estimates stay within the confidence intervals in the IV specification. According to the IV estimates, a 1 per cent increase in jobs in mining leads to an increase in wages of 0.07 per cent for the construction and services sectors and 0.15 per cent for the manufacturing sector. The relative larger magnitude found for the manufacturing sector suggests a larger level of labour market integration between manufacturing and mining than with the other sectors.

Table 3: Impact on wages

	Agriculture	Manufacturing	Construction	Services
OLS	0.008	0.023**	0.015*	0.023**
	(0.01)	(0.01)	(0.01)	(0.01)
IV	0.067	0.153**	0.073*	0.068*
	(0.04)	(0.07)	(0.03)	(0.04)
First stage				
Index	0.002***	0.003***	0.007***	0.003***
	(0.00)	(0.00)	(0.00)	(0.00)
F	8.10	9.02	9.33	8.08
N	4,974,758	10,473,980	3,197,244	40,350,239

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Clustered standard errors at the postal code in parentheses. The table reports the estimates from the OLS model and the IV model instrumenting the change in workers in mining using the price index.

Source: authors' computations based on data from the SARS-NT/CIT-IRP5 panel.

These elasticities are similar to the estimates obtained in Aragon and Rud (2013), who found an elasticity of workers' income with respect to the amount of input purchased by the local Peruvian mine of 0.17, and of Marchand (2012), who estimated an elasticity of wages with respect to the numbers employed in mining of 0.21 in West Canada.[14] On the other hand, Fetzer (2014) found a considerably larger elasticity of wages in manufacturing and services of 1.8 and 1.9, respectively, in the case of oil extraction in the United States in the early 2000s.

Overall, these findings indicate that local workers benefit/suffer from expansions/contractions in the mining sector as their wages are sensitive to changes in labour demand in extractive industries. However, the estimated elasticity, in line with the comparable studies mentioned above, is not particularly high: a 10 per cent reduction in the number of people employed in the mining sector results in a wage reduction of 1.5 per cent for workers in manufacturing and 0.7 per cent for workers in construction and services. However, considering the significant rigidities in the labour market in South Africa, which may cause lags in the responsiveness of wages to the shock, our estimates should be interpreted as a lower bound capturing only the short-term impact.

In the second step of our analysis we explore the impact on profitability. We estimate Equation 2 using both OLS and IV approaches. Importantly, the dependent variable captures so-called 'revenue' productivity rather than the physical productivity of the plants.[15] As such, it can be interpreted as an index of profitability, which also captures changes in prices of both outputs and inputs (and crucially of labour). As for the wage analysis, we present the estimates of both the OLS and the IV model in Table 4 separately for each of the four sectors: agriculture, manufacturing, construction, and services.

Our OLS estimates differ markedly from the results from the IV regressions. In particular, the OLS coefficient estimates are generally small and only well determined for the tradable sectors of agriculture (negative) and manufacturing (positive). However, the IV coefficients suggest that there is a strong and positive impact of mining on the profitability of local firms, with an elasticity of 0.85, 0.26, and 0.11 for agriculture, manufacturing, and services, respectively (the elasticity for construction is 0.08 but is not statistically significant). It is, however, important to point out that the standard errors are quite large and so are the confidence intervals, especially in the case of agricultural firms, where the relatively low number of observations and their geographical concentration makes the coefficient estimates less precise.

[14] More specifically, Marchand (2012) estimated that an 89.2 per cent increase in the number of workers in mining in West Canada increased earnings per capita by 19.6 per cent, while Weber (2014) found that an increase in mining activities of 26 per cent (measured as total production) increased wages by 2.4 per cent.

[15] See Appendix A for a more in-depth discussion of the TFPR estimation procedure.

Table 4: Impact on profitability

	Agriculture	Manufacturing	Construction	Services
OLS	–0.011*	0.005*	0.001	–0.003
	(0.01)	(0.00)	(0.00)	(0.00)
IV	0.846**	0.267***	0.079	0.110***
	(0.35)	(0.04)	(0.08)	(0.04)
First stage				
Index	0.002***	0.003***	0.007***	0.003***
	(0.00)	(0.00)	(0.00)	(0.00)
F	23.76	590.74	183.31	1,519.26
N	46,926	172,457	57,347	387,018

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors at the postal code in parentheses. The table reports the estimates from the OLS model and the IV model instrumenting number of workers in mining using the price index.

