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JEL Classification: F00, L16, L60, L72, O12, O13, Q30

Keywords: Dutch disease, traded sector, Natural resources, mining, labor intensity, Indonesia

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

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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 'Dutch disease', in which natural resources crowd out the traded sector and reduce growth (The Economist, 1977; van Wijnbergen, 1984), and has led to warnings of a seemingly incurable 'resource curse' (Gelb, 1988; Sachs and Warner, 2001). This literature has recently 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] Using detailed firm- and household-level data for the US, several studies find contrasting positive effects of local natural resource booms, or at 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 after a large open-pit gold mine in Peru increased local procurement (Aragón and Rud, 2013), to higher GDP per capita in Brazil (Cavalcanti et al., 2019), to more conflict in Colombia (Dube and Vargas, 2013), localized negative traded-sector employment effects in emerging markets (De Haas and Poelhekke, 2019), and an increase in municipal government spending in Brazil that does not translate into better public goods and services (Caselli and Michaels, 2013).

The literature has typically exploited 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 show that resource extraction techniques vary significantly in their labor intensity, and that this source of heterogeneity can reconcile positive and negative outcomes found in the literature. We analyze 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 across the country, and has a large and exporting manufacturing sector.

Combining detailed manufacturing plant-level panel data with deposit-level data, we find that in districts where mining of minerals is more capital intensive, mining booms cause an increase in plant-level employment. Specifically, employment rises by 2.6% in a district with average mining intensity when local mineral prices increase by 100 log points and mining is relatively

[1] As surveyed in Van der Ploeg (2011) and Van der Ploeg and Poelhekke (2017).

capital intensive. In contrast, mining booms in districts where mining is labor intensive reduce manufacturing employment by 1.2%. Further unpacking the effects, we show that the negative employment effect is driven by producers of more heavily traded manufactured goods, whereas producers of relatively less-traded manufactured goods can avoid a contraction of employment. The key mechanism, which we verify empirically, is that when the mining sector is booming, it only exerts strong upward pressure on local wages if its mining method is labor intensive. This makes local producers of heavily-traded goods less competitive during labor-intensive mining booms, whereas less-traded goods producers are able to pass on higher wage costs to consumers by raising prices. From the perspective of manufacturing plants, the local extraction technique can thus determine whether mining booms are good or bad.

Using novel well-level data, we control for oil & gas booms and show that these do not lead to a rise in manufacturing wages or a reduction in employment, which is consistent with oil & gas production being mostly offshore and highly capital intensive and specialized. Heterogeneity in extraction techniques thus helps to explain why many studies that have focused on capital-intensive natural resource extraction such as open-pit mining or oil & gas production do not find evidence for local crowding-out effects in the manufacturing sector during natural resource booms. In terms of magnitude, the effect of mining booms on local manufacturing in Indonesia is much larger than the effect of oil & gas booms in the US (Allcott and Keniston, 2018). However, we also do not find that the reallocation between sectors and reduction in activity by more-traded goods producers leads to a reduction in total factor productivity. This speaks against foregone 'learning by doing' productivity spillovers as described theoretically in Van Wijnbergen (1984) and Arrow (1962) and confirmed empirically in other contexts by Ellison et al. (2010), Greenstone et al. (2010) and Kline and Moretti (2014). Therefore, our findings do not provide empirical support for Dutch disease effects in the narrow sense, in which foregone productivity gains in non-resource tradeable goods sectors slow down overall economic growth.

Our identification strategy is to correlate exogenous shocks to the value of local natural resources in Indonesia that had been discovered by the start of our sample period with local manufacturing outcomes. Informed by the literature that has questioned the exogeneity of exploration and discoveries (Bohn and Deacon, 2000; Cotet and Tsui, 2013; Arezki et al., 2019; Cust and Harding, 2020), we use exogenous world prices that change the value of existing and pre-determined deposits. Based on deposit and well-level data, we compute measures of initial endowments of minerals and oil & gas, respectively, at the district level. We interact these with subsequent exogenous world price shocks and, in the case of mining, an indicator that captures the labor intensity of local extraction methods. The mining engineering literature posits that the locally applied extraction technique is determined by the exogenous geological shape of the deposit and not by the deposits' contained minerals or local labor market characteristics (see e.g. Hartman and Mutmansky, 2002). Using three separate databases, we empirically establish that different mining techniques (such as underground and open-pit mining) translate into very different degrees of labor intensity. In addition, our empirical specification controls for any remaining impact of local labor market characteristics and accounts for differential trends in manufacturing across individual districts. Our manufacturing data contains annual plant-specific information on all Indonesian manufacturing plants with 20 or more employees between 1990 and 2009. This allows us to control for plant fixed effects, which avoids selection effects and thereby improves identification. Furthermore, the richness of the data allows us to distinguish manufacturers of relatively more-traded and relatively less-traded goods and thus analyze whether each suffer less or benefit more from mining.[2]

We contribute to a growing literature that analyzes the impact of natural resources in within-country settings. Data on firms and counties in the US have shown that coal, oil, and gas booms, of which the recent boom was driven by novel shale extraction techniques, have had either small or no negative effects on manufacturing.[3] Black et al. (2005) find positive employment effects on non-tradeable sectors during the 1970s coal boom in their analysis of local labor markets in Kentucky, Ohio, Pennsylvania, and West Virginia, but no significant effects on the manufacturing sector. A long-run study of the southern US 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 & gas endowment of US$10 million per square mile, a natural resource boom that raises national oil & gas employment by 100 log points leads to an increase in population by 1.2%, employment by 2.8% and earnings per worker by 1.8%. The

[2] Since the data does not contain plants with less than 20 employees, we are unable to study entry and exit.

