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Good mine, bad mine: Natural resource heterogeneity and Dutch disease in Indonesia

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Good mine, bad mine: Natural resource heterogeneity and Dutch disease in Indonesia*

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Abstract

We analyse the local effect of exogenous shocks to the value of mineral deposits at the district level in Indonesia using a panel of manufacturing plants. To the best of our knowledge, we are the first to model and estimate the effect of heterogeneity in natural resource extraction methods. We find that in areas where mineral extraction is relatively capital-intensive, mining booms cause virtually no upward pressure on manufacturing earnings per worker, and both producers of traded and local goods benefit from mining booms in terms of employment. In contrast, labour-intensive mining booms drive up local manufacturing wages such that producers of traded goods reduce employment. This source of heterogeneity helps to explain the mixed evidence for 'Dutch disease' effects in the literature. In addition, we find no evidence that fiscal revenue sharing between sub-national districts leads to any spillovers.

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1 Introduction

Wealth in non-renewable natural resources (such as solid minerals and oil & gas) does not always lead to sustained economic development. This observation has long inspired a debate on the existence of a 'Dutch disease' (Van Wijnbergen, 1984) or even a seemingly incurable 'resource curse' (Gelb, 1988). It is now generally accepted that negative outcomes are conditional on institutions and macroeconomic management of subsoil wealth (Van der Ploeg, 2011). Recently, this literature has moved away from cross-country studies in which endogeneity issues are harder to address and started to exploit within-country variation to minimize the influence of confounding factors.[1] This approach has contributed to our understanding of the underlying mechanisms that may explain the negative aggregate correlation between resource wealth and growth. However, at the local level, and using detailed firm and household data for the US, several studies find positive effects of a local natural resource boom, or at the least no evidence for crowding out of manufacturing firms (Black et al., 2005; Michaels, 2011; Allcott and Keniston, 2018). For developing countries, the evidence is more mixed and ranges from an increase in real income for households close to a large gold mine in Peru (Aragón and Rud, 2013), to more conflict in Colombia (Dube and Vargas, 2013), localised negative traded-sector employment effects in emerging markets (De Haas and Poelhekke, 2016), and an increase in municipal government spending in Brazil that does not translate into higher public goods and services (Caselli and Michaels, 2013).

The literature has typically identified these effects by exploiting geographic variation in natural resource wealth and time variation in world prices or giant oil discoveries, but has not distinguished explicitly between different resources or extraction techniques. We argue that the labour intensity of resource extraction can reconcile positive and negative outcomes found in the literature. To the best of our knowledge, we are the first to model and estimate the effect of heterogeneity in natural resource extraction methods. We analyse the local effect of a booming natural resource sector within Indonesia, which is both a major producer of a variety of natural resources that are scattered around the country, and has a large and exporting manufacturing sector. Combining detailed manufacturing plant-level panel data with well- and deposit-level data, we find that in areas where resource extraction is more capital-intensive, booms cause virtually no upward pressure on manufacturing earnings per worker, and both producers of traded and local goods benefit from booms in terms of employment. In the average mining district, the manufacturing sector increases employment by 2 percent as local mineral prices double. In contrast, labour-intensive mining booms increase local manufacturing wages by 6 percent such that producers of relatively traded goods reduce employment by 1 percent. From the perspective of manufacturing plants, mining booms can thus be good or bad. This source of heterogeneity helps to explain why many studies that have focused on capital-intensive natural resource extraction such as oil and gas do not find evidence for local 'Dutch disease' effects. The effect of mining booms on local manufacturing is much larger than comparable effects in the US, but in Indonesia due to minerals rather than oil and gas extraction. We do not find evidence that the reallocation between

[1] As surveyed in Van der Ploeg and Poelhekke (2017) and Cust and Poelhekke (2015).

sectors and reduction in activity by traded goods producers leads to a reduction in total factor productivity. In addition, we find that the effects of natural resource booms are local despite the government's move to decentralization and increased mineral revenue sharing across regions, which has not lead to a noticeable spread of any benefits to non-extracting regions.

Our identification strategy is to correlate exogenous shocks to the value of local natural resources in Indonesia discovered by 1990 with local manufacturing outcomes in subsequent years. Using deposit and well-level data on the quantity, type and extraction method for each natural resource, we compute measures of initial endowments of oil, gas, metals, and other minerals at the district level, and interact them with subsequent exogenous world price shocks and an indicator that captures the extraction method's labour-intensity. For given labour market conditions, the locally applied extraction technique is determined by the geological shape of the deposit and not by the deposits' contained minerals. The choice of technique is made before extraction begins and we account for differential subsequent trends in manufacturing outcomes across districts of different labour-intensity in mining that are unrelated to the price shocks. We show that distinct extraction technologies translate into different degrees of labour-intensity by analysing variation in resource sector employment and migration across districts. While conditioning on the method of extraction, we analyse the effect of value shocks, which we refer to as 'mining booms', on the earnings per worker, employment and other outcomes of manufacturing plants. Although we control for oil and gas, the main focus of our analysis is on the mining sector since we expect mining booms to have larger effects on other sectors than oil and gas booms, as we explain in Section 2.

The fact that our data contains individual plants observed annually in the census between 1990 and 2009 allows us to control for manufacturing plant fixed effects, which improves identification compared to most of the existing literature. Using the 4-digit sector classification we also analyse whether plants producing traded manufacturing goods suffer more or benefit less from mining booms than producers of locally traded manufacturing goods.

Our empirical results fit a model of reallocation between sectors (Corden and Neary, 1982; Corden, 1984) adapted to multiple regions (Allcott and Keniston, 2014) to which we add labour-intensity of the resource sector. A booming natural resource sector raises the real exchange rate and thereby lowers the competitiveness of other tradable goods producers which sell at prices determined on world markets. This effect of reallocation of the economy away from tradable goods production is amplified if the natural resource sector is relatively labour-intensive and thus hires more workers during a boom, unless labour can be supplied through migration from other regions. In the absence of market failures, a natural resource boom increases welfare, in spite of the contraction of the tradable goods sector. However, empirical studies have provided evidence of market failures in the form of productivity spillovers from manufacturing firms to other nearby firms (Ellison et al., 2010; Greenstone et al., 2010; Kline and Moretti, 2014). If these are strong enough, then a smaller tradable goods sector can slow down overall economic growth and thus represent a 'disease'. However, and in line with Allcott and Keniston (2018), we do not find evidence for negative effects on total factor productivity.

Consumers may directly participate in higher local resource revenues caused by the boom, which increases their income and consumption. In addition, immigration of additional workers implies more local consumers. These factors constitute the within-country version of the 'spending effect'. Local goods producers can benefit from the increase in local demand because they can set and can thus raise prices. Overall, the spending effect outweighs the reallocation effect for these producers, inducing growth during natural resource booms. Unless labour mobility is high and/or the resource sector's labour intensity is low, the opposite holds for traded goods producers. Intuitively, they can hardly benefit from an increase in local demand because they are price takers and thus become less competitive due to higher local wages.

Resource extraction methods therefore predict different outcomes of a natural resource boom. If local extraction techniques are capital-intensive, earnings per worker will not be significantly affected by mining booms. Without a rise in wages there is no scope for crowding-out of the manufacturing sector. Consistently, we find that neither local nor traded goods manufacturers lay off workers during capital-intensive mining booms, but actually increase employment, suggesting that local manufacturing benefits through a spending effect. When local extraction techniques are labour-intensive local earnings per worker in the manufacturing sector increase, and the manufacturing sector overall does not benefit in terms of employment. While we do observe a slight increase in population during labour-intensive mining booms, this is insufficient to fully offset the upward pressure on wages. These results suggest the presence of a reallocation effect during labour-intensive booms which offsets the gains from the spending effect. Traded goods producers significantly *reduce* employment, while local goods producers increase employment. Further, only producers of local manufacturing goods charge higher prices during labour-intensive booms. These results confirm that local goods producers are able to pass on higher wages to consumers and are thus hardly affected by the reallocation effect.

The long-standing literature that investigated the resource curse empirically, starting with Sachs and Warner (1995, 2001), has debated its existence on the basis of cross-country data (Van der Ploeg, 2011). We contribute to a more recent growing literature that analyses within-country settings. Data on firms and counties in the US has shown that coal, oil, and gas booms, of which the recent boom was driven by novel shale extraction techniques, have had little or no negative effects on manufacturing.[2] Similarly, Black et al. (2005) find positive employment spillovers on non-tradable sectors during the 1970s coal boom in their analysis of local labour markets in Kentucky, Ohio, Pennsylvania, and West Virginia, but no significant spillovers to the manufacturing sector. A long-run study of the southern U.S. by Michaels (2011) finds that as population increased in booming regions also local public good provision increased, with positive effects on employment in agriculture and manufacturing. Using five-yearly data, Allcott and Keniston (2018) show that in a US-county with an additional oil and gas endowment of US$10 million per square mile, a natural resource boom that doubles national oil and gas employment leads to a statistically significant increase in population

[2] Although more aggregate county- and state-level data suggests more evidence for negative effects, c.f. James and Aadland (2011); Papyrakis and Gerlagh (2007).

by 1.2 percent, employment by 2.8 percent and earnings per worker by 1.8 percent. The manufacturing sector is also clearly procyclical with oil and gas booms in resource-abundant counties[3], although there is some limited evidence that highly-traded goods producers contract. In terms of income per capita, however, busts can more than reverse the effects of booms (Jacobsen and Parker, 2016).

We add to this literature by using annual plant-level data and distinguishing between different extraction methods used to take mineral resources out of the ground and the relative labour-intensity that this implies. Some deposits require a very capital- and skill-intensive extraction method, resulting in substantial positive spending effects but much less competition for labour with the local manufacturing sector. By analysing a developing country with different degrees of sectoral and regional labour mobility compared to the US, we place the results in the literature into perspective. Since we find labour mobility across districts in Indonesia to be lower, there is more scope for crowding out[4], while less specialized manufacturing may result in more sectoral labour mobility. Moreover, in a developing country potentially less firms are up- and downstream to the mining sector itself than in the US, where "linkages and complementarities to the natural resource sector were vital in the broader story of American economic success" (Wright and Czelusta, 2007).

Our study also relates to the growing literature that tests the effect of natural resources in a developing country context, which has focused more on political economy and household outcomes. Aragón and Rud (2013) analysed the expansion of a large gold mine in Peru, and find that real income of households living within 100 kilometers of the mine only increased after a policy change that required local procurement of services. Related to our mechanism, Dube and Vargas (2013) find that an exogenous increase in the price of coffee (which is labour-intensive in production) decreases armed conflict in Colombia because it increases the opportunity cost of fighting, while an increase in capital-intensive oil prices *increases* conflict, through increasing the gains from appropriation of oil income. The latter is consistent with a model of social conflict by Dal Bó and Dal Bó (2011). Caselli and Michaels (2013) show that corruption and embezzlement drive a wedge between the amount of fiscal transfers or royalty payments derived from offshore oil production, and municipal spending in Brazil, which may reflect the fact that giant oil discoveries are followed by reductions in democracy scores (Tsui, 2011).[5]

We also add to a literature that has examined a range of other related outcomes to natural resource booms, such as property prices that increase due to royalty payments or decrease due to environmental risk (Muehlenbachs et al., 2015), decreased entrepreneurship in coal and heavy industry-intensive cities (Glaeser et al., 2015), increased income leading to more health care spending (Acemoglu et al., 2013), the positive contribu-

3 Which could be explained by a reduction in local energy prices during the shale gas boom in the United States, since natural gas is hard to export (Fetzer, 2014).

4 For example, Beine et al. (2015) find evidence that immigration from other provinces mitigates the increase in the size of the non-tradable sector during natural resource booms in Canada, and also leads to spillovers from booming to non-booming provinces. Another mitigating factor may be a short-run increase in manufacturing output per worker as suggested by Cust et al. (2017). Nevertheless Papyrakis and Raveh (2014) find that an increase in the oil price leads to a reduction in international exports in natural resource provinces, while Marchand (2012) finds positive effects of oil price shocks on non-tradable sectors (construction, retail trade, services) but no effects on the manufacturing sector in oil provinces.

5 On the other hand, others find that giant oil discoveries are endogenous to improvements in institutions (Arezki et al., 2017). Strong institutions can also prevent negative outcomes after discovery (Mehlum et al., 2006).

tion of concentrated mineral wealth to estimates of the gains from trade (Fally and Sayre, 2018), increased crime rates (James and Smith, 2017), the rise of the Sicilian mafia (Buonanno et al., 2015), and increased risk of coups (Nordvik, 2018).

Finally, our study also builds on the early literature that has tested the 'natural resource curse' hypothesis using cross-country data. Many papers confirm the hypothesis by presenting evidence of a negative correlation between natural resource wealth or dependence and measures of economic performance (Sachs and Warner, 1995, 2001; Auty, 1990). However, others have provided evidence against it, such as Gallup et al. (1999), Alexeev and Conrad (2009) and James (2015).

The remainder of our paper is structured as follows. Section 2 provides background information for Indonesia. In Section 3 we present our theoretical framework, while Section 4 discusses data sources and the construction of key variables. Section 5 presents the empirical strategy and Section 6 results and robustness checks. Section 7 concludes.

2 Background

For our purposes, Indonesia provides an ideal testing ground. It is both a major producers of minerals and a significant producer and exporter of manufactured goods. The (non-mining) manufacturing sector (ISIC Revision 3, divisions 15 to 36) represented 23 percent of GDP on average between 1993 and 2009. In 2009, Indonesia exported 14 percent of manufacturing output, consisting mostly of food products and beverages, wood products, rubber products, textiles, communication equipment, and garments. These sectors alone employ 54 percent of manufacturing workers. Indonesia also exports a wide variety of raw minerals, including coal, tin, nickel, gold, and bauxite. The mining sector accounted for 4.54% of the country's GDP in 2009, and employed up to 31% of the total workforce in mining districts.[6] The deposits are relatively scattered across the country as Figure 1 shows, and occur both near the surface and deep underground. Indonesia was also an important producer of oil and natural gas over our sample period. In 2009, the oil and gas sector's contribution to GDP was 4.55 percent. However, while we always control for oil and gas production, our focus in on minerals for several reasons. First, the revenues generated by minerals mining have traditionally been shared much more with the producing district than oil and gas revenues, which almost exclusively accrued to the central government. Oil and gas revenues were not shared at all with the producing district until Indonesia's 'big bang' decentralization of 1999, and from then on, the producing district only received a mere 12 percent in total revenues (Resosudarmo, 2005; Agustina et al., 2012). By comparison, the producing district's share in mining land rents was 64 percent and its share in royalties between 32 and 64 percent between 1992 and 2009. This implies that, ceteris paribus, a mining boom has a larger potential to spur a

[6] Source: Indonesian Database for Policy and Economic Research (INDO DAPOER) for GDP; National labour force survey SAKERNAS for employment. See the Online Appendix for details. For simplicity, we refer to the set of minerals, coal and bauxite as 'minerals' from here onwards. Scientifically, coal and bauxite are not minerals, but rocks, while from a legal perspective, coal is often treated as a mineral. See *http://www.uky.edu/KGS/education/didcoal.htm*.

considerable *local* spending effect than an oil and gas boom.

In addition, mining is on average more labour-intensive than oil and gas extraction of which most is found offshore: between 1995-2009 and across the whole of Indonesia, the average contribution of the oil and gas sector to GDP in Indonesia over the same time period was 1.6 times higher than the share of mining[7], but the employment share of mining was more than double the employment share of oil and gas over same period.[8] Oil and gas production is also highly specialized – especially offshore production – which implies that the substitutability of labour across the oil and gas sector and other sectors may be relatively low and thus leave less scope for crowding out of manufacturing through labour reallocation at the local level.[9]

3 Model

We formulate a simple theoretical model which illustrates the effect of a natural resource boom on the resource sector and other sectors in multiple regions. It builds on the theoretical framework of Allcott and Keniston (2014), which itself extends Matsuyama (1992), Corden and Neary (1982) and Van Wijnbergen (1984) to multiple regions of one country. This implies that we abstract from the nation-wide consequences of changes in the nominal exchange rate and focus on local effects. The main novelty of our model is to condition the effects of a natural resource boom on the labour intensity of the extraction method used by the local natural resource sector.

3.1 Setup

There are multiple regions within a given country. We model each district k (for *kota* and *kabupaten*) as a small open economy, in which up to three sectors operate: the non-tradables sector, the tradable goods sector and the natural resource sector. We index these sectors as $j = \{n, m, r\}$. Each sector in district k comprises a composite firm that produces output X_{jk}, has productivity Ω_{jk} and employment l_{jk}. The aggregate production function is given by

$$X_{jk} = \Omega_{jk} F_{jk}(l_{jk}) = \Omega_{jk} l_{jk}^{1-\gamma_{jk}} \qquad j = \{n, m, r\}\ ,\ \gamma_{jk} \in [0, 1) \tag{1}$$

where γ_{jk} is a parameter that captures the labour intensity of sector j in district k; the smaller is γ, the higher is labour intensity. For the resource sector, the realization of γ_{jk} depends on the types of mineral deposits found in district k, if any. The production function is increasing and concave in labour: $F'_{jk}(l_{jk}) > 0$ and $F''_{jk}(l_{jk}) < 0$. While the price of the tradable goods sector's product (p_m) and the price of the resource

7 Source: SAKERNAS. On average 0.283 percent of working-age people worked in the mining sector (excluding quarrying), while 0.116 percent of working-age people worked in the oil and gas sector.

8 Source: Indonesia's national statistical agency *Badan Pusat Statistik* (BPS).

9 Substantial exports of oil, gas and minerals may also lead to an appreciation of the nominal exchange rate, which would lead to crowding out of the manufacturing sector, but our within-country empirical approach abstracts from nominal exchange rate effects.

sector's product (p_r) are exogenous and fixed on world markets, the price of non-tradables (p_{nk}) is endogenous and may thus vary by district.

Labour is paid wage w and is fully substitutable across sectors. Labour supply in district k equals L_k and is a function of the wage level: $L_k(w_k) \geq 0$, $L'(w) \geq 0$. For simplicity, we assume that each consumer supplies one unit of labour, thus there is full employment in all districts and no elasticity of hours worked. Labour supply elasticity is instead a function of labour mobility across districts: perfectly elastic labour supply is characterized by $L'(w) = \infty$ and perfectly inelastic labour supply is characterized by $L'(w) = 0$. $L'(w)$ is exogenously given and fixed.

There are barriers to entry in the resource sector, which implies that it makes positive profits: $p_r X_{rk} - w_k l_{rk} > 0$. A fraction σ of profits is accrued by local consumers. We denote a consumer's income received via profit participation in district k as π_k.[10] Therefore,

$$\pi_k = \frac{\sigma[p_r \Omega_{rk} F_{rk}(l_{rk}) - w_k l_{rk}]}{L_k(w_k)} > 0 \tag{2}$$

Labour supply only depends on the wage and not directly on income accrued via resource sector profits. In Online Appendix OA1, we show that this is sufficient to generate all model predictions.