Source: authors' computations based on data from the SARS-NT/CIT-IRP5 panel.

Combined, these findings suggest that, in the case of South Africa, mining activities have not been detrimental to local firms which instead experience higher levels of profitability when local extractive industries flourish. This is despite the fact that they also experience higher wages. These results are in line with Aragon and Rud (2013), who showed that also industries typically considered 'tradable' could benefit from increased prices and local demand following an expansion in local mining complexes.

In the final step of our analysis we examine the impact on job creation. To do so we estimate Equation 3 separately for the four sectors using both OLS and the IV approach. The estimated coefficients are shown in Table 5.[16]

Table 5: Local multipliers estimates

	OLS	IV	OLS	IV	OLS	IV
Agriculture	–0.01	–0.01	–0.01	–0.01	–0.01	–0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Manufacturing	–0.35	–0.09	–0.35	–0.09	–0.36	–0.10
	(0.27)	(0.19)	(0.27)	(0.19)	(0.28)	(0.20)
Construction	–0.00	–0.02	–0.00	–0.02	–0.00	-0.02
	(0.02)	(0.04)	(0.02)	(0.05)	(0.02)	(0.05)
Services	0.99**	2.40*	1.03*	2.44*	1.02*	2.50*
	(0.45)	(1.40)	(0.46)	(1.42)	(0.47)	(1.45)
Provincial trends	No	No	Yes	Yes	No	No
Dropped outliers	No	No	No	No	Yes	Yes
N	7,650	7,650	7,650	7,650	7,182	7,182
			First stage			
β index	–	0.002***	–	0.002***	–	0.002***
	–	(0.00)	–	(0.00)	–	(0.00)
F-stat	–	10.39	–	10.33	–	9.43

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Clustered standard errors at the postal code in parentheses. The table reports the estimates from the OLS model and the IV model instrumenting the change in workers in mining using the price index. Columns 1 and 2 show the benchmark model. Columns 3 and 4 include linear provincial time trends, while columns 5 and 6 display the results obtained after trimming the 5 per cent extreme values in the yearly changes in mining employment.

Source: authors' computations based on data from the SARS-NT/CIT-IRP5 panel.

According to the OLS specifications, the local multiplier for mining is only well determined and positive for the services sector. More specifically, the estimates indicate that for each job created/lost in the mining sector in a given postal code, one additional job was created/lost in the services sector. The IV results are qualitatively in line with those obtained from the OLS specification. In particular, we find

[16] We also estimate an alternative IV specification where we use both the benchmark price index and the one obtained by using only the main minerals to instrument changes in mining activities. For every specification we were unable to reject the null hypothesis that both instruments are valid.

non-significant results for agriculture, manufacturing, and construction, and positive and statistically significant multipliers for the services sector. However, the 95 per cent confidence intervals in the IV specifications are always broader than their OLS counterparts, and the point estimates are only significant at the 90 per cent confidence level. The IV point estimates are larger in magnitude, indicating that for each job created/lost in mining, about 2.5 more jobs in the services sector were created/lost.

This is consistent with other findings from the literature on local multipliers. For example, Moretti (2010) found that each additional job in the tradable sector in a given city in the United States creates 2.5 jobs in the local goods and services sectors. Reassuringly, our estimates are also in line with the figures provided by several studies on the expansion and contraction of mining activities, which are mostly US-based. At the lowest end of the spectrum, Black et al. (2005) found that for every three jobs lost in coal mining between the 1970s and the 1990s, one job was lost in services and non-tradable industries. Studies focusing on fracking (Fetzer 2014; Feyrer et al. 2017; Lee 2015; Tsvetkova and Partridge 2016; Weber 2014) and oil extraction in the United States in the early 2000s found multipliers of between 1.4 and 2.17, mostly driven by changes in jobs in non-tradable industries such as retail, transport, and construction.