[3] Although more aggregate county- and state-level data suggest more evidence for negative effects, c.f. James and Aadland (2011).

US manufacturing sector is also procyclical with oil & gas booms in resource-abundant counties, 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 distinguishing between different extraction methods used to take natural resources out of the ground and the relative labor intensity that this implies. By analysing a developing country with different degrees of sectoral and regional labor mobility compared to the US, we place the results in the literature into a broader perspective. Since we find that labor mobility across districts in Indonesia is low and because the country's less specialized manufacturing sector likely results in more sectoral labor mobility, there may be more scope for crowding out of manufacturing. Moreover, in a developing country potentially less firms are up- and downstream to the natural resource sector 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).

We also contribute to another literature that has focused more on political economy and household outcomes. Aragón and Rud (2013) analyze 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. Dube and Vargas (2013) also study heterogeneity in the labor intensity of commodity extraction, but in a different context: they find that an exogenous increase in the price of coffee (which is labor intensive in production) decreases armed conflict in Colombia because it raises the opportunity cost of fighting, while an increase in the price of capital-intensive oil production *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. This may reflect the fact that giant oil discoveries are followed by reductions in democracy scores (Tsui, 2011).[4] Finally, we also add to a literature that has examined a range of other related outcomes during natural resource booms, such as increased wage, royalty and business income after new hydrofracturing oil & gas production

[4] Strong institutions can also prevent negative outcomes after discovery (Mehlum et al., 2006).

(Feyrer et al., 2017), 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), and increased crime rates (James and Smith, 2017).

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

2 Theoretical effects of resource booms on manufacturing employment

We are interested in two sets of hypotheses. The first are inspired by the mining engineering literature which states that underground mining methods are most labor intensive. If this is indeed the case then we should find that underground mines employ more workers than open-pit or mixed-method mines of comparable size, and that mines with open-pit methods employ the least number of workers. The second set of hypotheses derives from the seminal models of Dutch disease at the national level by Corden and Neary (1982) and Van Wijnbergen (1984), which have recently been adapted to a multiregion setting by Allcott and Keniston (2018). We introduce varying degrees of labor intensity of mining to these models, to build intuition on how mining booms can crowd out manufacturing employment depending on the labor intensity of extraction techniques. Moreover, we treat manufacturing as not altogether traded, but allow for different degrees of de facto tradedness of goods produced. While several studies have developed quantitative spatial equilibrium models that analyze the welfare consequences of regional shocks (Redding, 2016; Redding and Rossi-Hansberg, 2017; Caliendo et al., 2017; Faber and Gaubert, 2019; Fajgelbaum and Gaubert, 2020; Burstein et al., 2020), a full welfare analysis of the natural resource sector would ideally also take resource-specific factors into account. These include policy at the regional and national level that may affect exploration effort leading to more discoveries, industrial policy of the development of up- and downstream industries, and macroeconomic management of resource wealth at the national level such as fiscal rules, sovereign wealth funds, and redistribution.

We start with a multiregion economy in which labor is (imperfectly) mobile across regions. In some of these regions natural resource deposits occur, which are mined with varying techniques that imply different degrees of labor intensity. We assume that the mining sector exports all mined minerals and thus abstract from downstream effects, which is realistic in a developing country setting. Mining is price-elastic and expands when exogenous world mineral prices increase, which we call a mining boom.[5] Other sectors in the economy are composed of tradeable and non-tradeable sectors, which each are impacted differently by the mining boom and respond in different ways, depending on whether the boom takes place in a region with labor- or capital-intensive mining. As is typically assumed, prices of tradeable goods are set on world markets while non-tradeable prices are endogenous and vary by region.

In this setting, we expect an exogenous positive shock to global mineral prices to have the following effects and testable hypotheses:

(i) First-order effects on the local economy

First, in regions with labor-intensive mining a mineral price increase results in stronger demand for labor than in regions where mining is capital intensive, driving up mining wages.[6] The upward pressure on mining wages is also stronger when labor supply is more inelastic across regions, limiting labor being supplied through migration. The more inelastic is labor supply across regions and the more workers are substitutable across sectors, sectors rather than regions compete for labor with the mining sector. A mining boom can thus result in reallocation of workers from other sectors to mining, and lead to upward pressure on other sectors' wages as well.[7]

Second, the mining boom results in a boost to local aggregate demand: to the extent that higher wages are not offset by higher prices, it implies more local spending power of workers and a larger local population, unless labor supply is perfectly inelastic across regions; and taxable

5 We establish in Online Appendix Table OA2 that this is indeed the case, using the production history of mines in Indonesia.