Consumers have Cobb-Douglas preferences over the consumption of non-tradable and tradable goods, which we denote by C_n and C_m, and the aggregate budget constraint of consumers is

$$(w_k + \pi_k)L_k(w_k) = p_{nk}C_{nk} + p_m C_{mk} \tag{3}$$

Utility maximization given this constraint yields that consumers spend a fraction α of the aggregate budget on non-tradables and a fraction $(1-\alpha)$ on tradable goods, thus yielding aggregate demand:

$$\alpha(w_k + \pi_k)L_k(w_k) = p_{nk}C_{nk} \tag{4}$$

$$(1-\alpha)(w_k + \pi_k)L_k(w_k) = p_m C_{mk} \tag{5}$$

Non-tradables cannot be imported, so that

$$C_{nk} = X_{nk} = \Omega_{nk} F_{nk}(l_{nk}) \tag{6}$$

must hold in equilibrium, and is reached through an adjustment of p_n. The sum of employment in the three sectors equals total labour supply and the market for labour clears:

10 In principle, consumers may accrue resource sector profits via direct profit participation or via tax cuts and/or redistribution by the regional, provincial or state government. In the case of Indonesia, the latter appears to be the more important channel as discussed in Section 2. For simplicity, we assume that only consumers residing in district k participate in resource sector profits generated in district k. In order for the model predictions to hold, it would be sufficient to assume that consumers of no other district accrue a larger fraction of the resource sector profits generated in district k than the consumers residing in district k.

$$l_{nk} + l_{mk} + l_{rk} = L_k(w_k) \tag{7}$$

Since each composite firm maximizes profits, in equilibrium the marginal product of labour of all sectors equals the wage:

$$w_k = p_{nk}\Omega_{nk}F'_{nk}(l_{nk}) = p_m\Omega_{mk}F'_{mk}(l_{mk}) = p_r\Omega_{rk}F'_{rk}(l_{rk}) \tag{8}$$

$$= p_{nk}\Omega_{nk}\left[\frac{1-\gamma_{nk}}{l_{nk}^{\gamma_{nk}}}\right] = p_m\Omega_{mk}\left[\frac{1-\gamma_{mk}}{l_{mk}^{\gamma_{mk}}}\right] = p_r\Omega_{rk}\left[\frac{1-\gamma_{rk}}{l_{rk}^{\gamma_{rk}}}\right] \tag{9}$$

3.2 The effects of a natural resource boom

We trace the effect of a natural resource boom through the model, which we define as an increase in the world price of natural resources, p_r. Alternatively, equivalent predictions follow from defining a boom as an increase in the resource sector's productivity, Ω_{rk}. This generates four predictions. We provide intuition below and delegate formal proofs to the Online Appendix.[11] To keep the notation parsimonious, we drop the k-subscript in the following.

Prediction 1: A natural resource boom increases (i) the wage and (ii), if labour supply is not perfectly inelastic, also population. Further, (iii) a natural resource boom increases resource sector employment.

The increase in the world price for natural resources increases the marginal product of labour in the resource sector, which responds by hiring more workers. Attracting these workers requires an increase in wages from other sectors (which in the Corden and Neary (1982) terminology is called the"resource movement effect"), or from other districts as long as $L'(w) > 0$. Such migration dampens the increase in wages, and the more so the higher is labour mobility across districts.

Prediction 2: A natural resource boom increases the production and price of non-tradables.

The non-tradable sector faces higher demand from wealthier local consumers after a rise in p_r. Since it is able to pass on the costs of increased wages to consumers via raising prices, it is profit-maximizing for the sector to respond by an increase in production. As long as labour supply is not fully inelastic, the rise in demand and production for non-tradables is caused by two factors: a) consumers participate in natural resource sector profits (i.e. $\sigma > 0$ and thus $\pi > 0$), which is the "spending effect" in Corden and Neary

[11] Note that in order to prove Predictions 1-3, it is sufficient to assume that the general production function is increasing and concave in labour, i.e. $F'_{jk}(l_{jk}) > 0$ and $F''_{jk}(l_{jk}) < 0$.

(1982), and b) an increase in population due to the rise in the local wage.[12] In the case of perfectly inelastic labour supply, population does not increase and thus the increase in demand is entirely driven by resource sector profit participation.

Prediction 3: A natural resource boom decreases the production of tradable goods.

The tradable goods sector faces an increase in input costs which it cannot pass on to consumers via raising its output price, since the latter is determined on world markets and thus exogenous. Therefore, it becomes less competitive and reduces production and employment, despite an increase in the demand for its product at the local level.

Prediction 4: Suppose a natural resource boom occurs in a district. The higher the labour intensity of the resource sector in the district, (i) the larger the resulting wage increase; (ii) the larger the increase in population, as long as labour supply is not perfectly inelastic; (iii) the larger the increase in the production of non-tradables, if labour supply is sufficiently elastic; (iv) the larger the increase in resource sector employment; (v) the larger the decrease in tradable goods production.

The higher the labour intensity of the resource sector, the more additional workers it employs as p_r increases, since the rise of the marginal product of labour due to a given change in p_r increases with the labour intensity of the resource sector's production process. A larger rise in employment requires a larger rise in the wage; and the latter, in turn, also attracts more workers from other districts and leads to a sharper decline of the tradable goods sector's employment. Regarding the expansion of the non-tradable sector, two competing forces are at play. On the one hand, a more labour-intensive resource sector implies more competition for local labour as the price of natural resources increases; on the other hand, the higher wage increase leads to more immigration, and thus demand for non-tradables. The relative strength of these forces depends on how mobile workers are across space.

3.3 Empirical tests of the model

We start by providing evidence for and exploiting the fact that *underground* mining is more labour-intensive than *open-pit* and other types of mining in Indonesia. In line with the sequence of the model, we then test Prediction 1 to see whether district-level population and/or manufacturing wages rise during a natural resource boom in districts using either extraction method. After analysing migration and input costs, we

[12] This implies that as long as labour supply is not perfectly inelastic, the non-tradables sector would expand also if there were no profit participation, i.e. $\pi = 0$. This is due to our assumption that labour supply is a function of the *nominal* wage. If it were a function of the real wage w/p_n, then in the case of $\pi = 0$, consumers residing in other districts would be indifferent between moving to the booming district or staying in their home district, ceteris paribus. This is because the advantage of higher nominal wages is fully offset by higher non-tradables prices in the case of $\pi = 0$. See Online Appendix OA1 for a formal argument.

test Predictions 2, 3 and 4. We do so by treating the manufacturing sector as heterogeneous in the extend to which its goods are traded locally versus (inter)nationally, and relating manufacturing-plant outcomes to geographical variation in districts' mineral endowments, heterogeneity in the local methods of extraction, and time variation in the relevant mineral prices on world markets.

For example, a local boom potentially only leads to competition for labour between the extraction sector and manufacturing if the mine requires more additional labour than can be supplied through immigration. If so, local wages will rise and local goods manufacturers will expand to meet excess demand while raising prices to compensate the larger wage bill. Only if the upward pressure on wages is large enough will traded goods manufacturers, who cannot pass on these costs to consumers, reduce employment. Not distinguishing between extraction methods can mask these effects, because only labour-intensive mining methods require a lot of labour, while capital-intensive mining does not. In the latter case a boom will increase mining revenue without much upward pressure on wages and thus leave less scope for crowding out of manufacturing. On the contrary, both local and traded goods producers may then benefit equally from the increase in aggregate wealth.

In addition, we test for the net effect of geographical spillovers. As long as workers are not fully immobile across space, population in a booming natural resource district increases. Absent international migration this necessarily leads to a decrease in population and demand in other districts. On the other hand, mining revenues generated in one district may create demand for manufactured goods in neighbouring districts, and increase neighbouring demand directly through limited revenue sharing.[13]

4 Data

For our purposes, we need data on changes in employment and other outcomes of individual firms as well as detailed information on the presence and activity of the resource sector across Indonesia. We therefore merge the district identifier in the firm-level census with the geographical coordinates of the near universe of minerals (including metals and coal), and oil & gas fields. We discuss all sources and variables below and provide additional details in the Online Appendix.

4.1 Natural resource endowments

We construct a database of mining by district by combining two proprietary data sources: the *Raw Materials Data* (RMD), which is provided by *SNL Metals and Mining*, and data provided by *MinEx consulting* (*MinEx*). Combined, these sources provide us with the location, mining method in use or planned, metals and minerals produced, resources in the ground, and year of discovery for each deposit.

We identify 82 mineral deposits that were discovered by 1990, spread across 40 out of the 282 districts that

[13] Before 1992, neighbouring districts and the provincial government did not participate in local mining rents and royalties. Thereafter, the provincial government received 16% of mining rents and 16% of royalties. On top of that, neighbouring districts have received 32% percent of royalties since 2001 (Resosudarmo, 2005; Agustina et al., 2012).

existed in 1990. The year 1990 is chosen to fix endowments at the start of the period for which we observe manufacturing outcomes.[14] The deposits represent a wide variety of minerals, which each have their own world price as shown in Figure 2.[15] The most common extraction method is open-pit mining, which was listed for 77 deposits in 36 districts, followed by 11 deposits in nine districts listed as operated or planned to be operated by underground mining, while only three deposits in three districts use placer mining techniques for deposits found in (former) river beds.[16]

To aggregate deposits with different minerals by district we first compute for each deposit the remaining discovered mineral ore resources as of 1990, measured in megatons.[17] We then sum across deposits by district and divide by the surface area of the 1990 district. We use ore rather than the mineral or metal content because the primary response to a price shock is arguably an adjustment of *ore* production: the more ore resources a developed deposit has, the larger its operations and the potential effects on the labour market. We thus define the district-level endowment measure r_k as follows:

$$r_k = \frac{\sum_d R_{dk}}{Area_k} \tag{10}$$

where R_{dk} stands for the ore resources of deposit d in district k in 1990. Finally, we scale r_k by its average across all positive realizations of r_k and label this $\tilde{r_k}$. Estimated coefficients can then be interpreted as the effect of increasing mineral endowment by the average endowment of mining districts.

For oil and gas endowments we rely on a novel source, the *Indonesia Oil and Gas Atlas* by Courteney et al. (1991), of which we digitize six volumes between 1988 and 1991. The six volumes list all oil and gas fields in Indonesia that had been discovered at the time of publication, as well as their precise location and "current daily production", which equals the most recent available production figure. The benefit is that we can include all fields without relying on an arbitrary size-cut off such as in the commonly used data base for giant discoveries (Horn, 2003). Unfortunately, field-specific oil and gas remaining resources in the ground are not reported. Therefore, we compute our proxy for oil and gas endowment as the sum of reported daily production of barrels of oil equivalent (BOE) over all fields within a district (using the closest year available to 1990 within the 1988-1991 period), divided by district size.[18] We scale this proxy in the same way as we scaled r_k, and denote it $\tilde{boe_k}$. 37 districts in 14 different provinces were producing oil and/or gas around 1990. Nine of these districts also contained minerals in 1990.

We relate these measures of endowment to world prices using a variety of sources for all the minerals and

[14] Because districts in Indonesia proliferate over time we aggregate to the 1990 district borders. For the period 1990-1993 we rely on Bazzi and Gudgeon (2018) and for other years on Indonesia's national statistical agency *Badan Pusat Statistik* (BPS).

[15] 22 deposits hosted coal (which contained 72.63 percent of total resources), 20 gold (7.31%), 12 tin (2.39%), nine copper (9.44%), eight silver (5.3%), seven nickel (1.42%), six bauxite (0.75%), four iron ore (0.68%), two manganese (0.0006%), one cobalt (0.05%), one diamonds (0.01%), one uranium (0.01%) and one zirconium (0.0002%).

[16] The numbers add to more than 82 because some mines use a combination of methods.

[17] If a deposit was mined before 1990, we deduct the mine's pre-1990 ore production from the initial resources. Resources are defined as "the concentration or occurrence of material of intrinsic economic interest in or on the Earth's crust in such form and quantity that there are reasonable prospects for eventual economic extraction" (Raw Materials Data Handbook, p.57)

[18] We convert cubic feet of natural gas to barrels of oil equivalent by using a standard conversion factor of 6,000.

metals. We discuss the construction of the mineral price index in detail in the next section, which interacted with initial endowments constitutes our measure of a local natural resource shock.

Table 1 provides descriptive statistics on natural resource endowments by province and shows the geographical dispersion of endowments, which includes the populous islands of Java and Sumatra.

Other district-level variables include *population* from the population census rounds 1990, 2000 and 2010 and the inter-census population surveys (SUPAS) of 1995 and 2005 as reported by the University of Minnesota's Minnesota Population Center (MPC), and the number of mining workers, which we approximate using the SAKERNAS household survey using the district-representative years 2007 to 2015.

4.2 Firm data

To measure firm activity we use the annual census of manufacturing plants (*Survei Industri* (SI)), which contains repeated observations on 59,031 manufacturing plants between 1990 and 2009 that employ at least 20 employees in a particular year. The data is collected and compiled by the BPS. The dataset contains detailed information on performance indicators, including employment, investment, material inputs, revenue, exports, price deflators, products sold, and the district in which the plant is located. In addition, it contains a 4-digit ISIC sector classification. The census covers the manufacturing sector and thus excludes mining operations. Table 2 presents the descriptive statistics.

Our main outcome variable is *employment* as reported in the census.[19] We do not observe hours worked so we construct plant-year level *earnings per worker* by dividing the total wage bill by the number of employees. *Revenue* as reported in the census is the value of goods produced. The *number of products sold* and the average *unit price* (equal to revenues divided by the total number of products sold) are only available from 1998 onwards, which restricts the sample size to 1998-2009 for these outcomes. Finally, we obtain total factor productivity from Javorcik and Poelhekke (2017).[20] We only observe continuing plants with 20 or more employees and thus cannot identify entry and exit. If mining booms have larger effects on smaller plants or result in plant exits, then our estimates provide a lower bound on the actual effect.

We use the detailed sector classification and export data to construct indicators for whether a plant mainly sells to local markets or whether it sells to non-local and foreign markets. This is important because local goods producers may be able to pass on higher labour costs to an expanded local market, while traded goods producers that are price takers would lose market share. While the manufacturing sector is usually

[19] Total employment at the plant level includes paid and unpaid workers. The reported number of total workers per plant corresponds to the respondent's assessment of the plant's average employment in the survey year.

[20] TFP calulation is based on the method by De Loecker Warzynski (2012) and Ackerberg et al. (2006). First, a separate translog production function for each two-digit ISIC sector is estimated, relating the log value added to (the log of) capital, labour, and materials (including squared terms and all interactions) and year and four-digit-ISIC-industry fixed effects. Input coefficients are allowed to vary by exporter and foreign ownership status. Demand for materials proxies for unobservable productivity shocks. This yields expected industry-level output, which then results in plant-year level deviations from expected output. In the second step, these are regressed using GMM on its lag, capital and labour input where current labour is instrumented with lagged labour as suggested by Ackerberg et al. (2006). Finally, the innovations of this regression capture TFP. Value added equals output net of inputs of material and energy. Capital is proxied with fixed assets, labour with the number of employees. All variables are expressed in Indonesian rupiahs, deflated using five-digit industry producer price indices.

regarded as altogether tradable, some manufacturing plants produce goods that are more tradable than others. Further, a plant's product may be highly tradable in its nature, but may de facto not be *traded* beyond the local economy. We first divide plants into a group that never exports (*non-exporters*) and a group that exports a positive fraction of its output in at least one year over our sample period (*exporters*).[21] However, non-exporters may nevertheless sell goods in other districts and provinces within Indonesia and be price-takers in those destinations.[22] We therefore also split plants into local goods producers and traded goods producers. *Traded goods producers* are plants that exported in at least one year in our sample period (and thus contains all *exporters*), and/or, are plants that have a low (below four-digit industry median) distance elasticity to trade. The latter equals the percentage change in trade volume as distance increases by one percent as calculated by Holmes and Stevens (2014) using industries' average shipment distance as reported in the US Commodity Flow Survey. Our sample includes 123 four-digit manufacturing industries, which results in "Ready-mixed concrete production" as the most locally-traded manufacturing sector, and "Manufacture of engines and turbines, except aircraft, vehicle and cycle engines" as the most traded sector.[23] Because similar data is not available for Indonesia we use US elasticities. This implicitly implies that we assume that the *ranking* of industries with respect to distance elasticity across the two countries is the same.[24] *Local goods producers* are thus all other plants, which have an above median distance elasticity.

Finally, some of the plants in our data may be upstream to the mining sector. *Upstream plants* are potential suppliers to mines and defined as those plants that operate in four-digit industries that sell an above median share of output to the mining sector. To compute this, we rely on input-output tables for the United States, as discussed in the Online Appendix.[25]

[21] Defining export status at the plant level might be problematic due to selection effects. For example, suppose that districts with positive 1990 mineral resources decide to implement exporter-friendly policies during the sample period, and that these policies only bite during mining booms. Also suppose that these policies cause new manufacturing plants (call them the group of plants A) to settle in such districts, and that in mining districts, there are other plants in the same industries as the exporting plants which do not export (group of plants B), but whose prices are not determined locally. If we then compare the performance of exporters vs. non-exporters, we may find no effect. A solution to this potential problem would be to define export status at the industry level, as this would put the group of plants A and B, respectively, in the same category. However, this is not possible since only in one of the 123 four-digit industries in our sample, no plant exported a positive fraction of output over the sample period. That said, we consider the likelihood of such selection issues as very low.

[22] A large fraction of tradable goods producers may not export their output due to insufficient competitiveness or bureaucratic reasons (see e.g. McLeod, 2006)

[23] Since the Holmes & Stevens measure is industry-specific, and some plants in our sample change industry over time, it is possible that a plant changes status over time. As we discuss in section 6.6.2, our results are robust to dropping industry-switchers.

[24] If this nonetheless introduces measurement error it will be harder to reject the null hypothesis that the effect of mining booms differs across producers of traded versus local goods producers.

[25] These tables are as of 2007 and provided by the Bureau of Economic Analysis (BEA). We prefer the US input-output tables since they distinguish more sectors than any Indonesian input-output table does, and thus allows a finer evaluation of an industry's linkage to the mining sector. While for many sectors using the input-output table of another country may give a poor image of the industry's linkage to other industries, this is not the case for the mining sector, as formal mining is done in a very standard way across the globe.

5 Empirical Strategy

Our main hypothesis is that an outcome variable of plant i in industry j in district k is affected by the intensity of mining activity in district k. We thus need exogenous variation in mining activity over time at the district level. Further, we expect the magnitude of the effect of mining booms to depend on the labour intensity of the local mining methods used. We establish the relevance of this margin in preliminary regressions in Section 6.1.

As suggested by the model, a natural resource boom is an increase in the world price of natural resources. Since districts may host multiple deposits each containing multiple minerals we construct a price index that captures the price level of resources found in existing deposits in each district, using as weights the district-specific share of mineral m in total initial 1990 resources. More precisely we define:

$$ln(MinPrice_{kt}) = ln\left[\frac{\sum_m [P_{mt} * \sum_d R_{mdk}]}{\sum_d R_{dk}}\right] \text{ if } \sum_d R_{dk} > 0, \text{ 0 otherwise}$$

where P_{mt} equals the world price of mineral m in year t indexed to base year 1990 and R_{mdk} equals the 1990 ore resources of mineral m in deposit d in district k. Figure 2 plots the development of P_{mt} for all minerals in our sample and shows periods with large price swings. For example, the steep increase in the price of iron ore as observed in 2005 will have no effect in districts without iron ore deposits (absent spillovers), and only a substantial effect in districts where iron ore makes up a large share of ore endowments. Fixing weights to the base year 1990 and using only deposits that were discovered by 1990 ensures exogeneity with respect to plant-level outcomes in subsequent years, conditional on plant (and district) fixed effects, which we absorb by first differencing. Finally, the mining method is closely related to the geological shape in which the deposit occurs, which is exogenous (Hartman and Mutmansky, 2002).