Outside the United States, Toews and Vezina (2020) found that each new FDI job following oil and gas discoveries in Mozambique generated an additional 2.1 formal jobs. Fleming and Measham (2014) found a local multiplier of 1.65 during the mining boom in Australia in the early 2000s, and Marchand (2012) estimated that for each job created in the mining sector in western Canada between the 1970s and the early 2000s, another job in local non-tradable sectors was created.

These findings indicate that there is a strong link between the mining sector and local non-tradable industries. Our findings are in line with this and imply that in the South African case, jobs will be lost in the services sector whenever the local mining sector contracts. We do not find evidence of a crowding-out effect of the manufacturing sector, implying that the expansion of mining activities does not come at the expense of the manufacturing sector in terms of job creation, or oppositely that their contraction does not immediately guarantee a rebound of local tradable industries. This suggests that whenever local mining activities suffer or halt, it has negative vertical spillover consequences for the non-tradable sector of the local economy, while the tradable sector is unable to absorb the excess labour supply.

5 Conclusion

In this paper we used administrative data containing detailed information on South African firms and workers to study the impact of the mining sector on the local economy. Interestingly, in spite of the historical and current importance of extractive activities for the country, this study represents the first attempt to quantify the impact on local wages, firm profitability, and job creation.

We found that, in line with the theoretical framework provided by Moretti (2010, 2011), expansions (contractions) in mining activities result in significant increases (decreases) in local wages, both in tradable sectors (manufacturing) and in non-tradable sectors (construction and services). However, contrary to expectations, our results show that profitability/productivity of local firms in the tradable sectors (manufacturing and agricultural) are not negatively impacted by mining expansions. Instead, a positive and significant impact on revenue productivity is found for firms operating in both manufacturing (tradables) and services (non-tradables). This suggests that in South Africa more vertical integration exists where local mines source at least part of their inputs from local manufacturing firms, and as such indirectly benefit them rather than crowding them out. In line with these findings, we find evidence of a positive and statistically significant local jobs multiplier for the non-tradable services ($\approx$1 to 2.5 new jobs created for each new job in mining) and no multiplier impact for firms in the tradable sectors, as countervailing forces (increases in wages and revenue productivity improvements) are at play.

The effects on local wages and the local job multipliers are in line with existing studies (Aragon and Rud 2013; Ticci and Escobal 2015). Our findings are therefore insightful not only for South Africa, but also for policy-makers in general as they are likely to be more representative of the effects of changes in mining intensities where the industry is mature and already well developed rather than booming.

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Appendix A

In order to obtain firm-specific profitability, we estimate for each of the 34 industries the elasticities of the total value added with respect to labour $\hat{\beta}_l$ (wages paid) and capital $\hat{\beta}_k$ (book value of fixed assets). We obtain the (log) total factor revenue productivity for a firm i as $tfpr_i = y - l \times \hat{\beta}_l - k \times \hat{\beta}_k$, where y is the (log) value of firms' output net of the costs of sales, l is the total amount of wages paid, and k is the (log) value of firms' capital.

The most immediate way to estimate such elasticities is through a simple regression of y on k and l. However, such estimates might be biased as the choice of labour and capital can be systematically correlated with shocks in productivity. In order to address this concern, we also estimate the production functions using the Ackerberg–Caves–Frazer (ACF) correction. Specifically, we use intermediate goods as the proxy for productivity and lagged variables of wages paid as instruments.

The elasticities from the OLS and ACF specifications are shown in Table A1. It is clear that the two methodologies return rather similar results. Our measure of $tfpr$ is based on the ACF elasticities as it is theoretically more sound.