6 We verify this empirically in Online Appendix Table OA2 using district-specific data.

7 Corden and Neary (1982) refer to this mechanism as the 'resource movement effect', and assume that workers are perfectly substitutable across sectors, resulting in one uniform wage rate.

mining rents can boost local demand if the national government partly redistributes these to producing regions.[8] The local aggregate wage-income effect is stronger in labor-intensive mining regions, while the local aggregate demand effect of redistribution does not depend on mining extraction techniques.[9] The higher the marginal propensity to consume non-tradeables, the more the boost to demand benefits sectors that produce non-tradeables, with the remainder being spent on tradeables supplied locally and by producers in other regions.

Third, the mining boom creates demand for goods supplied by upstream sectors, thereby potentially benefiting selected manufacturing industries.

A potential fourth effect is increased public spending at the local level following the redistribution of nationally taxed mining rents to producing regions. This can have cost-saving effects for other sectors, for example when these are spent on public goods such as infrastructure, as in Michaels (2011). This channel does not depend on the labor intensity of mining.

(ii) A boost to the non-tradeable sector

A mining boom benefits local non-tradeable producers through an increase in local aggregate demand, assuming that the marginal propensity to consume non-tradeables is sufficiently positive. The spending effect occurs in all types of mining regions, but is stronger for the non-tradeable sector if the boom occurs in a region with labor-intensive mining, because then more miners will earn higher wages. However, in that case the non-tradeable sector also suffers more from competition for workers, if they are at least to some degree substitutable across sectors. To supply the increase in local demand, non-tradeable producers will have to raise wages to retain workers. Since they sell locally to workers with higher wages, they can endogenously increase prices to pass on the higher wage costs (a real appreciation). Non-tradeable producers are therefore always able to raise employment to meet the increase in demand, while remaining profitable, as in Allcott and Keniston (2018). If the extra spending effect due to higher wages is stronger than the extra competition for labor effect, then non-tradeable employment rises more during labor-intensive than during capital-intensive mining booms.

[8] Corden and Neary (1982) refer to this mechanism as the ‘spending effect’.

[9] Assuming that rents per unit of output are equal between labor- and capital-intensive mining operations.

(iii) Crowding out of the tradeable sector

The tradeable goods sector is less likely to benefit from an increase in local aggregate demand, because demand for tradeables can be supplied through imports as well. In a boom to labor-intensive mining, tradeables producers also suffer from competition for workers, unless their workers are less substitutable with other sectors such as through a higher skill intensity. To retain workers, they would also have to pay higher wages. However, it is not profitable for them to do so because they are price takers and thus cannot pass on wage costs. Instead, they are forced to shed labor, and are thus crowded out by the labor-intensive mining boom. Competition for labor is less strong in regions with capital-intensive mining, where the net effect of a boom may be an expansion of tradeable employment. For example, if infrastructure spending is important for tradeable sectors, then redistributive government spending on infrastructure can benefit the tradeable sector.

(iv) Loss of productivity

If the positive productivity effects of learning by doing are concentrated in the tradeable sector, then crowding out of the tradeable sector may also lead to an economy-wide loss in total factor productivity over time.

(v) Regional spillovers

In a multi-region setting, the effects of the local mining boom may spill over into other regions. The more elastic is labor supply across regions, the more local labor demand in mining can be supplied by labor from other regions. This creates excess labor demand and also drives up wages in those regions. Part of the increase in local aggregate demand in mining regions may be supplied by tradeable sectors located in other regions. Finally, royalties may be redistributed to non-producing regions such that higher resource rents can boost demand and public spending in other regions as well.

Summarizing the effects on the tradeable sector, an exogenous increase in the returns to labor-intensive mining puts upward pressure on wages, leading traded-goods sectors to reduce employment. However, the wage effects are muted in capital-intensive mining regions where employment can grow through spending effects. Not taking into account the heterogeneity in the labor intensity of natural resource extraction methods masks these countervailing effects and may lead to spurious conclusions at the aggregate level.

3 Data

3.1 Indonesian context

Indonesia ranks fourth in the world by population size, and is both a major producer of minerals and a significant producer and exporter of manufactured goods. Therefore, the country provides an ideal testing ground. The (non-mining) manufacturing sector (ISIC Revision 3.1, divisions 15 to 37) represented 23% of GDP on average between 1993 and 2009. In 2009, Indonesia exported 14% of manufacturing output, consisting mostly of food products and beverages, wood products, rubber products, textiles, communication equipment, and garments. These sectors alone employed 54% 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.[10] The deposits occur both near the surface and deep underground, are relatively scattered across the country, and are found on all major islands – including the populous islands of Java and Sumatra as shown by Figure 1 in the Online Appendix. The government of Indonesia taxes underground mining and other types of mining virtually equally: mineral producers have to pay the same production royalty rate (which varies between 3 and 7%, depending on the mineral) irrespective of the applied mining technique.[11] These royalties are partially redistributed to producing districts, such that a mining boom has a large potential to spur a *local* spending effect. After Indonesia's 'big bang' decentralization of 1999 non-producing districts also started to share in royalties, but 64% of land rents and 32% of royalties still go to producing districts as

[10] Source: *Indonesian Database for Policy and Economic Research* (INDO DAPOER) for GDP; Indonesia's national labor force survey (SAKERNAS) for employment. See the Online Data Appendix for details on the labor force survey. 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. Source: `http://www.uky.edu/KGS/education/didcoal.htm`

[11] The only slight exception is coal, for which the royalty rate ranges between 3 and 7% for open-pit mines and between 2 and 6% for underground mines. Source: `https://www.pwc.com/id/en/publications/assets/mining-investment-and-taxation-guide-2010.pdf`.

per Law 25/1999.[12]

Indonesia is also an important producer of oil and natural gas. In 2009, the oil & gas sector's contribution to GDP was 4.55% and thus comparable to the share of the mining sector. However, oil & gas revenues were not shared with the producing district until decentralization, and from then on, the producing district only received 6% of total oil revenues and 12% of total gas revenues. Most oil & gas is found offshore requiring relatively more capital and skills, and the employment share of oil & gas was less than half the employment share of mining between 1995-2009.[13] For these reasons, we always control for oil & gas production, but focus on the mining of minerals.