Given this price level definition, we can write down our main estimating equation where we follow the approach of Allcott and Keniston (2018) for oil and gas development in the US, but adjust for the presence of multiple minerals and for variation in extraction techniques:

$$\begin{aligned} \Delta lnY_{ijkt} = \beta_1 \Delta[ln(MinPrice_{kt}) * \tilde{r_k}] + \beta_2 \Delta[ln(MinPrice_{kt}) * \tilde{r_k} * Underground_k] \\ + \beta_3 \Delta[ln(OilPrice_t) * \tilde{boe_k}] + \beta_4 \tilde{r_k} + \beta_5 \tilde{boe_k} + \beta_6 Underground_k + \beta_7 [\tilde{r_k} * Underground_k] \\ + \alpha_t * \omega_j + \epsilon_{ijkt} \end{aligned} \tag{11}$$

where Y_{ijkt} equals outcome Y of plant i in industry j in district k in year t, and $\alpha_t * \omega_j$ are four-digit industry-year effects. $Underground_k$ is a dummy that equals one if at least one deposit in district k that had been discovered by 1990 was operated or planned to be operated by underground mining. α_t are year fixed effects and ω_j are industry fixed effects. We estimate equation (11) for all plant-specific outcome variables and always cluster standard errors at the district-level.[26]

By first-differencing the outcome variable, we control for plant-specific and district-specific fixed effects. By dropping plants before or after they move from one district to another, we ensure that district fixed effects are nested within the plant fixed effects.[27] We choose a first-difference rather than fixed-effects estimator for two reasons: First, because the errors in equation (11) in levels are highly serially correlated and the first-differences estimator is thus more efficient; and second, because this allows us to control for differential trends in the outcome variables across districts that differ in terms of natural resource endowment and locally applied mining techniques. To account for these differential trends, we include in the equation the scaled mineral resource measure $\tilde{r_k}$ and oil equivalent production measure $\widetilde{boe}_k$. Similarly, we include a mining method dummy $Underground_k$ and its interaction with $\tilde{r_k}$ separately in order to control for differential trends in manufacturing outcomes in districts with labour-intensive mineral extraction methods. This also captures differences in labour market trends. β_1 is an unbiased estimate of the relative effect of a mining boom on a manufacturing plant's outcome Y as long as mining booms are uncorrelated with unobserved economic trends, conditional on the control variables in equation (11). β_1 measures a *relative* rather than *absolute* effect: the counterfactual is the change in outcome Y in the same year of a plant in the same industry, in a district that faces a smaller or no mining boom. For example, a doubling of local mineral prices has a $100{*}\beta_1$ percent relative effect on the outcome variable in a district with average 1990 mineral ore resources (i.e. $\tilde{r_k} = 1$), compared to a plant in a district with no mineral resources. At the same time, it can be interpreted as the differential effect of a given price increase in a district with endowments equal to $\tilde{r_k} = 2$ compared to a district with average endowments $\tilde{r_k} = 1$.

In the absence of geographic spillovers, β_1 will equal the absolute effect. Spillovers may occur via migration from other districts into the booming district, the revenue sharing scheme through which near districts benefit from mining booms, and an increase in demand for goods produced in near districts. In order to gauge the effect of spillovers and thereby also understand their effect on β_1, we develop two additional specifications. In the first, we test the effect of a mining boom in neighbouring districts on the home district's outcomes. In the second, we test the effect of a mining boom in other districts in the same province on the home district's outcomes. In Section 6.6.1 we show that these effects are small and insignificant, suggesting that β_1 comes close to a measure of the absolute rather than relative effect of a mining boom.

[26] We adjust the degrees of freedom for singleton industry-year groups, i.e. plants for which no other plant is in the same industry in a given year, following (Correia, 2015).

[27] For each such plant, we keep the longest period in which the plant stays in one district. We cannot be sure if these events are real or due to measurement error. In a robustness test we drop them entirely.

6 Results

6.1 Does labour intensity differ by extraction method?

A rise in local input costs during a natural resource boom is a necessary condition for the manufacturing sector to be negatively affected by the boom and any Dutch disease effects to occur. Our theoretical predictions highlight that the larger the labour intensity of the natural resource sector, the more wages rise during booms.

Our data distinguishes between underground, open-pit, and placer mining. According to Hartman and Mutmansky (2002) underground mining methods are most labour intensive because it is harder to operate and automate heavy machinery in underground tunnels.[28] Conversely, all non-underground mining methods (open-pit, open-cast, placer, auger mining and quarrying) are classified as non-labour-intensive. This suggests that on average, and considering relatively low wage levels, that underground mining in Indonesia is more labour-intensive than other types of mining and that mines that use a combination of underground and open-pit methods are also more labour intensive than pure open-pit mines. In theory, labour can be the predominant input in open-pit mining as well, if wages are sufficiently low. District fixed effects absorb labour market conditions that would induce open-pit mines to use mostly labour instead of capital, because even if labour market conditions change over time, it is unlikely that open-pit mines can switch from year to year between capital-intensive machinery and labour-intensive alternatives without incurring prohibitively high switching costs. Oil and gas extraction, some of which occurs offshore, is probably least labour intensive. We test this more formally using the SAKERNAS household survey, providing us with an estimate of the number of mining and oil & gas workers in each district, between 2007 and 2015.[29]

We first regress the dependent variable on the district's total 1990 mineral resources and its oil and gas production around 1990 (Table 3, column 1). Both variables are scaled by their respective average across districts with positive realizations, but not scaled by district size. We also include year fixed effects and cluster standard errors at the district level. The results suggest that a district with average 1990 mineral resources employs 39 percent more mining and oil & gas workers than a district with no 1990 mineral resources. In contrast, a district with average 1990 oil production employs only seven percent more mining and oil & gas workers than a district with no 1990 oil and gas production. This cannot be explained by a difference in overall relevance of mining compared to oil and gas extraction: An inspection of Indonesia's national accounts reveals that the average mining district only contributed 5% more to overall GDP than the average oil and gas district over 2007-2014. This corroborates our prior that oil and gas extraction is least labour-intensive.

[28] Our data is not more specific, but in theory these can be further broken down into cut-and-fill stoping, stull stoping, square-set stoping, room-and-pillar mining, stope-and-pillar mining, shrinkage stoping and sublevel stoping, where the first three methods belong to the class of "supported" underground methods (to prevent collapse) and the latter four to the class of "unsupported" mining methods. With the exception of stope-and-pillar mining and sublevel stoping, all of these methods are classified as relatively labour-intensive.

[29] Manning (2006) suggests that the survey is suitable for estimating long-term trends of employment, but that it is not suitable to study year-to-year changes.

In column 2 of Table 3, we include *underground mining*, a dummy equal to one if natural resource extraction was at least partly done using underground methods. The results suggest that conditional on the district's mineral endowment, mining employment in underground mining districts is 107% larger than in other districts.[30] Column 3 shows that this result is driven by the districts in which all deposits use only underground mining, rather than the districts in which both underground and open-pit mining occurs.[31] In column 4 we add province fixed effects to account for differential regional wages. The coefficient on oil and gas production is now close to zero and not significant, while the coefficient on underground and open-pit mining is now positive and (marginally) statistically significant, but the ranking in terms of labour-intensity is preserved. These results clearly support the claim that underground mining is more labour-intensive than other types of mining in Indonesia.

Our second test uses population data. If indeed underground mining is more labour-intensive, we would also expect a stronger population response to a booming mining sector that employs more labour, *relative* to other mining districts. Second, as highlighted by the model, low overall labour mobility is a necessary condition for wages to rise during a boom. Since population data is only collected every five years in Indonesia, we adapt equation (11) to examine the effect of mining and oil & gas booms on immigration. The dependent variable is the change in log population during four periods, covering 1990-1995, 1995-2000, 2000-2005, and 2005-2010. Table 4 presents the regression results, where we relate annual mineral price changes in three different ways to five-yearly population changes. The first measure takes the simple average of all five annual price changes (columns 1 and 2). In our second measure, we assume that price shocks towards the end of the five-year period have a stronger effect on the five-year change in population, and specifically determine the weights as $\omega = \{0.3, 0.25, 0.2, 0.15, 0.1\}$ (column 3). In our third measure, we simply compute the price shock as the difference between the current district-specific minerals price and its five-year lag (column 4). In each specification, we interact the price change measure with our scaled mineral resource measure $\tilde{r_k}$ – which we label *Mineral Resources 1990* in all tables – and with the interaction of $\tilde{r_k}$ and the dummy variable *Underground Mining*. In column 1, we estimate the average effect, while in columns 2-4 we distinguish between the two mining methods. Standard errors are clustered at the district, in order to account for possible serial correlation in the error term and heteroskedasticity.

The results suggest that an increase in the price of local minerals does spur immigration into mining districts (see column 1), dampening a response of wages. However, column 2 shows that labour mobility during mining booms clearly depend on local extraction methods. If mining is more capital-intensive, booms do not affect population. We also find that oil and gas booms do not spur significant immigration. This is consistent with oil and gas extraction being very capital-intensive and the fact that most revenue accrues to the central as opposed to local governments as explained in Section 2. Labour supply in Indonesia appears less responsive

[30] Online Appendix Table OA1 shows that the results of Table 3 on mining are very robust to restricting the dependent variable to mining employment only and excluding oil and gas production from the set of controls.

[31] We do not know the relative mix of methods used in deposits where both underground and open-pit is used. The three districts where all deposits use only underground mining are in the districts of Bogor and Lebak on densely populated Java, and Sintang on sparsely populated Kalimantan (Borneo). Dropping one of the 9 districts at a time does not affect the main results, see Online Appendix Table OA2.

to natural resource booms than in the United States, since Allcott and Keniston (2018) find that population significantly increases in oil and gas counties as the oil price doubles (by a mere 0.3 percent, however). When local mining is labour-intensive, labour supply in Indonesian mining districts does increase during boom times, although the effect is not large. Column 2 indicates that if the district-specific mineral prices double each year over a period of five years, then district population significantly increases by 6.1 percent, in the district with average mineral resources and where underground mining takes place. If the price of local minerals doubles compared to five years ago, the population of the average mining district significantly rises by 1.2 percent, if underground mining takes place (column 4). Because the size of the median price shock is 12%, the economic magnitude of the coefficients appears relatively small.[32] Overall, our results suggest that while labour is not immobile across space as a response to minerals price shocks, labour mobility is relatively low. This should lead to upward wage pressure and potential Dutch disease mechanisms, which we examine next.

6.2 Manufacturing Earnings per Worker

We estimate equation (11), using as dependent variable the log change in average earnings per worker and present the results in Table 5 for different groups of manufacturing plants. For ease of interpretation, we list the marginal effect of the price effect for districts that use underground, labour-intensive mining at the bottom. Column 1 shows that there is no average effect of mining nor of oil and gas booms on earnings per worker. However, column 2 shows that in districts with average mineral resources that use underground mining methods, a doubling of local mineral prices leads to a significant increase of earnings per worker by 5.9 percent. This novel result is consistent with our theoretical framework: if mining is labour-intensive, a mine needs to attract more additional workers to expand production, which requires a larger increase in wages. It also suggests that immigration into these districts is driven by higher wages, but is not elastic enough to keep wages flat. Relatively capital-intensive extraction methods such as open-pit mining and oil & gas extraction yield no wage response, perhaps because the higher degree of capital intensity requires workers with more specific skills that are imperfect substitutes for manufacturing workers, or because the elasticity of oil production to oil prices is lower. Anderson et al. (2018) indeed find that skill and capital-intensive *drilling* is more responsive to oil prices than oil production itself, which may be why Cust et al. (2017) find a positive response of wages after an oil price increase in districts that explored for oil and had success. We find that the intensive margin of extraction is more relevant for mining than for oil.

Columns 3-5 explore the differential effect of a mining boom on local versus traded goods producers. We find that the increase in earnings per worker during labour-intensive mining booms is driven by manufacturing plants producing local goods, who are more likely to be able to pass on wage costs to local consumers. Exporters and traded goods producers in general do not raise wages during a boom, but there is some limited evidence that exporting plants in labour-intensive mining districts may be worse off than exporters

[32] Calculated as the median of absolute mineral-specific price shocks, weighted by the frequency of occurrence of the mineral.

located in districts with capital-intensive mining methods. The coefficients are very robust to how we define producers of local and traded manufacturing goods, as a comparison of the results in column 2 and 4, and 3 and 5, reveals. However, because at the same time unobserved hours worked may increase, it is not a given that costs rise. We thus look at employment next.

6.3 Manufacturing employment

Table 6 presents the results for manufacturing employment. Column 1 shows that employment expands to meet excess demand for goods in now richer districts, although the effect is small and only significant with 90% confidence. However, conditioning on extraction methods in column 2 shows that manufacturing plants only hire significantly more workers during capital-intensive mining booms, while employment is unaffected by labour-intensive mining booms. Together with our results on earnings per worker, this suggests that manufacturing plants benefit from a spending effect during both capital- and labour-intensive mining booms (through resource revenue sharing with local governments), but that this benefit is offset by upward pressure on their wage bill during labour-intensive booms.[33] The beneficial (local) spending effect leads to an expansion of non-exporters and local goods producers, which does not depend on extraction methods.

A sudden increase in the value of oil production does not lead to more employment at the local level, because it accrues mostly to the central government. The negative albeit limited effects of factor reallocation between local and traded goods producers are apparent in columns 4 and 6, but only in labour-intensive mining districts. A boom then leads to a reduction in employment of 1% for exporters. Capital-intensive booms also feature a positive spending effect, but do not increase wages, which thus also raises employment for exporters and traded goods producers. In fact, and despite the theoretical result that traded goods producers and exporters benefit less from the spending effect, in this case exporting plants appear to benefit more than non-exporters. This could be due to increased demand for higher quality, which is offered by firms that compete in (inter)national markets.[34]

The results are again very consistent across the two chosen ways of identifying producers of local versus traded goods. For all remaining dependent variables, we therefore focus only on our preferred method, which takes both the plant-specific export status as well as the industry-specific distance elasticity into account.

6.4 Manufacturing revenue, products sold, and prices

Table 7 reports results on manufacturing revenues (Panel A), products sold (Panel B), and prices (Panel C). For capital-intensive booms, for all plants on average and for local goods producers, the coefficients are positive, but they are not significant. We do find large positive and significant effects during labour-

[33] Prediction 2 of the model also relates the spending effect to an increase in population via an increase in wages. The weak response of earnings per worker during capital-intensive booms in Table 5 suggest this channel is less empirically relevant.

[34] Note that we control for sector-year fixed effects, which absorb sector-specific global demand shocks that may correlate with mineral booms.

intensive booms for local goods producers. They increase average product prices (rather than units sold) by 15.3 percent as local mineral prices double (Panels B and C). Local goods producers are thus able to pass on the costs of higher wages and this directly translates into larger revenues (Panel A). Capital-intensive booms in contrast are only loosely related to higher prices and more products sold. Traded goods producers do not significantly change prices nor products sold during labour-intensive mining booms, but the combined effect nevertheless translates into somewhat higher revenue (1.2 percent), despite the contraction in employment. The oil price has again a much smaller or no effect with only a significant increase in revenues of 0.3 percent reflecting a very limited local spending effect from oil.

We thus find strong evidence in favour of the model and a reallocation of employment from traded to non-traded sectors, but only during labour-intensive mining booms. As in Corden and Neary (1982), this reallocation on its own is efficient and in theory welfare improving. In fact, we find that the manufacturing sector as a whole does not do worse in terms of employment in booming districts. To gauge potential longer term effects we next estimate the effect on total factor productivity.

6.5 Total Factor Productivity

Columns 1-3 of Table 8 present the results on the effect of contemporaneous mining booms on (innovations to) total factor productivity (TFP). While TFP is largely unchanged during capital-intensive booms, it significantly increases for local plants during labour-intensive booms. This is probably to a large extent driven by the significant and large increase in revenues. For traded goods producers, the small contraction in employment may result in negative 'learning by doing' effects as in Van Wijnbergen (1984) and Arrow (1962), but the results displayed in column 3 suggest that traded goods producers experience a marginally significant decrease in TFP during *capital*-intensive booms (when employment rises), while TFP is not significantly affected during labour-intensive booms (when employment contracts), at least in the short run. In column 4, we test whether such effects materialize with a lag. Specifically, we replace the dependent variable by the change in TFP between t and $t-5$. On the right-hand side, we replace the price shocks with respect to the previous year by the average change in annual prices. Thus, the coefficient must be interpreted as the effect of a doubling of minerals prices in each year over the five-year period. The coefficient is not significant: while we do observe that traded sector employment is crowded out during a labour-intensive mining boom, this has no effect on productivity. Although factor reallocation occurs, the evidence for a productivity-related 'Dutch disease' thus remains elusive.

6.6 Additional results and robustness checks

6.6.1 Regional spillovers and revenue sharing

So far we did not account for the possibility that regional spillovers affect the results. Testing for such spillovers sheds light on whether we estimate an effect that is relative to other districts, or an absolute effect of mining booms. In Table 9 we first repeat the baseline for comparison and in column 2 we control for mining booms/busts in neighbouring districts with which it shares a border.[35] We treat all neighbours as one single district and compute its mineral resources per square mile as of 1990 and price shock realizations analogously to the single-district computation. In column 3, we control for the average mining boom in other districts of the same province, which may have an effect on plants in the home district via natural resource revenue sharing (see Section 2). The coefficients on the spillover variables in column 2 and 3 are close to zero and statistically insignificant, which suggests that spillovers of local mining booms to neighbouring districts or districts in the same province are not empirically relevant on average. Combined with the evidence for relatively low labour mobility, we conclude that the coefficients in our main specification come close to representing absolute rather than relative effects.

In addition, we test whether increased revenue sharing with other districts since decentralization helps to spread any benefits of mining booms beyond the mining district itself.[36] In 1999 a new law on revenue sharing of natural resource rents between the national government, provinces, and districts was signed. Law 25/1999 stipulated that the producing district's share in royalties decreased from 64 to 32%, and that districts in the same province of the producing district would get 32% instead of 0%. We test whether increased revenue sharing between resource-rich and resource-poor districts after 1999 has led to (i) stronger spillovers of mining boom into neighbouring districts and other districts in the same province and to (ii) weaker spending effects in the booming district itself. Rather than adding another interaction we restrict the sample to the years 1999 and after, and rerun regressions (2) and (3). Columns 4 and 5 show that there is again no evidence for spillovers, and weak evidence on slightly smaller spending effects.

Finally, allowing for arbitrary correlation of the errors across space by clustering on district and year does not affect the main results (column 6). Because there are only 19 years and thus 19 clusters in the sample we follow best practise and do not cluster by year throughout (Cameron and Miller, 2015).

6.6.2 Robustness checks

Endowments in 1980

While labour market trends may differ between districts of varying mining intensity, we control for these in our main specification through including $\tilde{r_k}$ and its interaction with the underground mining dummy (see

[35] Since a number of districts are islands, they do not have neighbours according to our definition. This implies that the sample size in the robustness check of column 2 is slightly smaller compared to our baseline specification.

[36] Since we are interested in controlling for spillover effects due to revenue sharing and the latter occurs independently of the local mining methods, we do not feature an additional interaction with the underground mining dummy in this specification.

equation 11), and by fixing natural resource endowments in 1990 and thus before we observe plant-level outcomes. Thereby we also control for any systematically different unobserved exploration trends that may affect annual changes in manufacturing outcomes. Nevertheless, we further address this concern by timing mineral resources per square mile in 1980 in columns 2 of Table 10. We still scale by the average realization of mineral resources in the year 1990 such that the endowment is expressed in units of average 1990 endowment.Because 1980 endowments are smaller resulting in a mean of $\tilde{r}_{k,1980} = 0.675$, instead of 1 for $\tilde{r}_k$, we find larger coefficients but the overall pattern and marginal effect of labour-intensive booms is the same.

Industry switchers

Some plants switch industry and potentially also between the industry-level categories of local and traded goods producers, which may be correlated with local natural resource booms, and lead to measurement error and potentially bias the results if the industry-switch is endogenous. In column 3 we exclude all plants that ever switch 4-digit ISIC industry. Despite losing almost a third of observations, the coefficients are robust to this change.

Foreign and state owned plants

In column 4 of Table 10, we examine whether our results are homogeneous across plants of different ownership structure. Government ownership may for example insulate plants from Dutch disease effects. We control for lagged ownership by interacting the mining boom variable as well as its interaction with the underground mining dummy with a plant-specific foreign ownership and a government ownership dummy, respectively. The former equals one if the plant was partly or fully foreign-owned in $t-1$, and the government ownership dummy equals one if the plant was partly or fully owned by the local and/or central government in $t-1$. We find that foreign-owned plants benefit much more from capital-intensive booms than domestic private and government-owed plants. In particular, in the district with average mineral resources, foreign-owned plants increase employment by 14.8 percent as minerals prices double, while domestic private plants significantly increase employment by 2.5 percent and government-owned plants do not grow at all. The latter result suggests that the central or local governments do not use mining windfalls to shield or promote the manufacturing plants they partly or fully own, and that those plants benefit less from a rise in local purchasing power than is suggested by the results on privately-owned plants.[37] During labour-intensive booms, government owned plants are especially hit hard.