Table A1: Production function elasticities

	OLS		ACF	
Sector/industry	Labour	Capital	Labour	Capital
Agriculture	0.792	0.118	0.768	0.100
Manufacturing				
Food products	0.893	0.076	0.749	0.049
Textiles	0.855	0.059	0.690	0.035
Wood	0.867	0.049	0.664	0.033
Nuclear and oil	0.831	0.071	0.666	0.013
Chemicals	0.839	0.058	0.682	0.033
Non-metallic	0.861	0.065	0.729	0.039
Basic metals	0.866	0.076	0.696	0.050
Coke and petroleum	0.892	0.065	0.725	0.031
Electrical machinery	0.856	0.079	0.689	0.048
Radio and TV eq.	0.850	0.080	0.743	0.045
Transport	0.829	0.069	0.698	0.040
Furniture	0.818	0.073	0.712	0.048
Electricity and water	0.896	0.043	0.744	0.031
Optical eq.	0.771	0.129	0.717	0.079
Recycling	0.823	0.075	0.684	0.051
Steam and hot water	0.850	0.071	0.699	0.038
Water purification	0.813	0.082	0.688	0.048
Construction	0.795	0.082	0.715	0.052
Services				
Wholesale trade	0.861	0.068	0.742	0.046
Retail trade	0.886	0.043	0.753	0.032
Vehicle trade	0.871	0.061	0.822	0.049
Maintenance of vehicles	0.797	0.115	0.743	0.084
Hotels and restaurants	0.773	0.081	0.792	0.048
Transport	0.834	0.042	0.815	0.036
Post and communication	0.778	0.097	0.749	0.078
Financial intermediation	0.837	0.047	0.812	0.037
Insurance	0.757	0.092	0.737	0.087
Real estates	0.827	0.077	0.759	0.050
Computer and related activities	0.780	0.042	0.743	0.028
Health	0.818	0.044	0.725	0.029

Source: authors' computations based on data from the SARS-NT/CIT-IRP5 panel.

Appendix B: Data appendix

The South African administrative tax data used for this study is available at the National Treasury Secure Data Facility (NT-SDF). The two datasets used for the analysis are the Individual panel (National Treasury and UNU-WIDER 2019b) by Ebrahim and Axelson (2019) and the SARS-NT/CIT-IRP5 panel (National Treasury and UNU-WIDER 2019a; Pieterse et al. 2018).

The worker information used in the paper is from the individual panel. We use the variables *Gender* and *Date_of_birth* to determine the sex and age of the workers. The variables *Employment_start* and *Employment_end* is used to determine the number of months worked by each worker. The amount associated with source code 3601 captures the total wages received by a worker in the year of assessment. We divide the amount 3601 by the number of months worked to obtain the monthly wage. Finally, we get the post code and industry information from the variables *Post_addr_postal_code* and *Main_income_source_code,* respectively.

Firm-level information is from version 3.5 of the SARS-NT/CIT-IRP5 panel. The variable we use to proxy labour is total labour cost *(x_labcost)*. We construct the capital variable by the aggregating property, plant, and equipment *(k_ppe),* and other fixed assets *(k_faother*). We calculate value added by subtracting the cost of sales (g_cos2) from the sales revenue (g_sales). Finally, we deflate the variables using gross value added *(DEFL_GrossvalAddEconWide)* and gross domestic product (*GDPDeflatorEconWide)* deflator variables.

The main variables from the datasets are illustrated in the Table B1.

Table B1: Main variables from the Individual panel and the SARS-NT/CIT-IRP5 panel

Database name	Variable name	Variable description
Individual panel	Date_of_birth	Year of birth
	Gender	Gender
	Employment_start	Start date of employment in the year of assessment
	Employment_end	End date of employment in the year of assessment
	Main_income_source_code	Source code for main type of income from employer
	Source_code	Source code provided in the ITR12 or IRP5 return
	Amount	Amount provided in relation to the source code in the return
	Post_addr_postal_code	Postal address code
SARS-NT/CIT-IRP5 panel	x_labcost	Total labour costs
	k_ppe	Property, plant, and equipment
	k_faother	Other fixed assets
	g_sales	Sales revenue
	g_cos2	Cost of sales
	DEFL_GrossvalAddEconWide	Economy-wide deflator: gross value added
	GDPDeflatorEconWide	Economy-wide deflator: gross domestic product

Source: authors' illustration of the variables from the Individual panel and SARS-NT/CIT-IRP5 panel.