3.2 Natural resource endowments and mines

We construct a database of mining by district by combining two proprietary data sources: the *Raw Materials Data* (RMD) from *SNL Metals and Mining*, which covers mining worldwide, and data provided by *MinEx consulting* (*MinEx*) for Indonesia specifically. Combined with additional sources for a few missing data points (see the Online Data Appendix), these sources provide us with the location, mining method in use or planned, minerals produced, the quantity of resources in the ground, and year of discovery for each deposit. RMG also provides employment per mine, but only for a very small subset and for almost none of the Indonesian mines. We use the global information to estimate the labor intensity of different mining methods (conditional on country-year and mineral fixed effects).

We identify 82 mineral deposits that were discovered by 1990, spread across 40 of the 282 districts and 21 of the 26 provinces that existed in 1990, which highlights the geographic dispersion of mining.[14] The year 1990 is chosen to fix endowments at the start of the period for which we observe manufacturing outcomes. This greatly mitigates endogeneity concerns and is meaningful in terms of mining activity because most discoveries were made prior to 1990.

[12] The producing district's share in royalties was 70% over 1990-1992, 64% over 1992-1999, and 32% over 1999-2009. For land rents, its share was 70% over 1990-1992 and 64% over 1992-2009. Districts in the same province as the producing district jointly accrued 32% of royalties over 1999-2009. The province of the producing district did not participate in royalties or land rents over 1990-1992 but received 16% of both over 1992-2009.

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

[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 (2020) and for other years on the BPS.

The deposits jointly contain a wide variety of minerals.[15] 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.[16] We use resources rather than reserves because the former more closely reflects exogenous geology, since reserves are defined as "the economically mineable part of a measured or indicated mineral resource" (Raw Materials Data Handbook, p.58). 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 labor market. We sum across deposits by district and divide by the surface area of the district in square miles such that $r_k = \sum_d R_{dk}/Area_k$, where R_{dk} stands for the ore resources of deposit d in district k in 1990. Finally, we normalize r_k by its average across all positive realizations of r_k and label this $\tilde{r_k}$.

The most common extraction method applied to the deposits in our sample is open-pit mining, used in 77 deposits in 36 districts. 11 deposits in nine districts use underground mining, while three deposits in three districts use placer mining techniques for deposits found in (former) river beds. The extraction technique is never recorded with a time label and is thus time-invariant, which corroborates the insight from the mining engineering literature that it is determined by a fixed factor, namely geology. We use this information to construct an $Underground_k$ dummy for our baseline analysis, and assign a value of one to each district k that applies underground mining techniques in the extraction of endowment $\tilde{r_k}$ and zero otherwise. In additional regressions in the Online Appendix we further distinguish between the three districts in which only underground mining is applied and the six districts in which both underground and open-pit mining take place. The nine districts for which $Underground_k$ equals one are spread across eight provinces and contain multiple minerals, which are also mined using other techniques in other locations.

For oil & gas endowments we digitize a novel source, the *Indonesia Oil and Gas Atlas* by Courteney et al. (1988-1991). The six volumes of this source list all oil & gas fields in Indonesia

[15] 22 deposits contain coal (these deposits contained 72.63% of total 1990 resources in terms of volume), 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] 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).

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 database for giant discoveries (Horn, 2003). Unfortunately, field-specific oil & gas remaining resources in the ground are not reported. Therefore, we compute a proxy for oil & gas endowment equal to the sum over all fields within a district of reported daily production of barrels of oil equivalent (using a standard conversion factor of 6,000 for natural gas) and divide by district size. We normalize this proxy in the same way as r_k, and denote it $\tilde{boe}_k$. 37 districts spread across 14 provinces were producing oil and/or gas around 1990. Nine of these districts also contained minerals in 1990. Online Appendix Table OA1 provides descriptive statistics on natural resource endowments by province.

Oil and each solid mineral have their own world price, giving us in addition substantial variation over time as shown in Online Appendix Figure 2. Prices come from a variety of sources as described in the Online Data Appendix. We relate mineral endowments to prices by constructing a mineral price index, which we discuss in detail in Section 4.

3.3 Manufacturing census data

We use the annual census of manufacturing plants (*Survei Industri*), which contains repeated observations on 59,031 manufacturing plants between 1990 and 2009 that employ at least 20 employees. The data are collected and compiled by the BPS and contain detailed information on performance indicators, including employment, investment, material inputs, revenue, exports, and the district in which the plant is located. In addition, the data set contains a four-digit sector classification. The census covers the manufacturing sector and thus excludes mining operations. Ownership information allows us to exclude plants with (partial) government-ownership (which may be shielded from market forces), and focus on privately-owned plants, leaving 50,693 plants observed on average for six years. Table 1 presents the descriptive statistics.[17]

[17] Around 6% of plants record two or more districts over time. We cannot be sure if these events are real or due to measurement error. This is because districts split and proliferated over time in which district codes were reused and reassigned from time to time, and while we track these changes, some errors may remain. We do not entirely drop such plants, but keep the longest period in which a plant reports the same district. See the Online Data Appendix for details.