Upstream plants

Next, we check whether the results are driven by upstream plants that supply to the mining sector and may locate in and directly benefit from districts with mining. Because the upstream dummy is defined

[37] One potential explanation is that government-owned plants produce goods for the central government which are more tradable than the products of other plants. However, additional results that are available upon request show that also government-owned plants producing local goods do not significantly benefit from capital-intensive mining booms.

at the industry level we include year fixed effects and compare plants across industries. The coefficients in column 5 suggest that upstream plants do grow more than their counterparts during capital-intensive mining booms, and not during labour-intensive booms, but the coefficients are not significant. More importantly, we find that non-upstream plants significantly benefit from capital-intensive mining booms and less so during labour-intensive booms. This suggests that our baseline results are not driven by upstream plants, but by the mechanisms of the theoretical framework.[38]

Market power

In Table 11 we first address the fact that Indonesia has a large market share in the export of some minerals; one might be worried that global prices are not entirely exogenous to the country's manufacturing sector. For example, it may impose an export tariff to increase revenue and at the same time subsidize material input for downstream producers. If these are located near the mines than this may bias the estimate upwards, although it does not affect the differential impact between labour- and capital-intensive mining. In column 2 we thus exclude six districts that produce minerals in which Indonesia holds a large market share. These are tin and nickel, of which Indonesia was the second- and third-largest producer worldwide in 2009. This has virtually no effect on our results.

Different intrinsic supply elasticities of minerals

We next check whether the labour intensity of underground mining captures a higher price elastic type of mineral. If so, that would invalidate the model's focus on labour-intensity of the mechanisms. Our data does not suggest that underground mining is more common for specific minerals; all minerals that are mined underground (coal, gold, silver and copper) are also mined using other methods elsewhere in our sample. Nevertheless, we address this concern by comparing districts without mineral resources and districts with only one type of resource. Most minerals are found in districts that also host other minerals, but for coal we observe seven districts where only coal is found. This implies dropping 33 of 282 districts from our sample. In five of the coal-only districts, only open-pit mining was applied, while in the remaining two coal-only districts, both underground and open-pit mining was applied. If the concern is valid then the effect of coal price increases should not depend on the local extraction method. The results are displayed in Table 11, column 3. The coefficients estimated based on the restricted sample provide evidence against mineral-specific effects: the coefficients are very similar to those of the main specification and remain statistically significant and support the conclusion that mining methods matter.

Decentralization

[38] The percentage of foreign-owned plants is higher in mining districts than in non-mining districts, which could explain why foreign-owned plants benefit more from local mining booms than others, if they also tend to be upstream. However, neither upstream plants as measured via the BEA input-output table nor foreign-owned plants are the sole driver of our results; in both specifications, also other types of plants benefit during capital-intensive booms and all types of plants benefit less from labour-intensive mining booms in terms of employment.

Indonesia's 'big bang' decentralization in 1999 gave districts more control over the local economy. At the same time, minerals prices were much more volatile in the post-decentralization decade than in the decade before. If mining districts used their additional power to improve conditions for the local manufacturing sector *compared to non-mining districts*, then this would confound our coefficient estimates on mining booms. To take this concern into account, we include a full set of district times post-1999 dummies in the main specification. These control for differential trends in manufacturing employment in each individual district across the pre- and post-decentralization decade. As Table 11, column 4 shows, the results are very robust to this modification. More generally, the results of this robustness check provide evidence against the presence of any unobservable that has a similar trend as minerals prices and differently affects plants in districts with mineral resources.

Comparison to the US

For the United States, Allcott and Keniston (2018) find that as the oil price doubles, manufacturing employment in a county with an additional oil and gas endowment of one standard deviation increases by 0.3 percent. In contrast, for Indonesia our estimates suggest effects that are ten times as large. However, to allow a direct comparison we scale by a standard deviation of endowment as opposed to the average. The result is displayed in column 5. We now find that a doubling of local minerals prices increases manufacturing employment in capital-intensive mining districts – which are most comparable to U.S. oil and gas counties – by 8.8 percent, in a district with an additional mineral endowment of one *standard deviation*. This estimate is even larger, especially considering the large price swings of other minerals than oil in Figure 2. Column 6 suggests that in Indonesia this increase in employment is not dampened by an increase in wages, while Allcott and Keniston (2018) found a positive county-level estimate of 0.6%. Capital-intensive natural resource extraction methods in Indonesia may require specific skills that are not found in the local labour market, such that effective labour mobility between local manufacturing plants and capital-intensive mining is low.

The relative labour-intensity of single versus mixed-method mining

In Section 6.1 we showed that underground mining is more labour-intensive than other methods, and that districts in which all mines use only underground methods are most labour-intensive. In Table 12 we gauge whether this distinction also translates into different effects on manufacturing wages (Panel A) and employment (Panel B).[39] Indeed, we find that the upward pressure on manufacturing earnings per worker is larger in districts where only underground mining is applied than in districts where both underground and open-pit mining is applied. Moreover, the results in columns 2-5 confirm that the increase in earnings per worker is largely driven by local goods producers. The average amount of resources across districts that only use underground methods equals $r_k = 0.018$, while $r_k = 1.844$ for districts that use a combination of

[39] While it would be ideal to estimate a specification that takes the *continuous* fraction of 'underground resources' into account, this is not possible in practice. The reason is that in the deposits in which both underground and open-pit mining is applied, we do not know the distribution of resources in percent across the two mining techniques. See Online Appendix OA2 for further details.

underground and open-pit methods. We therefore calculate comparable marginal effects, which show that a doubling of local minerals prices increases manufacturing earnings per worker by $1.317 * 0.018 = 2.4$ percent in the average districts with only underground mining, while it increases manufacturing earnings per worker by $0.058 * 1.844 = 10.7$ percent in the average districts with both methods. Panel B shows that manufacturing employment in the average most-labour-intensive districts falls (-0.010), while it slightly increases in somewhat less labour-intensive districts (0.005), and only increases substantially in capital-intensive districts (0.035). Traded goods producers are most negatively affected when mining is most labour-intensive, judging by the marginal effects of Panel B, columns 8 and 10. We conclude that the relative labour-intensity of mining methods is key to understanding crowding out effects on manufacturing plants.

Potentially influential districts

Finally, in Online Appendix Table OA2 we show that the results are robust to dropping, one at a time, each district with underground mining. The sign, significance and magnitude of coefficients and marginal effects is qualitatively unaffected.

7 Conclusion

We estimate the impact of local mineral booms on manufacturing plants in Indonesia, exploiting detailed information on natural resource deposits and the method with which these are extracted. We highlight the different degrees of labour- and capital-intensity that these methods entail. Some mines are better than others, in terms of their effect on traded goods producers, depending on the mining sector's degree of labour intensity. As a result, we find that global price increases lead to upward wage pressure for manufacturing plants that are located in districts where mining operations are relatively labour-intensive. In line with a Corden and Neary (1982)-type model of factor reallocation with multiple districts, we find that local goods producers charge higher prices and pass on wage costs to wealthier local consumers and thus do not contract in terms of employment. However, and despite a positive local spending effect, traded goods producers who compete on national or world markets significantly reduce employment. In contrast, capital-intensive mining methods do not lead to higher local wages such that a positive local spending effect – such as through revenue sharing between the national and the local government – translates into an expansion of employment for all manufacturing plants.

We find that these effects are larger than in the US (Allcott and Keniston, 2018), reflecting more limited factor mobility across districts and limited spillovers. We add to the literature by showing that the positive effect of mining booms on local manufacturing is driven by booms in districts where mining is *capital*-intensive.

In labour-intensive mining districts, a doubling of minerals prices induces earnings per worker to significantly rise by 14.8 percent in a district with a one standard deviation larger mineral endowment. While there is no comparable estimate for developed countries, this coefficient appears large. Combined with our empirical evidence that traded goods producers shed workers during labour-intensive mining booms, this suggests that labour mobility between manufacturing and other sectors is high, and that labour mobility across space is more limited, as also suggested by our results on migration. Since these are common characteristics of developing countries, and labour-intensive mining is prevalent in many of them (RMG, 2011), our results arguably contain important lessons for other resource-rich developing countries. Moreover, revenue sharing between the national government and resource producing districts is substantial enough to generate a positive spending effect, although we find that Indonesia's decentralization and subsequent increase in natural resource revenue sharing with non-resource-rich districts has not spread noticeable benefits of capital-intensive mining booms. We leave to future research whether this is due to corruption or crowding out of other forms of government spending.

Our findings suggest that the volatility in world commodity prices leads to frequent reallocation shocks between mines and manufacturing sectors, but we did not find economically relevant repercussions in terms of TFP: evidence for a productivity related 'Dutch disease' remains elusive. Our results therefore suggest that these shocks are of a relatively transitional nature and do not necessarily affect long run growth, at least at the local level, which is consistent with commodities driving short run growth, but not long run growth at the aggregate level (Domenico and Peretto, 2018). In fact, the manufacturing sector as a whole – including both local and traded goods producers – does not contract after a local boom. Nevertheless, volatility creates uncertainty and may itself have significantly dampened private investment into the manufacturing sector, at least in natural resource-rich districts. In the US, such districts received more public investment and public goods (Michaels, 2011), but this is perhaps less likely in a developing country setting. Exploring this potential issue is another promising avenue for future research.

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Figures and Tables

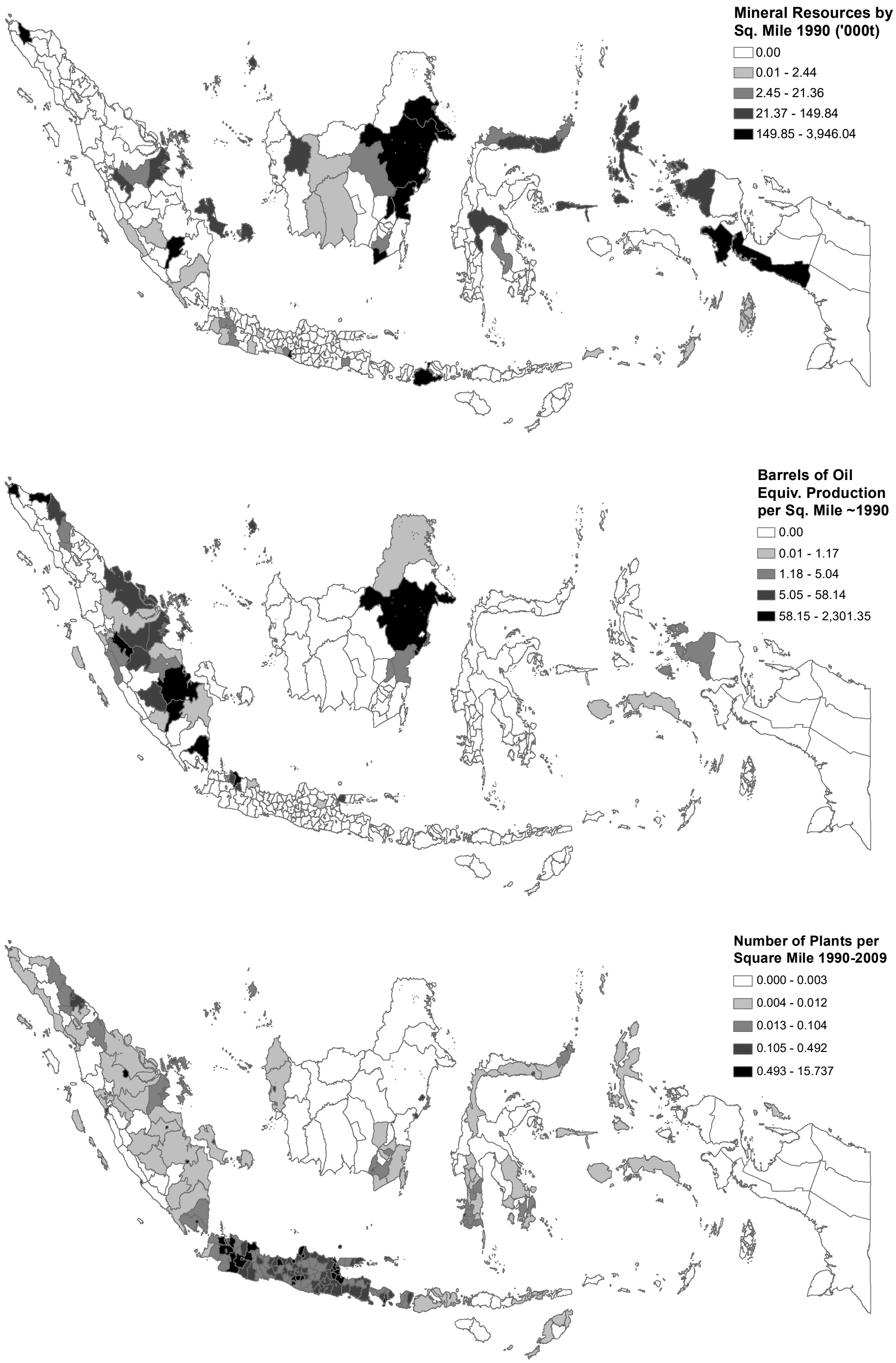

Figure 1: This map shows the geographical spread of mineral resources, oil & gas production and manufacturing plants. Mineral resources and oil & gas production are organized in quartiles based on positive realizations, while plant density is organized in quintiles.

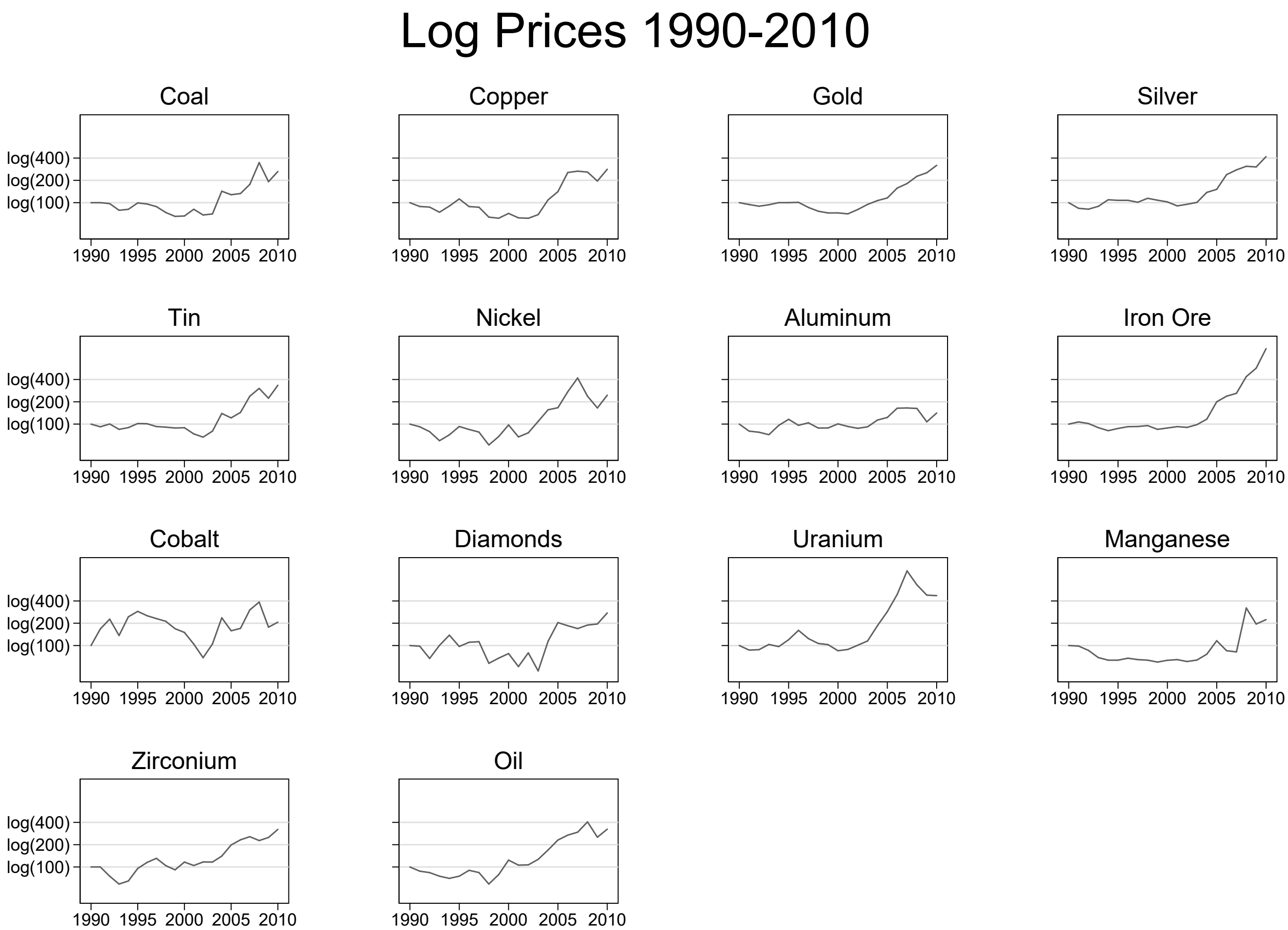

Figure 2: This figure shows the log of the indexed price series ($P_{1990} = log(100)$) of all minerals that were found in Indonesia in 1990. Minerals are arranged from top left to bottom right based on their share in total mineral resources. The oil price is at the bottom right. See Online Appendix OA5 for the individual price series sources.

Table 1: Resource intensity and extraction techniques by province

Province	Districts	Mining Districts	oil & gas Districts	Mineral Ore Resources / Area 1990	Mining techniques	Minerals	oil & gas Production / Area, 1990
Bali	8	0	0	0			0
Bengkulu	4	1	0	0.41	UG,OP	Gold, Silver	0
Central Java	35	2	0	0.64	OP	Iron Ore, Manganese	0
Central Kalimantan	6	3	0	0.91	OP,Placer	Aluminum, Gold, Silver, Zirconium	0
Central Sulawesi	4	1	0	0.61	OP	Copper	0
Dista Aceh	10	1	2	27.37	OP	Copper	23.28
DI Yogyakarta	5	1	0	227.95	OP,Placer	Iron Ore	0
DKI Jakarta	5	0	1	0			197.12
East Java	37	1	3	0.10	OP	Iron Ore	0.40
East Kalimantan	6	3	4	152.31	UG,OP	Coal, Gold, Silver	335.86
East Nusa Tenggara	12	0	0	0			0
Irian Jaya (Papua)	9	2	1	41.85	UG,OP	Copper, Gold, Nickel, Silver	0.21
Jambi	6	0	3	0			1.58
Lampung	4	1	1	0.09	UG,OP	Gold	26.08
Maluku	4	2	1	8.21	OP	Copper, Gold, Nickel, Silver	0.06
North Sulawesi	6	3	0	43.86	OP	Copper, Gold	0
North Sumatra	17	0	2	0			0.44
Riau	7	2	5	5.04	OP	Aluminium, Coal, Tin	10.40
South Kalimantan	10	3	1	591.34	OP,Placer	Coal, Diamonds	0.23
South Sulawesi	23	1	0	8.19	OP	Nickel, Cobalt	0
South Sumatra	9	3	5	286.68	UG,OP	Coal, Gold, Silver, Tin	127.73
Southeast Sulawesi	4	1	0	2.00	OP	Nickel	0
West Java	24	3	5	1.21	UG,OP	Gold, Manganese, Silver	245.13
West Kalimantan	7	3	0	5.59	UG,OP	Aluminum, Uranium	0
West Nusa Tenggara	6	1	0	205.50	OP	Gold, Copper	0
West Sumatra	13	1	3	6.61	UG,OP	Coal	20.17
TOTAL	281	39	37				

Table 1 provides descriptives statistics on mineral resources, oil and gas production intensity and mineral resource extraction techniques at the province level. *Mineral Ore Resources /Area 1990* indicates mineral ore resources per district in thousand tons per square mile in 1990. *oil & gas Production / Area 1990* indicates the production of oil and gas per square mile in terms of barrels of oil equivalent, around the year 1990. *Mining Techniques* indicates the extraction techniques that were applied on mineral resources under development as of 1990 or techniques planned to be applied on resources that had been discovered but were not yet being developed in 1990. *UG* stands for underground, *OP* for open-pit and *Placer* for Placer mining. *Minerals* are those that were extracted, or planned to be extracted from discovered deposits, as of 1990. Bangka and Belitung are treated as one district; see Online Appendix OA2 for details.

Table 2: Summary Statistics on selected Dependent and Independent Variables

Variable	Sample Districts	Mean	p(50)	sd	Min	Max	N
District-year data							
Mining Workers/Total Workers	Res90>0	0.040	0.017	0.053	0	0.313	351
oil & gas W./Total W.	BOE Prod >0	0.006	0.002	0.011	0	0.065	333
log(Mining Workers)	All	7.446	7.301	1.584	3.503	12.104	1,207
log(Mining & oil & gas W.)	All	7.512	7.432	1.549	3.553	12.104	1484
Δlog(Population)	All	0.070	0.057	0.166	-2.224	1.418	942
	Res90>0	0.105	0.097	0.116	-0.161	0.690	109
	Res90>0,UG=1	0.115	0.092	0.156	-0.161	0.690	30
$\tilde{r_k} \times \Delta$log(Minerals Price)	Res90>0	0.056	0.000	0.781	-6.978	8.306	780
$\tilde{r_k} \times \Delta$log(Minerals Price)*UG	Res90>0,UG=1	0.061	0.000	0.928	-5.617	6.685	180
$\widetilde{boe}_k \times \Delta$log(Oil Price)	BOE Prod >0	0.059	0.000	0.708	-6.658	6.323	740
District data							
Total Mineral Resources 1990	Res90>0	1.000	0.048	2.103	0.0001	9.601	39
	Res90>0,UG=1	2.308	0.017	3.632	0.001	9.601	9
Total BOE Production ~1990	BOE Prod >0	1.000	0.013	4.204	0.000	25.717	37
$\tilde{r_k}$	Res90>0	1.000	0.060	2.539	0.0004	11.736	39
	Res90>0,UG=1	1.235	0.045	3.097	0.0005	9.446	9
$\tilde{r}_{k,1980}$	Res90>0	0.675	0.024	2.013	0.0005	9.470	23
	Res90>0,UG=1	1.606	0.013	3.529	0.0005	9.470	6
$\widetilde{boe}_k$	BOE Prod >0	1.000	0.024	2.820	0.000	14.002	37
Plant-year data							
Δlog(Employees)	All	0.001	0.000	0.306	-5.669	5.281	343,751
	All (local plants only)	-0.002	0.000	0.254	-4.601	4.564	140,261
	All (traded plants only)	0.004	0.000	0.338	-5.669	5.281	203,440
Δlog(Earnings per Worker)	All	0.135	0.098	0.593	-10.519	11.318	343,466
Δlog(Revenues)	All	0.132	0.089	0.816	-14.472	15.251	319,881
Δlog(Product Units sold)	All	0.076	0.000	1.940	-21.879	20.594	193,783
Δlog(Unit Price)	All	0.034	0.031	1.912	-21.616	21.031	193,726
Δlog(TFP)	All	0.003	0.003	0.051	-0.972	0.958	214,787
$\Delta_5$log(TFP)	All (traded plants only)	0.016	0.016	0.078	-1.273	1.064	62,430
Foreign Ownership	All	0.070	0.000	0.256	0.000	1.000	343,751
	Res90>0	0.097	0.000	0.295	0.000	1.000	25,273
	Res90>0,UG=1	0.146	0.000	0.353	0.000	1.000	12,151
Government Ownership	All	0.165	0.000	0.371	0.000	1.000	343,751
	Res90>0	0.177	0.000	0.381	0.000	1.000	25,273
	Res90>0,UG=1	0.228	0.000	0.420	0.000	1.000	12,151
Plant data							
Upstream share in %	Res90>0	0.057	0.022	2.22	0	0.13	4,480

Total Mineral Resources 1990 indicates the mineral ore resources as of 1990 scaled by its mean across all districts with positive mineral resources in 1990. *Total BOE Production ~1990* equals the production of barrels of oil equivalent around the year 1990, scaled by its mean. *Unit Price* is computed as total revenues over product sold. *TFP* is total factor productivity. $\Delta_5$log(TFP) equals the change between year t and $t-5$. $\tilde{r_k}$ equals *Total Mineral Ore Resources /Area, 1990* scaled by its mean across all districts with positive mineral resources in 1990. $\tilde{r}_{k,1980}$ uses the amount of resources in 1980 but still scales by average mineral resources in 1990. *Foreign* and *Government Ownership* equals one if the plant was partly or fully foreign-owned or government-owned, respectively. *Upstream share in %* is equal to the percentage of direct and indirect sales to the mining sector and is industry-specific. *Res90>0* refers to the subset of districts with positive mineral ore resources as of 1990; *UG=1* restricts to districts for which a positive fraction of resources was extracted or planned to be extracted by underground mining. *BOE Prod >0* refers to the subset of districts which produced oil and/or gas around 1990.

Table 3: The labour intensity of different types of natural resource extraction

Dependent variable	ln(# Mining and oil & gas Workers)			
	(1)	(2)	(3)	(4)
Total Mineral Resources 1990	0.39***	0.30***	0.40***	0.18*
	(0.086)	(0.107)	(0.098)	(0.092)
Total BOE Production ∼1990	0.07***	0.05**	0.07***	-0.01
	(0.018)	(0.023)	(0.021)	(0.023)
Underground Mining		1.07**		
		(0.505)		
100% Underground Mining			2.45***	1.96***
			(0.185)	(0.236)
Underground & Open-Pit Mining			-0.05	1.17*
			(0.566)	(0.691)
Year FE	Yes	Yes	Yes	Yes
Province FE	No	No	No	Yes
Observations	1,484	1,484	1,484	1,484
adj. R^2	0.119	0.137	0.163	0.416

In this table we analyse whether underground mining is more labour-intensive than other types of mining. The sample period is 2007-2015, the unit of observation is a district-year. The dependent variable is the log of an approximation of the number of mining and oil & gas workers (see Online Appendix OA7). *Total Mineral Resources 1990* equals mineral ore resources as of 1990 scaled by its mean across all districts with positive mineral resources in 1990. *Total BOE Production ∼1990* equals the production of barrels of oil equivalent around the year 1990, scaled by its mean for producing districts. *Underground Mining* is a dummy that equals one if at least one of the 1990 deposits in the district was operated or planned to be operated by underground mining. *100% Underground Mining* is a dummy that equals one if *all* 1990 deposits were operated or planned to be operated by underground mining. *Underground & Open-Pit Mining* is a dummy that equals one if both underground and open-pit mining was applied or planned to be applied in order to extract the district's 1990 mineral resources. Standard errors in parentheses are clustered at the district level. *** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level.

Table 4: Mineral price shocks and immigration into mineral-rich districts

Dependent variable	Δ_5 ln(Population$_t$)			
	(1)	(2)	(3)	(4)
Mineral Resources 1990 × $\mathbf{W_1}\Delta$ln(Minerals Price)	0.044**	0.000		
	(0.021)	(0.035)		
Mineral Resources 1990 × $\mathbf{W_1}\Delta$ln(Minerals Price) × Underground		0.060*		
		(0.035)		
BOE Production ∼1990 × $\mathbf{W_1}\Delta$ln(Oil Price)	-0.019	-0.019		
	(0.037)	(0.037)		
Mineral Resources 1990 × $\mathbf{W_2}\Delta$ln(Minerals Price)			-0.030	
			(0.018)	
Mineral Resources 1990 × $\mathbf{W_2}\Delta$ln(Minerals Price) × Underground			0.082***	
			(0.027)	
BOE Production ∼1990 × $\mathbf{W_2}\Delta$ln(Oil Price)			-0.018	
			(0.028)	
Mineral Resources 1990 × Δ_5Minerals Price				0.000
				(0.007)
Mineral Resources 1990 × Δ_5Minerals Price × Underground				0.012*
				(0.007)
BOE Production ∼1990 × $\Delta_5$ln(Oil Price)				-0.004
				(0.007)
Mineral Resources 1990	-0.005	0.001	0.005	0.001
	(0.003)	(0.005)	(0.004)	(0.005)
BOE Production ∼1990	0.003	0.003	0.005	0.003
	(0.004)	(0.004)	(0.004)	(0.004)
Population 1990	-0.029***	-0.029***	-0.029***	-0.029***
	(0.009)	(0.009)	(0.009)	(0.009)
Observations	939	939	939	939
adj. R^2	0.040	0.040	0.040	0.040
Marginal effect of mining boom for underground mining=1		*0.061****	*0.052***	*0.012****
		(0.018)	*(0.025)*	*(0.003)*

This table shows the effect of global mineral price shocks on immigration into mineral-rich districts versus districts with relatively smaller or no mineral resources. Conceptually, the underlying specification is equation (11), while in practice we adjust the specification in terms of timing, since population is only recorded every five years. The sample period is 1990-2010. The unit of observation is a district-period; the dependent variable is the change in log total population across the periods 1990-1995, 1995-2000, 2000-2005 and 2005-2010. *Mineral Resources 1990* equals mineral ore resources per square mile as of 1990 scaled by its mean across all districts with positive mineral resources in 1990. *Total BOE Production ∼1990* equals the production of barrels of oil equivalent per square mile around the year 1990, scaled by its mean for producing districts. We also include the interaction of *Mineral Resources 1990* with the weighted change in the log price of minerals present in the district in 1990. The weight of each mineral equals its share in total 1990 mineral resources. We capture minerals price shocks over the five-year periods in different ways. In columns 1 and 2, $\mathbf{W_1}$ is the simple average of the five annual price shocks. In column 3, the weight $\mathbf{W_2}$ of a given price decreases as it lies further in the past; in particular, the weights are 0.3, 0.25, 0.2, 0.15 and 0.1 for periods t through $(t-4)$. In column 4, we simply compute the price shock as the difference between the current district-specific minerals price and its five-year lag. *Underground Mining* equals one if at least one of the 1990 deposits in the district was operated or planned to be operated by underground mining. The marginal effect at the bottom of the table equals the sum of the first two coefficients in the given column. All specifications contain dummies for the years 2000, 2005 and 2010. Standard errors in parentheses are clustered at the district level. ***Significant at 1% level; **Significant at 5% level; *Significant at 10% level.

Table 5: Mineral price shocks and plant-level manufacturing earnings per worker

Dependent variable →	Δln(Average earnings per worker)					
Sample →	All Plants	All Plants	Non-Exporters	Exporters	Local Goods Producers	Traded Goods Producers
	(1)	(2)	(3)	(4)	(5)	(6)
Mineral Resources 1990 × Δln(Minerals Price)	0.022 (0.020)	-0.012 (0.021)	0.019* (0.010)	-0.043 (0.028)	0.018* (0.011)	-0.042 (0.026)
Mineral Resources 1990 × Δln(Minerals Price) × Underground Mining		0.071*** (0.021)	0.093*** (0.011)	0.049* (0.028)	0.094*** (0.011)	0.047* (0.026)
BOE Production ∼1990 × Δln(Oil Price)	-0.002 (0.003)	-0.002 (0.003)	-0.001 (0.002)	-0.004 (0.005)	-0.005 (0.005)	-0.001 (0.003)
Mineral Resources 1990	0.000 (0.002)	0.002 (0.003)	-0.003 (0.004)	0.007*** (0.003)	-0.004 (0.004)	0.007*** (0.003)
BOE Production ∼1990	-0.000 (0.001)	-0.000 (0.001)	-0.000 (0.001)	0.000 (0.001)	0.001 (0.001)	-0.001 (0.001)
Underground Mining		0.001 (0.002)	0.007** (0.003)	-0.004 (0.004)	0.004 (0.003)	-0.001 (0.003)
Mineral Resources 1990 × Underground Mining		-0.005* (0.003)	-0.003 (0.004)	-0.006** (0.003)	-0.001 (0.004)	-0.007** (0.003)
Observations	343,466	343,466	224,078	119,250	140,167	203,249
# Plants	49,836	49,836	35,851	13,985	23,101	29,650
adj. R^2	0.034	0.034	0.035	0.037	0.032	0.036
Marginal effect of mining boom for underground mining=1		*0.059**** *(0.003)*	*0.112**** *(0.004)*	*0.006* *(0.005)*	*0.112**** *(0.004)*	*0.005* *(0.005)*

This table shows the effect of global mineral price shocks on the change in earnings per worker in different groups of manufacturing plants in mineral-rich districts versus districts with relatively smaller or no mineral resources. The underlying specification is equation (11). The sample contains all formal manufacturing plants with at least 20 employees for the years 1990-2009. The dependent variable is the annual change in log average earnings per worker at each plant. We interact the plant's home district mineral resources as of 1990 with a time-varying, district-specific weighted mineral price shock. The weight of each mineral's price shock equals its share in total 1990 resources. *Mineral Resources 1990* equals mineral ore resources per square mile as of 1990 scaled by its mean across all districts with positive mineral resources in 1990 ($\tilde{r_k}$ in equation (11)). *Total BOE Production ∼1990* equals the production of barrels of oil equivalent per square mile around the year 1990, scaled by its mean for producing districts ($\widetilde{boe}_k$ in equation (11)). *Underground Mining* is a dummy that equals one if at least one of the 1990 mineral deposits in the district was operated or planned to be operated by underground mining (which typically requires more labour than open-pit or other types of mines). The marginal effect at the bottom of the table equals the sum of the first two coefficients in the given column. We classify a plant as exporter if it exported a positive share of its output in at least one year during the sample period. The group 'Local Goods Producers' includes all plants which operate in a four-digit industry whose average U.S. distance elasticity is above the industry median *and* are non-exporters. The plants in the opposite category are thus either international exporters *or* have a relatively low distance elasticity according to our measure. All specifications contain four-digit industry-times-year fixed effects. The difference-in-difference specification absorbs plant-fixed effects. Standard errors in parentheses are clustered at the district level. ***Significant at 1% level; **Significant at 5% level; * Significant at 10% level.

Table 6: Mineral price shocks and plant-level manufacturing employment

Dependent variable →	Δln(# Employees)					
Sample →	All Plants	All Plants	Non-Exporters	Exporters	Local Goods Producers	Traded Goods Producers
	(1)	(2)	(3)	(4)	(5)	(6)
Mineral Resources 1990 × Δln(Minerals Price)	0.020*	0.035***	0.021***	0.048**	0.021***	0.048**
	(0.010)	(0.010)	(0.007)	(0.022)	(0.007)	(0.022)
Mineral Resources 1990 × Δln(Minerals Price) × Underground Mining		-0.033***	-0.006	-0.057**	-0.006	-0.056***
		(0.010)	(0.007)	(0.022)	(0.007)	(0.022)
BOE Production ~1990 × Δln(Oil Price)	-0.001	-0.001	0.000	-0.001	0.002	-0.002
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Mineral Resources 1990	0.001	0.000	0.006*	-0.004	0.006*	-0.005
	(0.001)	(0.002)	(0.003)	(0.004)	(0.003)	(0.004)
BOE Production ~1990	0.002***	0.002***	0.001***	0.003***	0.001	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Underground Mining		0.010***	0.008***	0.009***	0.007***	0.011***
		(0.002)	(0.001)	(0.003)	(0.001)	(0.002)
Mineral Resources 1990 × Underground Mining		-0.000	-0.003	0.003	-0.003	0.003
		(0.002)	(0.003)	(0.004)	(0.003)	(0.004)
Observations	343,751	343,751	224,235	119,378	140,261	203,440
# Plants	49,851	49,851	35,864	13,987	23,106	29,662
adj. R^2	0.016	0.016	0.016	0.017	0.015	0.017
Marginal effect of mining boom for underground mining=1		*0.003**	*0.015****	*-0.009****	*0.015****	*-0.009****
		(0.002)	*(0.002)*	*(0.002)*	*(0.002)*	*(0.002)*

This table shows the effect of global mineral price shocks on the change in employment of different groups of manufacturing plants in mineral-rich districts versus districts with relatively smaller or no mineral resources. The underlying specification is equation (11). The sample contains all formal manufacturing plants with at least 20 employees, over the period 1990-2009. The dependent variable is the annual change in log number of workers at each plant. See Table 5 for the description of independent variables and column labels. The marginal effect at the bottom of the table equals the sum of the first two coefficients in the given column. All specifications contain four-digit industry-times-year fixed effects. The difference-in-difference specification absorbs plant-fixed effects. Standard errors in parentheses are clustered at the district level. ***Significant at 1% level; **Significant at 5% level; * Significant at 10% level.

Table 7: Mineral price shocks and plant-level revenues, sales and prices

Sample →	All Plants	Local Goods Producers	Traded Goods Producers
Panel A	**Δln(Revenues)**		
	(1)	(2)	(3)
Mineral Resources 1990 × Δln(Minerals Price)	0.019	0.041	0.001
	(0.018)	(0.037)	(0.024)
Mineral Resources 1990 × Δln(Minerals Price) × Underground Mining	0.067***	0.112***	0.010
	(0.018)	(0.037)	(0.025)
BOE Production ∼1990 × Δln(Oil Price)	0.003**	0.004	0.002
	(0.002)	(0.002)	(0.003)
Observations	319,881	135,132	184,701
adj. R^2	0.033	0.038	0.034
Marginal effect of mining boom for underground mining=1	*0.085****	*0.153****	*0.012***
	(0.004)	*(0.006)*	*(0.006)*
Panel B	**Δln(Number of Product Units sold)**		
	(4)	(5)	(6)
Mineral Resources 1990 × Δln(Minerals Price)	0.049	0.032	0.063
	(0.045)	(0.036)	(0.053)
Mineral Resources 1990 × Δln(Minerals Price) × Underground Mining	-0.024	-0.025	-0.024
	(0.047)	(0.036)	(0.058)
BOE Production ∼1990 × Δln(Oil Price)	0.011	0.010	0.008
	(0.016)	(0.008)	(0.026)
Observations	193,783	82,148	111,609
adj. R^2	0.165	0.208	0.146
Marginal effect of mining boom for underground mining=1	*0.025**	*0.007*	*0.039*
	(0.014)	*(0.008)*	*(0.025)*
Panel C	**Δln(Unit Price)**		
	(7)	(8)	(9)
Mineral Resources 1990 × Δln(Minerals Price)	-0.006	0.032	-0.039
	(0.043)	(0.047)	(0.041)
Mineral Resources 1990 × Δln(Minerals Price) × Underground Mining	0.072	0.121**	0.012
	(0.045)	(0.047)	(0.048)
BOE Production ∼1990 × Δln(Oil Price)	-0.016*	-0.011	-0.018
	(0.010)	(0.009)	(0.020)
Observations	193,726	82,132	111,568
adj. R^2	0.170	0.214	0.150
Marginal effect of mining boom for underground mining=1	*0.066****	*0.153****	*-0.027*
	(0.014)	*(0.010)*	*(0.026)*

This table shows the effect of global mineral price shocks on the annual change in log plant-level revenues, products sold and unit prices, of different groups of manufacturing plants in mineral-rich districts versus districts with relatively smaller or no mineral resources. The underlying specification is equation (11). The sample contains the entire population of manufacturing plants with at least 20 employees for the years 1990-2009 in Panel A, and 1998-2009 in Panels B and C, due to data availability. Both revenues and the number of products sold are directly reported by the plant in the census. To compute the unit price (Panel C), we compute the ratio of the two. See Table 5 for the description of independent variables and column labels. The marginal effect at the bottom of the table equals the sum of the first two coefficients in the given column. All specifications contain four-digit industry-times-year fixed effects. The difference-in-difference specification absorbs plant-fixed effects. We always include *Mineral Resources 1990*, *Underground Mining*, their interaction and *BOE Production ∼1990*, but do not report their coefficients. Standard errors in parentheses are clustered at the district level. *** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level.