[**Table 1 about here**]

Employment equals the total number of employees reported by each plant. We do not observe individual wages nor hours worked so as a proxy for wages we divide the *total wage bill by the number of employees*. *Revenue* as reported directly in the census is the value of goods produced. The average *unit price* is equal to revenue divided by the total number of product items sold, but is not available before 1998. Finally, we obtain *total factor productivity* from Javorcik and Poelhekke (2017).[18]

While the manufacturing sector is usually regarded as tradeable, some manufacturing plants produce goods that are more tradeable than others. Furthermore, a plant's product may be highly tradeable by its nature, but may *de facto* not be traded beyond the local economy. We use the detailed sector classification to construct an indicator for whether a plant mainly sells to local markets or whether it sells to non-local and foreign markets.

Specifically, we split plants into *more-traded goods producers* and *less-traded goods producers*. More-traded goods producers are plants that export in at least one year in our sample period (and thus contain all international exporters), and/or are plants that belong to a four-digit sector with a below-median distance elasticity to trade as calculated by Holmes and Stevens (2014). Less-traded goods producers are thus all other plants, which have an above-median distance elasticity.[19] The distance elasticity equals the percentage change in trade volume as distance increases by one percent, using industries' average shipment distance as reported in the *US Commodity Flow Survey*.[20] Our sample includes 123 four-digit ISIC Rev.3.1 manufacturing industries, of which "Manufacture of articles of concrete, cement and plaster" is the least-traded manufacturing sector. Five industries have an estimated distance elasticity of zero, including for example "Publishing of newspapers, journals and periodicals".[21] The reason for using US elasticities is that similar data are not available for Indonesia. The assumption that comes with this choice is that the *ranking* of industries with respect to distance elasticity across the two

[18] See the Online Data Appendix for details.

[19] Alternatively, we could use solely the international exporter status of a plant, but this runs into potential selection effects since a large fraction of tradeable goods producers may not export their output internationally due to insufficient competitiveness or bureaucratic reasons (see e.g. McLeod, 2006).

[20] See the Online Data Appendix for details.

[21] 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 (tradedness) status over time. As we discuss in Section 5.3, our results are robust to dropping industry-switchers.

countries is the same.[22] In 2009, the less-traded sector employed 770,000 workers in 10,000 plants, while the more-traded sector employed 3.5 million workers in 14,000 plants. Of these, 8.5% and 7.5% of employment is located in districts with mineral resources, respectively.

Finally, some of the plants in our data may be upstream to the mining sector. We define *upstream plants* as those plants that operate in four-digit industries that sell an above-median share of output to the mining sector. To compute this share, we rely on Input-Output tables for the United States, as discussed in more detail in the Online Data Appendix.

4 Empirical Strategy

Our main hypothesis is that the intensity of mining activity affects plant-level outcomes, and that this varies by extraction technique and the degree of tradedness of produced goods. Since we observe the location of plants at the district level we need exogenous variation in mining activity at the district level and over time. We achieve this by interacting initial mineral endowments with changes in exogenous world prices of local minerals.

Each district may contain several deposits, and each deposit potentially contains multiple minerals. We thus 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 resources. More precisely we define:

$$Mineral\ Price\ Index_{kt} = \sum_m P_{mt} \frac{R_{mk}}{R_k} \quad \text{if } R_k > 0, \text{ 0 otherwise}$$

where P_{mt} equals the world price of mineral m in year t indexed to base year 1990, $R_{mk} = \sum_d R_{mdk}$ and thus the sum of 1990 resources in tons of ore of mineral m across all deposits d in district k, and $R_k = \sum_m \sum_d R_{mdk}$, i.e. the district's total 1990 mineral resources. Figure 2 in the Online Appendix plots the development of indexed world prices P_{mt} for all minerals in our sample and shows periods with large price swings. The definition of the mineral price index (MPI) ensures that, for example, the steep increase in the price of iron ore in 2005 will have no effect in districts without iron ore deposits (absent spillovers), and only a substantial effect in

[22] 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 more- versus less-traded goods producers.

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.[23]

We further expect the labor intensity of mining to depend on the locally applied extraction technique. We establish the relevance of this margin using a global sample of mines. For a small subset of these mines, a cross-section of years between 2002 and 2011, we observe employment, but unfortunately not for most mines in Indonesia. However, we can control for country C_c, year of employment information T_t (or country-by-year) and (main) mineral fixed effects M_m. Conditional on these fixed effects we have no reason to believe that mining in Indonesia is different from mining in other countries. We thus regress the log of mine-level employment on a dummy for the mining extraction technique, the log of the size of the mine in terms of deposit resources and a set of country, time and main mineral fixed effects, and cluster standard errors at the country level:

$$\begin{aligned} ln(\#MineEmployees)_{dt} = {} & \delta_1 Underground_d \\ & + \delta_2 ln(MineralResources)_d + C_c + T_t + M_m + \upsilon_{dt} \end{aligned} \tag{1}$$

Based on this novel source of heterogeneity as captured by a positive and significant coefficient $\hat{\delta}_1$, we relabel the district-level dummy $Underground_k$ to $\textit{Labor-intensive Mining}_k$.