Table 8: Mineral price shocks and plant-level Total Factor Productivity (TFP)

Dependent variable →	Δln(TFP)			$\Delta_5$ln(TFP)
Sample →	All Plants	Local Goods Producers	Traded Goods Producers	Traded Goods Producers
	(1)	(2)	(3)	(4)
Mineral Resources 1990 × Δln(Minerals Price)	-0.001	0.001	-0.004*	
	(0.001)	(0.002)	(0.002)	
Mineral Resources 1990 × Δln(Minerals Price) × Underground Mining	0.006***	0.006**	0.005**	
	(0.001)	(0.002)	(0.002)	
BOE Production ∼1990 × Δln(Oil Price)	-0.000	0.001**	-0.001	
	(0.000)	(0.000)	(0.001)	
Mineral Resources 1990 × $\mathbf{W_1}\Delta$ln(Minerals Price)				-0.001
				(0.017)
Mineral Resources 1990 × $\mathbf{W_1}\Delta$ln(Minerals Price) × Underground Mining				0.021
				(0.023)
BOE Production ∼1990 × $\mathbf{W_1}\Delta$ln(Oil Price)				0.001
				(0.004)
Observations	214,787	90,126	124,605	62,430
adj. R^2	0.088	0.104	0.087	0.101
Marginal effect of mining boom for underground mining=1	*0.004****	*0.007****	*0.001*	*0.021*
	(0.000)	*(0.000)*	*(0.001)*	*(0.015)*

This table shows the effect of global mineral price shocks on the annual change plant-level total factor productivity (TFP) of different groups of manufacturing plants in mineral-rich districts versus districts with relatively smaller or no mineral resources. Our sample contains the entire population of manufacturing plants with at least 20 employees. In columns 1-3, the dependent variable is the change in TFP between t and $t-1$. The underlying specification is equation (11), the sample period 1990-2009. See Table 5 for the description of independent variables in columns 1-3. In column 4, the dependent variable is the change in TFP between t and $t-5$. On the right-hand side, the price change is not measured between t and $t-1$ as in columns 1-3, but as the simple average price change across t and $t-1$, $t-1$ and $t-2$, $t-2$ and $t-3$, $t-3$ and $t-4$ and $t-4$ and $t-5$. The sample period is therefore 1995-2009 instead of 1990-2009. The marginal effect at the bottom of the table equals the sum of the first two coefficients in the given column. All specifications contain four-digit industry-times-year fixed effects. The difference-in-difference specification absorbs plant-fixed effects. We always include *Mineral Resources 1990*, *Underground Mining*, their interaction and *BOE Production ∼1990*, but do not report their coefficients. Standard errors in parentheses are clustered at the district level. ***Significant at 1% level; **Significant at 5% level; * Significant at 10% level.

Table 9: Additional results: Regional spillovers and revenue sharing

Dependent variable →	Δln(# Employees)					
	Baseline	Booms nearby	Booms in same province	Booms nearby, after 1999	Booms in same province, after 1999	Two-way clustering
	(1)	(2)	(3)	(4)	(5)	(6)
Mineral Resources 1990 × Δln(Minerals Price)	0.035***	0.034***	0.033***	0.032**	0.032**	0.035***
	(0.010)	(0.011)	(0.009)	(0.014)	(0.013)	(0.003)
Mineral Resources 1990 × Δln(Minerals Price) × Underground Mining	-0.033***	-0.032***	-0.031***	-0.036***	-0.035***	-0.033***
	(0.010)	(0.011)	(0.009)	(0.014)	(0.013)	(0.002)
BOE Production ~1990 × Δln(Oil Price)	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Neighbours' Mineral Resources 1990 × Δln(Neighbours' Minerals Price)		0.005		0.003		
		(0.022)		(0.022)		
Neighbours' Mineral Resources 1990 × Δln(Neighbours' Minerals Price) × Neighbours' Underground Mining		0.001		0.006		
		(0.024)		(0.024)		
Neighbours' BOE Production ~1990 × Δln(Oil Price)		-0.001		0.001		
		(0.001)		(0.001)		
OthersProv Mineral Resources 1990 × Δln(OthersProv Minerals Price)			0.003		0.002	
			(0.003)		(0.003)	
OthersProv BOE Production ~1990 × Δln(Oil Price)			-0.002		-0.001	
			(0.001)		(0.002)	
Observations	343,751	342,065	343,751	196,189	196,935	343,751
adj. R^2	0.016	0.015	0.016	0.004	0.004	0.016
Marginal effect of mining boom for underground mining=1	*0.003**	*0.003*	*0.003**	*-0.004**	*-0.004***	*0.003*
	(0.002)	*(0.002)*	*(0.002)*	*(0.002)*	*(0.002)*	(0.004)

This table shows the results of robustness checks of the baseline result. To facilitate the comparison, column 1 displays the results of our baseline specification (Table 6, column 1). In column 2, we control for mining booms/busts in neighbouring districts where we treat all neighbours as one district and compute its mineral resources and price shock analogously to the single-district case. In column 3, we control for the average mining boom/bust in other districts of the same province. Columns 4 and 5 repeat the specifications of columns 2 and 3, respectively, estimated over the period 2000-2009. Standard errors in parentheses are clustered at the district level, except in column 6 where we cluster at both the district and year. The difference-in-difference specification absorbs plant-fixed effects. We always include all combinations of interacted terms, but do not report their coefficients. *** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level.

Table 10: Robustness I: 1980 endowments, industry switchers, ownership and upstream plants

Dependent variable →	$\Delta\ln(\#\text{ Employees})$				
	Baseline	Resources 1980	No industry switchers	Ownership Controls	Upstream Controls
	(1)	(2)	(3)	(4)	(5)
Mineral Resources 1990 × $\Delta\ln$(Minerals Price)	0.035***		0.037***	0.025***	0.026***
	(0.010)		(0.011)	(0.004)	(0.010)
Mineral Resources 1990 × $\Delta\ln$(Minerals Price) × Underground Mining	-0.033***		-0.030***	-0.024***	-0.019**
	(0.010)		(0.011)	(0.004)	(0.010)
BOE Production ~1990 × $\Delta\ln$(Oil Price)	-0.001	-0.001	-0.002	-0.001	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Mineral Resources 1980 × $\Delta\ln$(Minerals Price)		0.066***			
		(0.009)			
Mineral Resources 1980 × $\Delta\ln$(Minerals Price) × Underground Mining		-0.064***			
		(0.009)			
Mineral Resources 1990 × $\Delta\ln$(Minerals Price) × Foreign Ownership (t-1)				0.123**	
				(0.056)	
Mineral Resources 1990 × $\Delta\ln$(Minerals Price) × Foreign Ownership (t-1) × Underground Mining				-0.015	
				(0.058)	
Mineral Resources 1990 × $\Delta\ln$(Minerals Price) × Government Ownership (t-1)				-0.033	
				(0.027)	
Mineral Resources 1990 × $\Delta\ln$(Minerals Price) × Government Ownership (t-1) × Underground Mining				-0.052*	
				(0.029)	
Mineral Resources 1990 × $\Delta\ln$(Minerals Price) × Upstream share > 50pctl					0.019
					(0.039)
Mineral Resources 1990 × $\Delta\ln$(Minerals Price) × Upstream share > 50pctl × Underground Mining					-0.021
					(0.038)
Observations	343,751	343,751	230,353	343,751	343,826
adj. R^2	0.016	0.016	0.014	0.016	0.009
Marginal effect of mining boom for underground mining=1	*0.003**	*0.003**	*0.007****	*see*	*0.007****
	(0.002)	*(0.001)*	*(0.002)*	*below*	*(0.001)*

*Marginal effect of a capital-intensive boom on: Domestic private plant: 0.025*** (0.004) ; Foreign-owned plant: 0.148** (0.059) ; Government-owned plant: -0.008 (0.024)*

*Marginal effect of a labour-intensive boom on: Domestic private plant: 0.001 (0.002) ; Foreign-owned plant: 0.109** (0.015) ; Government-owned plant: -0.084*** (0.014)*

This table shows the results of robustness checks of the baseline result. Column 2 measures endowments in 1980. Column 3 drops all plants that ever change four-digit industry. In column 5 *Foreign* and *Government Ownership* are plant- and year-specific dummies which equals one if the plant was partly or fully foreign-owned or government owned, respectively. In column 6 *Upstream share > 50 pctl* equals one if the industry sells an above median share to the mining sector. All specifications contain four-digit industry-times-year fixed effects. The difference-in-difference specification absorbs plant-fixed effects. We always include all combinations of interacted terms, but do not report their coefficients. Standard errors in parentheses are clustered at the district level. *** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level.

Table 11: Robustness II: market power, mineral-specific effects, decentralization, and rescaling

Dependent variable →	Δln(# Employees)					Δln(Earnings per worker)
	Baseline	Excluding Tin & Nickel	Same Mineral	After 1999 FE	AK2017 scaling	AK2017 scaling
	(1)	(2)	(3)	(4)	(5)	(6)
Mineral Resources 1990 × Δln(Minerals Price)	0.035***	0.035***	0.034***	0.036***		
	(0.010)	(0.010)	(0.010)	(0.010)		
Mineral Resources 1990 × Δln(Minerals Price) × Underground Mining	-0.033***	-0.033***	-0.031***	-0.033***		
	(0.010)	(0.010)	(0.010)	(0.010)		
BOE Production ~1990 × Δln(Oil Price)	-0.001	-0.001	-0.001	-0.001		
	(0.001)	(0.001)	(0.001)	(0.001)		
Mineral Resources 1990 (AK2017) × Δln(Minerals Price)					0.088***	-0.029
					(0.024)	(0.052)
Mineral Resources 1990 (AK2017) × Δln(Minerals Price) × Underground Mining					-0.082***	0.177***
					(0.024)	(0.052)
BOE Production ~1990 (AK2017) × Δln(Oil Price)					-0.002	-0.006
					(0.003)	(0.009)
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
District × After 1999 FE	No	No	No	Yes	No	No
Observations	343,751	342,274	319,591	343,750	343,751	343,466
adj. R^2	0.016	0.016	0.015	0.017	0.016	0.034
Marginal effect of mining boom for underground mining=1	*0.003**	*0.003*	*0.003**	*0.003**	*0.006**	*0.148****
	(0.002)	*(0.002)*	*(0.002)*	*(0.002)*	*(0.004)*	*(0.008)*

This table shows the results of further robustness checks and of a rescaling exercise. In column 2, we drop the six districts which hosted tin or nickel resources in 1990. In column 3, we restrict our sample to those districts which had only one type of mineral resource in 1990 (coal) and those districts that had no mineral resources in 1990. This implies dropping 33 of 282 districts from our sample. In column 4, we include the interaction of a district dummy and a dummy which equals one for the years during and after Indonesia's decentralization. In columns 5 and 6, we adjust the scaling of our endowment variables to its standard deviation in order to make our results comparable to those of Allcott and Keniston (2018). In column 6, the dependent variable is the change in log earnings per worker. We always include all combinations of interacted terms, but do not report their coefficients. The difference-in-difference specification absorbs plant-fixed effects. Standard errors in parentheses are clustered at the district level. *** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level.

Table 12: Robustness III: The relative labour-intensity of single versus mixed-method mining

Sample →	All Plants	Non-Exporters	Exporters	Local Goods Producers	Traded Goods Producers
Panel A	**Δln(Average earnings per worker)**				
	(1)	(2)	(3)	(4)	(5)
Mineral Resources 1990 × Δln(Minerals Price)	-0.012	0.019*	-0.043	0.018*	-0.042
	(0.021)	(0.010)	(0.028)	(0.011)	(0.026)
Mineral Resources 1990 × Δln(Minerals Price) × 100% Underground Mining	1.329***	2.846***	0.475	3.313***	0.357
	(0.458)	(0.537)	(0.631)	(0.515)	(0.586)
Mineral Resources 1990 × Δln(Minerals Price) × Underground & Open-Pit Mining	0.070***	0.092***	0.048*	0.093***	0.047*
	(0.021)	(0.011)	(0.028)	(0.011)	(0.026)
BOE Production ∼1990 × Δln(Oil Price)	-0.002	-0.001	-0.004	-0.005	-0.001
	(0.003)	(0.002)	(0.005)	(0.005)	(0.003)
Observations	343,466	224,078	119,250	140,167	203,249
adj. R^2	0.034	0.035	0.037	0.032	0.037
Marginal effect of mining boom in the average *100% underground mining district*	*0.023****	*0.051****	*0.008*	*0.059****	*0.006*
Marginal effect of mining boom in the average *underground & open-pit mining district*	*0.108****	*0.205****	*0.010*	*0.206****	*0.009*
Panel B	**Δln(# employees)**				
	(6)	(7)	(8)	(9)	(10)
Mineral Resources 1990 × Δln(Minerals Price)	0.035***	0.021***	0.048**	0.021***	0.048**
	(0.010)	(0.007)	(0.022)	(0.007)	(0.022)
Mineral Resources 1990 × Δln(Minerals Price) × 100% Underground Mining	-0.623***	0.241	-1.262***	0.472**	-1.236***
	(0.169)	(0.204)	(0.309)	(0.225)	(0.223)
Mineral Resources 1990 × Δln(Minerals Price) × Underground & open-pit Mining	-0.032***	-0.006	-0.057**	-0.007	-0.056**
	(0.010)	(0.007)	(0.022)	(0.007)	(0.022)
BOE Production ∼1990 × Δln(Oil Price)	-0.001	0.000	-0.001	0.002	-0.002
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Observations	343,751	224,235	119,378	140,261	203,440
adj. R^2	0.016	0.016	0.017	0.015	0.017
Marginal effect of mining boom in the average *100% underground mining district*	*-0.010****	*0.005*	*-0.022****	*0.009***	*-0.021****
Marginal effect of mining boom in the average *underground & open-pit mining district*	*0.005**	*0.028****	*-0.015****	*0.027****	*-0.015****

We separate districts into those in which both underground and open-pit mining was used or planned, and those in which all 1990 resources were extracted or planned to be extracted by underground mining only. We interact the respective dummy variables with the annual change in the district's minerals prices. See Table 5 for the description of the other independent variables and column labels. At the bottom of the table, we show marginal effects. We present the marginal effect of a mining boom in the *average* 100% underground mining district and in the *average* underground and open-pit mining district, respectively. These are obtained by multiplying the sum of the relevant coefficients by 0.018 and 1.844, respectively, such that we take into account that districts that only hosted pure underground resources in 1990 have much less mineral endowment than the average mining district, and less than districts that hosted both underground and open-pit resources. All specifications contain four-digit industry-times-year fixed effects. The difference-in-difference specification absorbs plant-fixed effects. We always include all combinations of interacted terms, but do not report their coefficients. Standard errors in parentheses are clustered at the district level. ***Significant at 1% level; **Significant at 5% level; *Significant at 10% level.

Online Appendix

“Good mine, bad mine: Natural resource heterogeneity and Dutch disease in Indonesia”

Paul Pelzl and Steven Poelhekke

19 July 2018

OA1 Model Proofs

Prediction 1

Proof. To see that Prediction 1, (i) and (ii) hold, use the labour market equilibrium condition (7) to rewrite the resource sector's profit maximization condition to $p_r \Omega_r F_r'(L(w) - l_m - l_n) = w$. Initially, after a rise in p_r the marginal product of labour exceeds its marginal cost. To restore equilibrium, the wage and/or labour supply must rise. If labour supply is perfectly inelastic, i.e. $L'(w) = 0$, then only the wage increases. If $L'(w) > 0$, then also population increases as a result of the rise in wages, since labour supply does not rise without a wage increase, while a wage increase does trigger an increase in labour supply. Finally, for $L'(w) = \infty$ the wage increases by a negligible positive increment because $\lim_{L'(w)\to\infty} \partial w/\partial p_r = 0$.
To see that Prediction 1, (iii) holds, we use the fact that resource sector profits equal $p_r \Omega_r F_r(l_r) - w l_r$. Assume that resource sector employment remains constant. Further, consider first the case of perfectly inelastic labour supply, i.e. $L'(w) = 0$. The non-tradable sector holds employment constant given that resource sector employment stays constant by assumption and labour supply is unchanged. To see this, first substitute equation (6) into equation (4) to obtain

$$\alpha(w + \pi)L(w) = p_n \Omega_n F_n(l_n) \tag{12}$$

Equation (8) states that $p_n = w/(\Omega_n F_n'(l_n))$ and $w = p_r \Omega_r F_r'(l_r)$. Substituting these expressions as well as equation (2) into equation (12) and rearranging yields

$$\frac{F_n(l_n)}{F_n'(l_n)} = \alpha L(w) + \sigma\alpha \left[\frac{F_r(l_r)}{F_r'(l_r)} - l_r\right] \tag{13}$$

This equation expresses non-tradable employment as a function of resource sector employment. Taking the first-order derivative with respect to p_r yields

$$\frac{\partial \frac{F_n(l_n)}{F_n'(l_n)}}{\partial p_r} = \alpha L'(w)\frac{\partial w}{\partial p_r} - \sigma\alpha \frac{\partial l_r}{\partial p_r}\frac{F_r(l_r)F_r''(l_r)}{\left[F_r'(l_r)\right]^2} \tag{14}$$

Given our assumptions $\partial l_r/\partial p_r = 0$ and $L'(w) = 0$, the right-hand side of equation (14) equals zero, which implies $\partial l_n/\partial p_r = 0$.[40] We have thus shown that if labour supply is perfectly inelastic and we assume that the

[40] Given that $F_n(l_n)$ is increasing in l_n but concave, a change in l_n increases $F_n(l_n)$ but decreases $F_n'(l_n)$, which implies that a change in l_n cannot leave $F_n(l_n)/F_n'(l_n)$ unchanged. Therefore, $\partial \frac{F_n(l_n)}{F_n'(l_n)}/\partial p_r = 0$ implies $\partial l_n/\partial p_r = 0$.

resource sector's employment remains constant as the price of the its good rises, non-tradable employment remains constant as well. At the same time, employment in the tradable goods sector falls, since $\partial w/\partial p_r > 0$. Therefore, the labour market does not clear: total labour demand is lower than total labour supply. This means that it is impossible that resource sector employment does not rise after a rise in p_r when $L'(w) = 0$. Now consider the case of $L'(w) > 0$. The rise in the wage after an increase in p_r is now smaller compared to when $L'(w) = 0$. This implies that it is profitable to increase employment for the resource sector as p_r rises. ■

Prediction 2

Proof. Given that $F_r(l_r)$ is increasing and concave in l_r, that $L'(w) \geq 0$, and the results that $\partial w/\partial p_r > 0$ and $\partial l_r/\partial p_r > 0$, the right-hand side of equation (14) is positive. This implies that non-tradables employment and thus output are increasing in the price of natural resources. To see this, first note that $\partial \frac{F_n(l_n)}{F_n'(l_n)}/\partial l_n = 1 - \frac{F_n(l_n)F_n''(l_n)}{[F_n'(l_n)]^2} > 0$. Now suppose that $\partial l_n/\partial p_r \leq 0$: this would imply that an increase in p_r would weakly decrease $F_n(l_n)/F_n'(l_n)$, since $\partial \frac{F_n(l_n)}{F_n'(l_n)}/\partial l_n > 0$. However, this is impossible, since we have shown that $\partial \frac{F_n(l_n)}{F_n'(l_n)}/\partial p_r > 0$. A natural resource boom thus increases non-tradeable production. Given $\partial l_n/\partial p_r > 0$, it must also be that the price of non-tradables increases with p_r, since $F_n(l_n)$ is concave and $w = p_n \Omega_n F_n'(l_n)$. ■

We claimed in section 3.2 that in the case of perfectly inelastic labour supply, the increase in non-tradables production is fully caused by the positive fraction of profits accruing to the local population ($\sigma > 0$ such that $\pi > 0$). As long as labour supply is not fully inelastic, the non-tradable sector also faces an increase in demand due to an increase in population. Both results are immediate from equation (14). For $L'(w) = 0$, the first of the two terms equals zero, thus if also $\sigma = 0$, then $\partial l_n/\partial p_r = 0$. For $L'(w) > 0$, the first of the two terms of equation (14) is positive, thus it holds that $\partial l_n/\partial p_r > 0$ if $\sigma = 0$.

In footnote 12, we claimed that the result that the non-tradable sector expands even when $\pi = 0$ as long as $L'(w) > 0$, because of our assumption that labour supply is a function of the *nominal* wage. If it were a function of the real wage w/p_n, then if π were equal to zero, workers would be indifferent between booming and non-booming districts. Therefore, in this case we would need the assumption that they move rather than stay in order to maintain the result that population and non-tradables production increase as p_r rises. To see this more formally, consider the case of $L'(w) = 0$ and $\sigma = 0$ (which implies $\pi = 0$). Equation (14) tells us that the non-tradable sector does not expand after a rise in p_r. This shows that the purchasing power and thus demand for non-tradables of the consumers in the booming district is unchanged. Since the wage increase is highest if $L'(w) = 0$, this implies that also for all other realizations of $L'(w)$, the purchasing power of consumers and thus non-tradable output in the booming district does not increase with a rise in p_r if $\pi = 0$.

Prediction 3

Proof. This is immediate from the profit maximization condition of the tradable goods sector, $w = p_m \Omega_m F'_{mk}(l_m)$: Since p_m is exogenous and $\partial w/\partial p_r > 0$, concavity of $F_{mk}(l_m)$ requires a reduction in employment to satisfy the condition again after the rise in p_r. If labour supply is perfectly elastic, the decrease in tradables production is virtually zero since the increase in the wage is virtually zero. ■

Prediction 4

Proof. We start by showing that the increase in the wage is stronger the more labour-intensive the local resource sector is, i.e. $\partial \left(\frac{\partial w}{\partial p_r}\right)/\partial \gamma_r < 0$. We first show that $\partial w/\partial \gamma_r < 0$. To see this, assume that $\partial w/\partial \gamma_r = 0$. We know that in equilibrium, the marginal product of labour in the resource sector equals its marginal cost: $w = p_r \Omega_r F'_r(l_r) = p_r \Omega_r \frac{1-\gamma_r}{l_r^{\gamma_r}}$. Taking the first order derivative of this expression with respect to γ_r yields

$$\frac{\partial \left[p_r \Omega_r \frac{1-\gamma_r}{l_r^{\gamma_r}}\right]}{\partial \gamma_r} = p_r \Omega_r \left[-\frac{1}{l_r^{\gamma_r}} + (\gamma_r^2 - \gamma_r)\frac{1}{l_r^{(\gamma_r+1)}}\frac{\partial l_r}{\partial \gamma_r}\right] \tag{15}$$

Evaluated at the current level of employment, this equals $-p_r \Omega_r / l_r^{\gamma_r} < 0$, which implies that the marginal product of the current workforce decreases. Since we just assumed wages to remain constant, the resource sector's marginal cost of labour now exceeds its marginal benefit. This situation is not profit-maximizing, thus the resource sector reduces employment.[41] The tradable goods sector keeps employment constant under constant wages. Finally, the non-tradable sector reduces employment as labour intensity of the resource sector decreases. To see this, first note that resource sector profits decrease as γ_r increases and the wage stays constant.[42] Further, since the wage stays constant by assumption, also labour supply stays constant. Given that π is a positive function of resource sector profits, the left-hand side of equation (4), which is a result of consumers' utility maximization, is therefore now smaller than the right-hand side. Thus, for equation (4) to hold again after the rise in γ_r, it must be that either p_n or C_n decrease, or both. As long as only p_n decreases and C_n stays constant or rises, the non-tradables sector does not maximize profits any more, as can be seen from equations (8) and (9). Thus, consumption of non-tradables must fall, which implies that production and thus employment of non-tradables must fall, given equation (6). We know that in equilibrium, the labour market clears: $l_n + l_m + l_r = L(w)$. Since resource sector and non-tradables employment decrease and tradables employment is constant, it cannot be that both the labour market clears and (4) holds. Thus, it is impossible that $\partial w/\partial \gamma_r = 0$. To the contrary, as γ_r increases, the wage must decrease to increase labour demand and decrease labour supply (if $L'(w) > 0$), to restore equilibrium. We thus conclude

41 Rewrite equation (9) to $l_r = \left[\frac{p_r \Omega_r (1-\gamma_r)}{w}\right]^{1/\gamma_r}$ and take the derivative with respect to γ_r, which yields, given our assumption of $\partial w/\partial \gamma_r = 0$, $\frac{1}{(\gamma_r - 1)\gamma_r^2}\left[\frac{p_r \Omega_r (1-\gamma_r)}{w}\right]^{1/\gamma_r}\left\{\gamma_r - (\gamma_r - 1)\, ln \left[\frac{p_r \Omega_r (1-\gamma_r)}{w}\right]\right\} < 0$, given that $l_r > 1$.

42 We have just shown that if γ_r increases and the wage stays constant, the resource sector reduces employment. Now, if the profits under lower employment are not lower than before the increase in γ_r, then it is impossible that the resource sector was maximizing profits prior to the increase in γ_r. Thus, profits fall as γ_r increases and the wage stays constant.

that $\partial w/\partial\gamma_r < 0$.

Now take two realizations of γ_r: $\gamma_{r,low}$ and $\gamma_{r,high}$. Since $\partial w/\partial\gamma_r < 0$, it holds that $w|_{\gamma_r=\gamma_{r,low}} > w|_{\gamma_r=\gamma_{r,high}}$. Suppose that $\partial\left(\frac{\partial w}{\partial p_r}\right)/\partial\gamma_r > 0$ and assume that p_r rises to infinity. As long as the wage does not converge to a finite number, this implies that in the new equilibrium, $w|_{\gamma_r=\gamma_{r,low}} < w|_{\gamma_r=\gamma_{r,high}}$. This is impossible, since $\partial w/\partial\gamma_r < 0$. Now, we know that the wage does not converge to a finite number as p_r rises to infinity, since in that case, equation (8) would not hold. Therefore, it must be that $\partial\left(\frac{\partial w}{\partial p_r}\right)/\partial\gamma_r \leq 0$.
Equation (9) makes clear that the wage formation is influenced by the profit maximization problem of the resource sector in the wake of an increase in the price of its good. The fact that the maximization problem depends on γ_r implies that also the wage formation depends on γ_r, thus $\partial\left(\frac{\partial w}{\partial p_r}\right)/\partial\gamma_r \neq 0$. This completes the proof that $\partial\left(\frac{\partial w}{\partial p_r}\right)/\partial\gamma_r < 0$. To gain some intuition on this result, recall that in equilibrium, $w = p_r\Omega_r\left[\frac{1-\gamma_r}{l_r^{\gamma_r}}\right]$, and thus

$$\frac{\partial w}{\partial p_r} = \frac{\Omega_r(1-\gamma_r)}{l_r^{\gamma_r}}\left[1 - \frac{p_r\gamma_r}{l_r}\frac{\partial l_r}{\partial p_r}\right] \tag{16}$$

Now consider the two extreme cases $\gamma_r = 0$ and $\gamma_r = 1$ (which we excluded, but is possible in theory). In the former case, $\partial w/\partial p_r = \Omega_r > 0$: labour is most productive, and thus as the price of the resource sector good increases, the sector is willing to raise wages the most in order to attract additional workers. In the latter case of $\gamma_r = 1$, $\partial w/\partial p_r = 0$: since the use of labour does not increase output, the resource sector obviously does not raise wages to attract workers as the price of its good increases. In between these two extreme cases, the larger is γ_r, the smaller the wage increase the resource sector optimally offers in order to attract additional workers.

Prediction 4, (ii) follows immediately from $\partial\left(\frac{\partial w}{\partial p_r}\right)/\partial\gamma_r < 0$. As long as labour supply is not perfectly inelastic, i.e. as long as $L'(w) > 0$, a larger wage increase following a rise in p_r when γ_r is lower implies a larger increase in population.

To prove Prediction 4, (iii), we first write out non-tradable employment explicitly by substituting the production functions and its first derivatives with respect to labour, respectively, into equation (13):

$$l_n = \alpha(1-\gamma_n)\left[L(w) + \sigma\left(\frac{l_r}{1-\gamma_r} - l_r\right)\right] \tag{17}$$

We then derive $\partial l_n/\partial p_r$:

$$\frac{\partial l_n}{\partial p_r} = \alpha(1-\gamma_n)\left[L'(w)\frac{\partial w}{\partial p_r} + \sigma\frac{\partial l_r}{\partial p_r}\left(\frac{1}{1-\gamma_r} - 1\right)\right] \tag{18}$$

Taking the derivative of this expression with respect to γ_r yields

$$\frac{\partial\left(\frac{\partial l_n}{\partial p_r}\right)}{\partial \gamma_r} = \alpha(1-\gamma_n)\left\{L'(w)\frac{\partial\left(\frac{\partial w}{\partial p_r}\right)}{\partial \gamma_r} + \sigma\left[\frac{\partial\left(\frac{\partial l_r}{\partial p_r}\right)}{\partial \gamma_r}\left(\frac{1}{1-\gamma_r}-1\right) + \frac{\partial l_r}{\partial p_r}\frac{1}{(1-\gamma_r)^2}\right]\right\} \tag{19}$$

We now evaluate the sign of $\partial\left(\frac{\partial l_n}{\partial p_r}\right)/\partial\gamma_r$ under all possible realizations of $L'(w)$. Let us define

$$-\frac{\sigma\left[\frac{\partial\left(\frac{\partial l_r}{\partial p_r}\right)}{\partial \gamma_r}\left(\frac{1}{1-\gamma_r}-1\right) + \frac{\partial l_r}{\partial p_r}\frac{1}{(1-\gamma_r)^2}\right]}{\left[\frac{\partial\left(\frac{\partial w}{\partial p_r}\right)}{\partial \gamma_r}\right]} \equiv B \tag{20}$$

Now the following relationships hold:

$$L'(w) > B \;\rightarrow\; \frac{\partial\left(\frac{\partial l_n}{\partial p_r}\right)}{\partial \gamma_r} < 0 \quad ; \quad L'(w) = B \;\rightarrow\; \frac{\partial\left(\frac{\partial l_n}{\partial p_r}\right)}{\partial \gamma_r} = 0 \quad ; \quad L'(w) < B \;\rightarrow\; \frac{\partial\left(\frac{\partial l_n}{\partial p_r}\right)}{\partial \gamma_r} > 0$$

To get some intuition on these results, consider the two extreme cases of labour supply elasticity. In the case of $L'(w) = \infty$, it is clear from expression (19) that $\partial\left(\frac{\partial l_n}{\partial p_r}\right)/\partial\gamma_r < 0$, since $\partial\left(\frac{\partial w}{\partial p_r}\right)/\partial\gamma_r < 0$. Intuitively, conditional on a given labour intensity of its production process, the resource sector increases employment most after a given rise in the price of its good when $L'(w) = \infty$. It is then cheapest to attract additional workers and raise employment. All newly-hired employees immigrate from other districts, thus the non-tradable sector faces no competition for labour from the resource sector as the latter expands. At the same time, each immigrant into the booming district increases aggregate demand for the non-tradable sector. Thus, the larger the increase of the resource sector's labour demand, the larger the expansion of the non-tradable sector. Now, since an increase in the resource sector's labour intensity increases its rise in demand for labour as the price of its good increases (see Prediction 4, (iv)), it is intuitive that for $L'(w) = \infty$, $\partial\left(\frac{\partial l_n}{\partial p_r}\right)/\partial\gamma_r < 0$.

Now consider the other extreme case of labour supply elasticity, $L'(w) = 0$, and assume that $\gamma_r = 0$. In this scenario, labour is most productive in the production of the resource sector good and immobile across districts. For these reasons, the non-tradable sector faces sharp competition for additional labour from the resource sector. Thus, there is little scope for the non-tradable sector to raise employment as p_r increases. Now suppose that γ_r is larger, and equal to $1-\epsilon$, where ϵ is a positive but infinitesimally small number. In this case, the resource sector employs virtually no labour, and thus its partial-equilibrium wage response to an increase in p_r is virtually zero. At the same time, resource sector profits increase – as always when p_r rises –, and consumers participate in this rise in profits, which increases their purchasing power. Since the wage the resource sector offers is virtually unchanged, this implies that there is considerable scope for the non-tradable sector to raise wages and production, until a new equilibrium is reached. This illustrates that in our example of $L'(w) = 0$ and $\gamma_r = 0$, $\partial\left(\frac{\partial l_n}{\partial p_r}\right)/\partial\gamma_r > 0$, as can be seen from equation (19).

To see that Prediction 4, (iv) holds, assume that $L'(w) = 0$ and that the rise of resource sector employment after a rise in p_r does not depend on its labour intensity, i.e. $\partial\left(\frac{\partial l_r}{\partial p_r}\right)/\partial\gamma_r = 0$. We have shown that the wage increase after a rise in p_r increases with the labour intensity of the resource sector, i.e. decreases with γ_r: $\partial\left(\frac{\partial w}{\partial p_r}\right)/\partial\gamma_r < 0$. This implies that the lower is γ_r, the more workers the tradable goods sector lays off after an increase in p_r. Further, since $L'(w) = 0$, labour supply stays constant. Given our assumption that the resource sector's rise in employment after a rise in p_r is independent of γ_r, this implies that the elasticity of non-tradable sector employment with respect to a given rise in resource sector employment must rise with the latter's labour intensity (i.e. $\partial\left(\frac{\partial l_n}{\partial l_r}\right)/\partial\gamma_r < 0$). However, equation (19) shows that given our assumptions $L'(w) = 0$ and $\partial\left(\frac{\partial l_r}{\partial p_r}\right)/\partial\gamma_r = 0$, the opposite holds: $\partial\left(\frac{\partial l_n}{\partial p_r}\right)/\partial\gamma_r > 0$. This implies that labour demand is lower than labour supply after a rise in p_r in the assumed case of $L'(w) = 0$, $\gamma_r = 0$ and $\partial\left(\frac{\partial l_r}{\partial p_r}\right)/\partial\gamma_r = 0$, which implies that the latter is impossible. In order for labour demand to equal labour supply and thus restore equilibrium, it must be that $\partial\left(\frac{\partial l_r}{\partial p_r}\right)/\partial\gamma_r < 0$. We have thus shown that if labour supply is completely inelastic, the resource sector increases employment more upon an increase of the price of its good when its production function is more labour-intensive. Now, since it is most expensive to raise employment when $L'(w) = 0$, this implies that $\partial\left(\frac{\partial l_r}{\partial p_r}\right)/\partial\gamma_r < 0$ holds for any realization of $L'(w)$.

Prediction 4, (v) follows directly from Prediction 4, (i) and the profit maximization condition of the tradable goods sector, $w = p_m\Omega_m F'_m(l_m)$. The larger the labour intensity of the resource sector, the larger the increase in wages after a rise in p_r, and thus the larger the decrease in tradable goods sector employment must be in order to restore equilibrium. ■

Proof that $L_k = L_k(w_k)$ and $L_k = L_k(w_k, \pi_k)$ yield the same predictions

The advantage of defining labour supply only as a function of the wage is to make the model more tractable and to ensure that $\partial w/\partial p_r > 0$ for all realizations of $L'(w)$ (see Prediction 1). To see that the direction of all predictions are unchanged, suppose that $L_k = L(w_k + \pi_k)$, and $L'(\cdot) > 0$. This implies that an increase in p_r leads to a weakly smaller increase in the wage compared to the case of $L_k = L(w_k)$. To see this, consider first the case $L'(\cdot) > 0$: In this scenario, the increase in resource sector profits alone after the rise in p_r already stimulates an increase in labour supply, and thus a smaller (for sufficiently low $L'(w_k)$) or no (for sufficiently large $L'(w_k)$) increase in the wage is necessary to increase resource sector employment to the new profit-maximizing level after the rise in p_r. Second, consider $L'(\cdot) = 0$: In this scenario, the change in the wage due to an increase in p_r is equal to the case of $L_k = L(w_k)$, since all additional labour must come from other sectors. The weakly smaller rise in the wage as p_r rises in turn implies that the strength of the effects of Predictions 1, (ii) and (iii) as well as the effects of Predictions 2-4 change, but the direction of every effect is unchanged.

OA2 Mining Data

Combining *RMD* and *MinEx* data

The data sources we use to compute district-specific mineral resources as of 1990 are *Raw Materials Data* (*RMD* in the following) and *MinEx Consulting* (*MinEx* in the following). Both datasets claim full coverage, and indeed, the majority of deposits listed in one dataset are also reported in the other. We also double-checked the reported deposits with public data from the USGS *Mineral Resources Data System* (MRDS) (which lists less deposits than *RMD* and *MinEx*). We match deposits across the data sources using the name of the deposits. For all remaining deposits, we carefully check if a deposit in a given dataset corresponds to a deposit in the other dataset, using additional variables such as deposit location and ore resources. If a deposit remains unmatched after this procedure, we nonetheless included it into our sample. In total, we identify 82 mineral deposits which had positive mineral resources in 1990. 49 of these deposits are listed in both datasets, while the remaining 33 are only listed in one source. These 33 deposits have statistically significantly lower mineral resources as of 1990 compared to those listed in both datasets. 24 of the 33 deposits are unique to *MinEx* and nine are unique to *RMD*. For matched deposits for which information is available in both datasets for a specific variable, we use the *MinEx* data (see below for variable-specific details). We are more confident about the accuracy of the *MinEx* data because a test in Google Earth reveals that the *MinEx* location data is more precise compared to *RMD*.

Location of resources

Both *RMD* and *MinEx* report the location of a deposit in terms of latitude and longitude. For the set of deposits that were operated by a mine over our sample period and for which different latitude and longitude data is reported by *MinEx* and *RMD*, we entered the location data into Google Earth and regard the location displaying a mine as the correct one. Since the *MinEx* data proves more accurate among these deposits, we also choose to use the *MinEx* data when in neither of the locations we saw a mine (which can be due to a mine no longer being operated). For three deposits, our data sources do not provide data on the location; we retrieved these via Internet search (sources available on request). With the chosen latitude and longitude data at hand, we first identify the home district of the deposit as of 2016, using Google Maps. In a second step, we assign the district to its 1990-district, if the two differ, using district proliferation tables provided by Indonesia's national statistical agency, *Badan Pusat Statistik* (BPS), and information provided by Bazzi and Gudgeon (2018).

Time of discovery of resources

Only *MinEx* reports the year of discovery. It is missing for around one third of deposits. Since we are only interested whether discovery took place before 1990, for several of these deposits we can answer this question due to the fact that production started before 1990. For all remaining deposits, we attempted to find out if discovery was prior to 1990 via Internet search. We achieved this for 42 deposits, mostly using company yearbooks or mining information websites.[43] Further, we infer that the discovery, if at all, took place after 1990 if in 2016 (the year in which we obtained the then up-to-date *MinEx* data), the deposit's status is either "Advanced Exploration", "Emerging Project" or different subgroups containing the term "Feasibility Study". For all deposits that are only listed in the *RMD* dataset, we also use the pre-1990 production start-up rule, Internet search (23 deposits) and the deposit's status to infer the discovery date, in this order. Concerning deposit status, we infer that the discovery, if at all, took place *after* the most recent year for which the deposit's status is either "Project, no specification", "Conceptual", "Feasibility", "Prefeasibility", "Abandoned Project" or "Abandoned". For the remaining deposits from both datasets with missing discovery date, we infer it as the year of production start-up minus the median difference between discovery year and production start-up year across all mines for which we have information on both, which is 8 years.[44]

Multi-mineral deposits

For a given deposit, *RMD* reports annual production figures per extracted mineral. This implies that we know about the existence of a specific mineral in a given deposit only if the mineral was extracted in any year over the period the *RMD* data covers, which is 1975-2011. 11 deposits in our final sample (thus with positive 1990 ore resources) that are listed in *RMD* produced more than one mineral at any point in time between 1975 and 2011. These 11 deposits are spread across 11 districts. Unfortunately, we do not know the share of each mineral in total ore resources for the 11 deposits. We thus infer the share of mineral m in total resources using the average ratio of ore production of mineral m over total ore production of the respective deposit, using all years in which the deposit was operated and production data is available. Since production is reported in terms of metal, not ore, we convert metal to ore using the reported mineral-specific grades of each deposit. If the latter is not reported, we infer it by computing the average grade of the respective mineral using the available information among all deposits containing that mineral. In the 11 districts that hosted at least one multi-mineral deposit, we incorporate the inferred shares of respective minerals in multi-mineral deposits into our computation of the "general mineral price level" of the district.

MinEx only lists the main mineral of a given deposit. Therefore, inferring mineral-specific resources for a given deposit is not possible for those that were potentially hosting multiple minerals but were only listed in *MinEx*. For all these deposits, we are forced to assume that the main mineral is in fact the only contained mineral. Given the low percentage of multi-mineral deposits in *RMD* and the fact that deposits only listed in *MinEx* have low ore resources, we do not expect this to affect our results.