We then model plant-level outcomes Y_{ijkt} of plant i in four-digit industry j in district k in year t as a function of $f(\cdot)$ and of plant fixed effects μ_i that capture unobserved heterogeneity of plants within districts. $f(\cdot)$ is a function of the interactions of normalized mineral resources per square mile in the local district $\tilde{r_k}$, world prices of minerals contained in these deposits MPI_{kt}, and the mining technique dummy $\textit{Labor-intensive Mining}_k$:

$$lnY_{ijkt} = f(\tilde{r_k},\, MPI_{kt},\, \textit{Labor-intensive Mining}_k) + \mu_i + \nu_{ijkt}$$

[23] We control for district-specific fixed effects and trends to capture any systematic differences between more recent and older deposits.

We first difference both sides of the equation to take care of serial correlation in the error term ν_{ijkt} and to get rid of the plant fixed effects. This also absorbs district fixed effects and the variables and interaction terms that only vary across districts k:

$$
\begin{aligned}
\Delta lnY_{ijkt} = \gamma_1 \left[\Delta ln(MPI_{kt}) * \tilde{r_k}\right] \\
+ \gamma_2 \left[\Delta ln(MPI_{kt}) * \tilde{r_k} * \textit{Labor-intensive Mining}_k\right] + \eta_{ijkt}
\end{aligned}
$$

$[\Delta ln(MPI_{kt}) * \tilde{r_k}]$ captures the mining boom. The boom is larger for a larger price shock, and for a given price shock the mining boom is larger in districts with greater endowments. The price shock $\Delta ln(MPI_{kt})$ and its interaction with *Labor-intensive Mining*$_k$ are not separately included because $MPI_{kt} = 0$ for districts with no mineral resources.[24]

The error term η_{ijkt} may still be correlated with the mining boom, such as through global commodity prices driving a simultaneous oil & gas boom. We therefore include as control variables initial oil & gas intensity interacted with the oil price $[\Delta ln(OilPrice_t) * \tilde{boe}_k]$, four-digit industry-times-year fixed effects $T_t S_j$, and district-specific trends τ_k to account for the possibility that shocks are persistent (Ciccone, 2011).[25] Our approach is similar to Allcott and Keniston (2018) for oil & gas development in the US, but we adjust for the presence of multiple minerals and for variation in extraction techniques. The regression equation is thus:

$$
\begin{aligned}
\Delta lnY_{ijkt} = \beta_1 \left[\Delta ln(MPI_{kt}) * \tilde{r_k}\right] \\
+ \beta_2 \left[\Delta ln(MPI_{kt}) * \tilde{r_k} * \textit{Labor-intensive Mining}_k\right] \\
+ \beta_3 \left[\Delta ln(OilPrice_t) * \tilde{boe}_k\right] + T_t S_j + \tau_k + \epsilon_{ijkt} \qquad (2)
\end{aligned}
$$

Industry-year effects control for different industry compositions across mining and non-mining

24 Given the definition of the price index, its separate inclusion would not provide additional information: the impact of a local mining boom would then partly be captured by the coefficient on $\Delta ln(MPI_{kt})$ and partly by the coefficient on $[\Delta ln(MPI_{kt}) * \tilde{r_k}]$ for capital-intensive mining districts, and by $[\Delta ln(MPI_{kt}) * \tilde{r_k} * \textit{Labor-intensive Mining}_k]$ for labor-intensive mining districts. This would suggest that the marginal effect of the price shock is non-zero for $\tilde{r_k} = 0$, while it is only defined for $\tilde{r_k} > 0$.

25 The district-specific trends τ_k absorb different trends for different values of $\tilde{r_k}$, $\tilde{boe}_k$, *Labor-intensive Mining*$_k$ and $[\tilde{r_k} * \textit{Labor-intensive Mining}_k]$. The industry-times-year fixed effects absorb the direct effect of a change in the oil price.

districts or global industry-specific demand shocks that may be correlated with mineral price changes. Since first-differencing absorbs district fixed effects we control for the possibility that the choice for a certain extraction technique in or before 1990 depended not only on geology but also on time-invariant local labor market conditions that may also affect the manufacturing sector. The district-specific *trends* τ_k absorb trending local labor market conditions and control for different trends in manufacturing outcomes in districts with labor-intensive extraction methods.

We estimate equation (2) with OLS and always cluster standard errors at the level of treatment (the districts).[26] The main outcomes of interest are plant-level employment (number of workers), the total wage bill divided by the number of workers as a proxy for wages, unit prices (the average price per unit sold), and revenue. We start with a large panel of all privately-owned manufacturing plants and then split the sample into plants that produce goods that are more or less heavily traded.