[43] For some deposits, we proxy discovery with the year of establishment of the company (or branch) which operated the deposit, if the name of the company or branch contains the name of the deposit. Since for all these deposits that year was after 1990 this turned out to be equivalent to dropping the deposits from our sample.

[44] We drop one single (small) deposit from our sample for which neither the discovery year nor production start-up year is reported.

Inferring missing ore resources data

Ore resource data is missing for a number of deposits in our dataset. Whenever this is the case but ore *reserves* data is non-missing, we infer ore resources as ore reserves times the mineral-specific average ratio of resources and reserves in our dataset.[45] In case there is no other deposit of the same mineral with non-missing resources and reserves data, we infer resources as reserves times the average ratio of resources and reserves across all deposits and minerals. If both reserves and resource data are missing, we retrieve resources or reserves data using Internet research. There are no deposits that were discovered before 1990 for which we were unable to retrieve resources or reserves data.

Ore reserves and resource data is missing for all tin deposits in both *RMD* and *MinEx*. Therefore, we retrieve the missing data via Internet search. Since we could not obtain deposit-specific resources data, we use resources data of public operator *PT Timah*, which has a monopoly on tin mining in Indonesia. Total tin resources of *PT Timah*, and thus Indonesia, amounted to 1.06 Million tons of tin as of 2008, according to the annual report of PT Timah of that year. We were unable to retrieve ore reserves data for an earlier year. In order to infer tin resources as of 1990, we add total tin production over 1990-2008 to the 2008 figure, using annual production data from *Indonesia's Department of Mines and Energy*, which is made available by the *U.S. Bureau of Mines*. Since *RMD* and *MinEx* do not contain any grade information for Indonesian tin deposits, we convert the resulting number to tons of *ore* rather than tons of tin using the average ratio provided by different sources. Specifically, according to *earthsci.org*, "Indonesia produces tin mainly from alluvial deposits" (*http://earthsci.org/mineral/mindep/depfile/tin.htm*), and the ratio of ore and tin from alluvial deposits ranges between 0.01 and 0.015 per cent across different sources; we thus infer a ratio of 0.0125 for our analysis. Since *PT Timah* annual reports do not indicate the distribution of resources across Indonesia's tin deposits, we infer the shares using mine-specific annual production data from *Indonesia's Department of Mines and Energy*. While data on annual aggregate tin production in Indonesia is available from 1949-2008, mine-specific production data is only available for the period 1978-1988 (see Wu, 1982-1989), thus we compute the production shares using the data from this period. Since we cannot attribute tin deposits in these data in the districts Bangka and Belitung to either of the two districts, we treat these two 1990-districts as one district in our analysis. Approximately 91% of Indonesian tin production took place in mines located in the Bangka-Belitung archipelago on average over 1978-1988. We thus infer the tin reserves of Bangka-Belitung as this percentage times our measure of total tin reserves as of 1990. The remaining 9% of tin production over 1978-1988 took place in mines in the Riau archipelago; we thus inferred 1990 tin resources of the 1990-district Riau using the same method.

[45] These ratios are obtained from *RMD*, since *MinEx* only reports ore resources. Resources are "the concentration or occurrence of material of intrinsic economic interest in or on the Earth's crust in such form and quantity that there are reasonable prospects for eventual economic extraction" (Raw Materials Data Handbook, p.57). Reserves are defined as "the economically mineable part of a measured or indicated mineral resource" (p.58).

Computation of district-specific 1990 ore resources

We first compute mineral ore resources as of 1990 for each deposit. We then sum 1990 resources across all deposits in a district and divide the result by the district size in square miles.

If a deposit was discovered before 1990 but did not start production before that year, the deposit's 1990 resources simply equal its initial resources. If a deposit was operated by a mine before 1990, we deduct the mine's pre-1990 ore production from the initial resources to arrive at the deposit-specific ore resources as of 1990. For all deposits contained in *RMD*, this is done using annual production data. For all deposits unique to *MinEx*, annual production data is not reported, thus we infer total production before 1990 as average annual production times the number of production years before 1990.[46] In the *RMD* data, in some cases, pre-1990 production of a mine is only reported in terms of metal, rather than ore. In this case, we compute the average ratio of ore and metal production of the specific mine and metal for each year in which both are available, and use this ratio to infer ore production in a given pre-1990 year in which it is missing. If ore production is not available for any year, then we instead use the mine- and metal-specific *grade* to infer ore production from metal production. If the grade is not reported by our data sources, we tried to retrieve it via Internet search. If this search was unsuccessful, we infer ore production using the average grade of the same metal (i) in the same district, (ii) in the same province or (iii) in Indonesia overall – in this order, based on the distribution of metals across space and data availability. For five mines which started production before 1990 and which are reported in *RMD*, pre-1990 production data is entirely unavailable. In these cases, we infer pre-1990 production as the average yearly (post-1990) production across years in which production data is reported in *RMD*, multiplied by the number of pre-1990 production years. In one case, we do not have any information on production; in this case, we infer 1990 ore resources as initial resources.

OA3 Oil and Gas data

The *Indonesia, Oil and Gas Atlas* is divided into six volumes, each of which covers a certain geographical area. Specifically, these are North Sumatra and Natuna (Volume 1, 1989), Central Sumatra (Volume 2, 1991), South Sumatra (Volume 3, 1990), Java (Volume 4, 1989), Kalimantan (Volume 5, 1991) and Eastern Indonesia (Volume 6, 1988). We assign a field producing oil and/or gas to its respective 1990 district by first identifying the 2017-district in which the field is located, using data on the field's latitude and longitude provided in the data source. We then identify the corresponding 1990 district using district proliferation tables (see Online Appendix OA2). If a field is located offshore, we assign it to the closest district in terms of geographical distance.

[46] *MinEx* reports both "initial resources", the year of production commencement and "current resources". The moment in time in which the latter is reported varies by mine. We compute annual average production as the difference between initial resources and current resources, divided by the number of years between production commencement and the year in which current resources are reported.

OA4 Population data

Our data source for district-level population over time is the *Minnesota Population Center* (MPC). The MPC collects and makes available population data that is produced every five years by the BPS. While yearly population data would be preferred and is also reported by Statistics Indonesia through the World Bank's *Indonesia Database for Policy and Economic Research* (INDO DAPOER), these data appear unreliable since they are derived using predicted trends in fertility, mortality and migration between provinces (using the 1995 inter-census population data as reference point), and are not corrected ex-post using census or inter-census data. The MPC data misses population figures for Aceh in 2005 since no inter-census population survey was held in this province due to the Indian Ocean tsunami of December 2004. Further, in 1995 data is missing for 12 provinces, which are: South Kalimantan (includes 3 districts with positive 1990 mineral resources), West Kalimantan (3), East Kalimantan (3), Central Kalimantan (3), South Sulawesi (1), Central Sulawesi (2), Southeast Sulawesi (1), North Sulawesi (3), Irian Jaya (now called Papua) (2), and Maluku (2).

OA5 Price data

As highlighted in the main text, we work with prices that constitute global benchmarks rather than the prices of specific Indonesian blends. While differences in quality across Indonesian blends and the blends we work with may mean that their prices are not equivalent, we claim that the (percentage) *change* in the price of the specific blend we work with is a decent proxy for the (percentage) change in revenues accrued by the producer of the respective mineral in Indonesia, in a given year. Whenever applicable, the prices we use are those of the respective metal rather than the ore/rock, since the latter heavily depends on the ore's actual metal content and is thus not comparable across ores of different grades. For all prices, we compute and use annual averages.

For copper, nickel, tin, aluminium and cobalt, we use the prices determined on the London Metal Exchange (LME).[47] For gold and silver, we use the prices determined on the London Bullion Market, which is a wholesale over-the-counter market for the trading of gold and silver.[48] Due to availability and data quality, the prices we use for manganese, diamonds, chromium, zirconium and uranium are those paid domestically in the United States.[49] For iron ore and coal, it is harder to identify an observed price that comes close to a single world price. For iron ore, we use the price China pays per metric ton on average in a given year, since China is a geographically close and important importer of iron ore.[50] For coal, we choose to work with the price of Australian coal instead of other coal types, due to data quality and the fact that price changes are likely most aligned with Indonesian coal, given that China is a key client of both Australian and Indonesian

[47] Source: *United States Geological Survey* (USGS).
[48] Source: London Bullion Market Authority (LBMA).
[49] Uranium prices are from the IMF, all other prices from the USGS.
[50] Source: IMF: http://www.imf.org/external/np/res/commod/index.aspx

coal.[51] For crude oil, we use the price of West Texas Intermediate (WTI), which is a benchmark for the prices of other crude oil sorts.[52] We do not account for natural gas prices separately, both in order to follow the tradition of the literature and because natural gas prices are in any case highly correlated with crude oil prices.

OA6 Manufacturing Census Data

Cleaning

We drop plant-years in which production worker employment is larger than total employment, as well as plant-years in which the reported number of employees is below 20.[53] Further, we drop six plants that have a district ID that does not correspond to any district ID we observe in our BPS list of district IDs. Around 6% of plants are reported to operate in different (mostly two) 1990-districts in different years. This could be caused by changes in district borders that are not explained by district splits or, more likely, by plants moving from one 1990-district to another during our sample period. Importantly, the plant fixed effects that we control for by first-differencing our outcome variables at the plant level only nest district-specific fixed effects if plants in our sample do not change 1990-district. We therefore keep the plant's district-years of the 1990-district it stayed in for the longest time period over 1990-2009, and drop the plant's other district-year observations.

Defining local versus traded goods producers

For each of the 473 six-digit industries of the 1997 *North American Industry Classification System* (NAICS 1997), Holmes and Stevens (2014) estimate a (constant) distance elasticity, which equals the percentage change in trade volume as distance increases by one percent. They do so using the 1997 *U.S. Commodity Flow Survey* (CFS) data, which documents the destination, product classification, weight and value of a broad sample of shipments that leave manufacturing plants. Holmes and Stevens (2014) estimate an industry's constant distance elasticity via a standard log-log specification typically used in the trade literature. This specification has distance adjustment, which increases with industry-specific trade costs, on the left-hand side and distance on the right-hand side. Intuitively, the higher the trade costs of a specific industry, the shorter its optimal average shipment distance (equivalently, the higher its distance adjustment). Ready-Mix Concrete (4.2), Ice (3.0) and Asphalt (2.9) have the highest estimated distance elasticity. In turn, 29 industries have an estimated distance elasticity of zero, including Semiconductors, Analytical laboratory instruments and Aircraft, in which transportation costs are very low relative to product value.

We use the estimates of Holmes and Stevens to classify plants into local and traded goods producers. Our

[51] Source: IMF: http://www.imf.org/external/np/res/commod/index.aspx

[52] Source: *Energy Information Administration* (EIA)

[53] The fact that only few plants had less than 20 employees made clear to us that indeed, if a plant that had been registered the year before went below the threshold of 20 employees, it was not registered in the following year. We conclude that realizations of employees below 20 must be typos.

plant-level data contains information on the 4-digit sector of each plant. The industry classification system is the 2000 version of the *Klasifikasi Baku Lapangan Usaha* (KBLI 2000). This roughly corresponds to Revision 3.1. of the *International Standard Industry Classification* (ISIC Rev. 3.1), however not one-to-one. Therefore, we first use KBLI 2000 and ISIC Rev.3.1 documentation files to determine the equivalent, or closest in nature, ISIC Rev.3.1 code of all KBLI 2000 codes. Next, we walk from ISIC Rev. 3.1 to NAICS 1997 using concordance tables provided by the *United States Census Bureau*. Since our sample contains 123 (ISIC Rev. 3.1) industries, in the great majority of cases, one four-digit ISIC Rev.3.1 industry code matches with more than one NAICS 1997 code. In all these cases, we compute the ISIC-realization of the distance elasticity as the average realization across all the NAICS industries matching with the particular ISIC code.

Defining upstream plants

The 2007 input-output tables of the *Bureau of Economic Analysis* (BEA) distinguish three mining industries that, taken together, we refer to as the "the mining sector" : 1. "Coal mining"; 2. "Iron, gold, silver and other metal ore mining"; and 3. "Copper, nickel, lead and zinc mining". Details on the concordance of the ISIC Rev.3.1 codes used in the manufacturing census and the BEA codes used in the input-output tables are described further below. For each of the 389 industries j that are distinguished in the 2007 Input-Output tables of the BEA, we compute its 'upstreamness' to the mining sector as the ratio of the (weighted) sum of its direct and indirect sales to the mining sector (as defined above) and its total sales:

$$Upstream_{jk} = \frac{\sum_m Sales_{j,m} \times (R_{km}/R_k)}{\sum_j Sales_j} + \sum_{-J} \left[\frac{Sales_{j,-j}}{\sum_j Sales_j} * \frac{\sum_m Sales_{-j,m} \times (R_{km}/R_k)}{\sum_j Sales_{-j,j}} \right] \in [0,1] \quad (21)$$

where $-J$ denotes the set of all industries apart from j, k is the district identifier as usual and m={*Coal mining; Iron, gold, silver and other metal ore mining; Copper, nickel, lead and zinc mining*}. R_{km} equals the total 1990 resources of the minerals contained in group m in district k and R_k the total 1990 mineral resources in district k. The chosen upstream measure thus takes into account which minerals are locally produced, which makes it industry- and district-specific rather than only industry-specific. Therefore, if for example industry j is only upstream to the coal mining sector and there are no coal deposits but only gold deposits as of 1990 in district k, then we don't classify plants in industry j in district k as upstream, such that $Upstream_{jk} = 0$. The reasoning behind this choice is that in our empirical analysis, we try to test whether any effect of a local mining boom is driven by plants that are upstream to the *local* mining sector. Using our previous example, we do not expect plants that sell to the coal sector to benefit or suffer more from a gold boom in their home district than plants in the same district that do not sell to any of the three mining sectors, since neither group of plants sells to the sector *Iron, gold, silver and other metal ore mining*. On the other hand, if coal deposits were present in district k, then the plants selling to the coal sector might perform differently, and the more important the coal mining sector is in district k, the more so.

The industries in the BEA input-output tables are classified using BEA codes. We first walk from the BEA codes to the 2002 NAICS codes, and then match those with the ISIC Rev.3.1 codes, using concordance tables provided by the *United States Census Bureau*. The census data reports 133 distinct four-digit ISIC Rev. 3.1 manufacturing industries, while the BEA tables feature 389 industries. As a consequence, in the great majority of cases, one four-digit ISIC industry code matches with more than one BEA code. In all these cases, we compute the realization of $Upstream_{jk}$ as the average realization across all the BEA industries matching with the particular ISIC code. We argue that the inferred value provides a reasonable approximation, since the realizations of $Upstream_{jk}$ are very similar across BEA codes that match with the same ISIC code.

OA7 SAKERNAS Data

While the household survey SAKERNAS was initiated in 1976, only from 2007 onwards, the survey data has been representative at the district level. In any given year after 2006, only the August round is representative at the district level, which is why we use data from those rounds. SAKERNAS has covered all 1990-districts in the August rounds in 2007-2015 except the years 2013 (five districts missing) and 2015 (one district missing) and includes data on between 490,468 (in 2014) and 953,172 (in 2010) individuals.[54] This implies a coverage of between 0.2 and 0.4 percent.

We use SAKERNAS to approximate the number of workers employed in the mining or oil and gas sector (see Table 3) and the number of workers employed in the mining sector (see Table OA1) in a given district and year, from 2007-2015. To compute the prior, we first compute the weighted *share* of surveyed individuals who reported to work in the mining or oil and gas sector, in a given district-year. The numerator of this share is the weighted number of respondents in the district-year who state that their main activity in the past week was working *and* who report to work in one of the following sectors: *Coal Mining and Peat Excavation*, *Uranium and Thorium Mining*, *Metal Mining*, *Oil and Gas*. The denominator is the weighted number of respondents in the district-year. We use the sample weight attached to each individual respondent in the data. We multiply the computed share by the district population according to the most recent available population census or inter-census population survey, from the specific year's perspective, and take the log of the result.[55] To approximate the number of mining workers, we repeat the above exercise, but exclude oil and gas workers from the numerator of the share.

As a descriptive statistic, in Table 2 we also report the average district-year specific *fraction* of mining and oil and gas workers to total workers and the fraction of mining workers to total workers, over 2007-2015. For a given district and year, the numerators of these shares are equivalent to the numerators just described

[54] In a given district, certain census blocks are selected, in which 16 households are sampled (10 from 2011 onwards). All individuals sampled in a certain census block obtain the same weight, which depends on the relative importance of the census block in terms of overall district representation.

[55] We multiply the share of mining workers in 2015 with the population data from 2010, since the results of the 2015 inter-census population survey have not been published by the MPC yet.

above. The denominator of both shares is the weighted number of surveyed individuals who state that their main activity in the past week was working.

Table OA1: Mining workers

Dependent variable →	log(# Mining Workers)			
	(1)	(2)	(3)	(4)
Total Mineral Resources 1990	0.39***	0.29**	0.38***	0.17
	(0.124)	(0.133)	(0.132)	(0.111)
Underground Mining		1.15**		
		(0.473)		
100% Underground Mining			2.35***	1.96***
			(0.283)	(0.262)
Underground & Open-Pit Mining			0.24	1.23**
			(0.548)	(0.585)
Year FE	Yes	Yes	Yes	Yes
Province FE	No	No	No	Yes
N	1,207	1,207	1,207	1,207
adj. R^2	0.108	0.133	0.155	0.402

In this table we analyse whether underground mining is more labour-intensive than other types of mining. The sample period is 2007-2015, the unit of observation is a district-year. The dependent variable is the log of an approximation of the number of mining workers in a given district in a given year. We describe how we compute this variable in Online Appendix OA7. *Total Mineral Resources 1990* equals mineral ore resources as of 1990 scaled by its mean across all districts with positive mineral resources in 1990. *Underground Mining* is a dummy that equals one if at least one of the 1990 deposits in the district was operated or planned to be operated by underground mining. *100% Underground Mining* is a dummy that equals one if *all* 1990 deposits were operated or planned to be operated by underground mining. *Underground & open-pit Mining* is a dummy that equals one if both underground and Open-Pit mining was applied or planned to be applied in order to extract the district's 1990 mineral resources. Standard errors in parentheses are clustered at the district level. *** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level.

Table OA2: Dropping one labour-intensive district at a time

Dependent variable →	Δln(# Employees)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Mineral Resources 1990	0.035***	0.035***	0.035***	0.035***	0.035***	0.035***	0.035***	0.035***	0.035***
× Δln(Minerals Price)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Mineral Resources 1990	-0.033***	-0.033***	-0.033***	-0.032***	-0.033***	-0.032***	-0.089*	-0.032***	-0.032***
× Δln(Minerals Price)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.047)	(0.010)	(0.010)
× Underground Mining									
BOE Production ∼1990	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
× Δln(Oil Price)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	343,684	332,996	343,735	343,411	343,306	343,571	343,663	343,509	343,727
adj. R^2	0.016	0.015	0.016	0.016	0.016	0.016	0.016	0.016	0.016
Marginal effect of mining boom	0.003*	0.003*	0.003	0.003*	0.003*	0.003	-0.054	0.003*	0.003
for underground mining=1	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.047)	(0.002)	(0.002)

This table presents the results of another robustness check on the effect of global mineral price shocks on the change in employment of different groups of manufacturing plants in mineral-rich districts versus districts with relatively smaller or no mineral resources (compare to Table 6). The dependent variable is the plant-specific log yearly change in employment. We exclude a different underground mining district in each column. We define a district as underground mining district if at least one of the 1990 deposits in the district was operated or planned to be operated by underground mining. Since nine out of 40 mining districts fulfil this criterion, Table OA2 features nine specifications. Our sample contains all formal manufacturing plants with at least 20 employees in the included districts in Indonesia, over the period 1990-2009. See Table 5 for the description of independent variables and column labels. All specifications contain four-digit industry-times-year fixed effects. The difference-in-difference specification absorbs plant-fixed effects. Standard errors in parentheses are clustered at the district level. ***Significant at 1% level; **Significant at 5% level; * Significant at 10% level.