The main coefficients of interest are β_1 and β_2. When β_2 is significant we also calculate whether $\beta_1 + \beta_2$ is significantly different from zero: this captures the marginal effect of the mining boom $\Delta ln(MPI_{kt}) * \tilde{r_k}$ when *Labor-intensive Mining*$_k$ equals one. In principle β_1 (or $\beta_1 + \beta_2$) measures a *relative* effect: the empirical counterfactual is the change in outcome Y of a plant in the same industry in the same year in a district that faces a smaller or no mining boom. For example, an increase of local mineral prices by 100 log points leads to a change in outcome Y of a plant in a district with average 1990 mineral ore resources (i.e. $\tilde{r_k} = 1$) by approximately 100 $\times$ β_1 percent, relative to a plant in a district with no mineral resources. We can also interpret β_1 as the differential effect of a given price increase on a plant in a district with endowments equal to $\tilde{r_k} = 2$ compared to a plant in a district with average endowments, i.e. $\tilde{r_k} = 1$. In the absence of geographic spillovers, one can regard β_1 as an *absolute* effect. In Section 5 we test for such spillovers but we find these to be small and insignificant.

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

5 Results

5.1 Does labor intensity differ by extraction method?

Our data distinguishes between underground, open pit, and a range of less-used mining techniques (placer mining, in-situ leaching, offshore mining, tailings). According to Hartman and Mutmansky (2002), underground mining methods are most labor intensive because it is harder to operate and automate heavy machinery in underground tunnels.[27] Conversely, all non-underground mining methods are classified as non-labor intensive. This suggests that on average underground mines are most labor intensive in production, and that mines that use a combination of underground and open-pit methods are more labor intensive than pure open-pit mines.

We test this hypothesis more formally in three different ways using three different data sources that jointly cover mining activity globally and in Indonesia. As our first test we estimate equation (1) using employment data of a cross-section of mines around the world from the *Raw Materials Data* (RMD). While this data set lists 8,830 deposits and mines in 145 countries, employment data are available for only 518 mines in 63 countries, and the year of employment information varies by mine over the period 2002-2011. 230 of these mines apply only open-pit mining, 213 only underground mining, 54 both underground and open-pit mining and 21 mines apply other or unknown mining techniques. The number of employees across the 518 mines (of which two are located in Indonesia) ranges between 13 and 10,550 and averages at 1,084 employees. The results are reported in Table 2 and indicate that a mine that applies underground mining uses about 65% more labor than otherwise similar mines (column 1). Column 2 shows that the coefficient is larger for mines that apply *only* underground mining and smaller for mines that apply both underground and open-pit mining, which is consistent with the mining engineering literature. Conditional on the control variables and fixed effects, column 3 suggests that there is no significant heterogeneity with respect to a country's level of development as measured by GDP per capita. The results are

[27] Our data is not more specific, but in theory underground mining methods 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 labor intensive.

robust to replacing country and year (of employment information) fixed effects by country-times-year fixed effects, which fully absorb any potential impact of country-specific and time-varying labor market characteristics such as mining in a 'low-wage country' (column 4); and to excluding mines that neither apply underground nor open-pit mining (column 5).

In the Online Appendix we provide two additional tests (Tables OA3 and OA4): one based on district-level data derived from Indonesia's labor force survey (SAKERNAS), and one using district-level (working-age) population data. These show that the number of mining workers in underground mining districts is 114% larger than in non-underground mining districts with the same resource endowments, and the result is robust to controlling for regional labor market characteristics. We also show that oil & gas extraction is least labor intensive, and that an increase in the price of local minerals spurs working-age population growth in mining districts, but only when mining is more labor intensive. However, the magnitude of the coefficient suggests that labor mobility is relatively low, such that there is scope for upward wage pressure.

We conclude that there are significant differences in labor intensity between extraction techniques and that underground mining is most labor intensive.

[**Table 2 about here**]

5.2 Mining heterogeneity and manufacturing outcomes

We now turn to our main results, using the heterogeneity in the labor intensity of mining techniques to reconcile the mixed effects that mining booms have on manufacturing outcomes.

Table 3 starts by regressing the change in log manufacturing plant employment on both mining and oil & gas booms using a large sample of privately-owned plants between 1990 and 2009. We control for a wide range of fixed effects, including plant fixed effects, district-specific trends, and four-digit industry-times-year effects, absorbing unobserved potential confounding factors such as local or industry-wide demand and labor market trends.

We do not find evidence for a general loss of employment during a mining boom, for plants located in a district with average mineral endowments, relative to plants in districts with much less or no mining at all. If anything, manufacturing employment appears to be positively affected by mining booms and unaffected by oil & gas booms. The difference between mining and oil &

gas may be due to fiscal rules: oil & gas rents accrue mostly to the national government, while mining rents are shared much more with local districts, creating the potential for an increase in local aggregate demand and local government spending.[28] Alternatively, there may be more direct input-output links between the mining sector and local manufacturing, which we come back to in Section 5.3.

Looking at other outcomes in columns 3, 5 and 7, including the change in the log ratio of the wage bill to employment, unit price inflation of manufactured goods, and growth in plant-level revenue, we find that only revenue increases significantly during the average of mining booms across all extraction techniques. At the same time, there is no evidence that oil & gas booms affect manufacturing in any way. On average, there is thus no evidence for crowding out.

This conclusion changes once we estimate equation (2) and introduce the dummy for labor-intensive mining in columns 2, 4, 6, and 8. The results unveil that a mining boom's effect on manufacturing is fundamentally different if it applies to a district where mining uses labor-intensive extraction techniques as opposed to capital-intensive techniques. Looking first at employment growth, we find that when capital-intensive mining is applied, manufacturing plants expand by 2.6% in the district with average mineral endowments when mineral prices increase by 100 log points, or when a given price increase occurs in a district with twice the average endowments. In sharp contrast, a mining boom of equal magnitude taking place in a district where mining uses *labor*-intensive extraction techniques results in a *contraction* of manufacturing employment, by 1.2%, as listed in the bottom row.[29] Labor-intensive mining booms also drive up average manufacturing wages, by 13.3%. These results are consistent with labor-intensive mines bidding up wages to attract workers (see Online Appendix Table OA2), which leads to some workers being released by plants in the manufacturing sector that cannot afford the higher wages. Unit prices also rise by 23% (implying a real appreciation), which likely leads to the rise in revenue by 22%. Capital-intensive mining booms do not increase average wages (because the total wage

[28] Although Cassidy (2019) finds that transitory fiscal shocks from the limited sharing of oil & gas windfalls slowly increase expenditure of capital, infrastructure, and education, which have the potential to be beneficial for the manufacturing sector.

[29] In the Online Appendix (Table OA5) we show that when splitting labor-intensive mining into pure underground and mixed-method mining, both these relatively labor-intensive methods have significantly different effects on manufacturing outcomes than capital-intensive mining. Moreover, pure underground mining (which is most labor intensive) has much larger effects on manufacturing outcomes than mixed-method mining. This further confirms the relevance of heterogeneity in mining extraction techniques.

bill increases in tandem with employment) nor do plants significantly increase prices, although revenue does increase somewhat. We also find that oil & gas booms yield no wage response. These results are consistent with labor being a secondary input in open-pit mining and oil & gas extraction. They might also reflect that a higher degree of capital intensity requires workers with more specific skills that are imperfect substitutes for manufacturing workers, or that the elasticity of oil production to prices is relatively low (Anderson et al., 2018).[30]

There are several plausible explanations for the positive effect of capital-intensive mining booms on manufacturing employment and revenue. On the one hand, some plants may benefit by being able to supply more intermediate capital goods to the booming resource sector directly. We find some evidence in favor of this hypothesis in Section 5.3. On the other hand, manufacturing plants may respond to a boom in local demand and/or larger public spending, which does not happen through higher local wages but through redistribution of national mining revenues that to a large extent flow back to mining districts and their provinces. District governments may use this to lower taxes for households (increasing local private demand), lower taxes for firms, invest directly in the local economy, or increase the provision of public goods such as infrastructure. Using district-level expenditure data from Indonesia's Ministry of Finance, we present supportive evidence showing that mining booms lead to larger public spending on industry sectors as well as trade and regional business development, both of which clearly benefit manufacturing plants (see Online Appendix Table OA7, Panel A). In addition, panel data over 2002-2004 from the Regional Autonomy Watchdog KPPOD reveals a positive impact of mining booms on the district-level quality of infrastructure (Panel B). Our results therefore echo those in Michaels (2011) who shows that Southern US counties that used natural resource wealth to improve infrastructure did better in the long run.

[Table 3 about here]

We conclude that accounting for heterogeneity in mining extraction techniques does show

30 Anderson et al. (2018) find that *drilling* responds more to oil prices. This extensive margin, the exploration phase, may be why Cust et al. (2019) find a positive response of average wages after an oil price increase (in a sample of both private and state-owned manufacturing plants in Indonesia), in districts that explored for oil and had success. Here, we do not observe the exploration phase and focus on the intensive margin of extraction, and find the complementary result that an increase in the value of existing mineral deposits raises averages wages only if mining is labor intensive.

evidence of crowding out of manufacturing employment, but only near labor-intensive mining. Whether the (local) aggregate effects of resource booms are positive or negative thus depends on the labor intensity of extraction, which is a novel result in the literature. The negative employment effect is arguably dampened by the simultaneous rise in prices and revenue, since this helps to compensate the rise in average wage payments. The increase in prices further suggests that not all manufacturing plants are price takers on global markets and that many supply the local market and can take advantage of the boost to local demand. Next, we therefore analyze heterogeneity in the degree to which manufacturing plants produce traded goods and are price takers on international markets. Although the manufacturing sector is often seen as traded, we should find that crowding out is worse for plants that are producers of relatively more-traded goods because such producers cannot simply raise prices and must find other margins of adjustment to the local mining boom.

More-traded versus less-traded manufacturing plants

Table 4 shows results of estimating equation (2) for a sample of relatively more-traded goods producers in Panel A, and for relatively less-traded goods producers in Panel B, for the same four outcome variables. To split the sample, we define more-traded plants as plants that belong to an industry with below-median distance elasticity in terms of its goods (see Holmes and Stevens, 2014), or that export internationally. Results are robust to using international exporter status only. We report marginal effects of mining booms for labor-intensive mining in the bottom row, but only when these are meaningful, which is when the interaction term suggests that mining has a significantly different effect on the outcome variable when mining is labor intensive versus when mining is capital intensive.

Panel A shows that more-traded goods producers lose even more employees than the average manufacturing plant: a labor-intensive mining boom results in a drop of employment of 1.8%. This can be rationalized within our theoretical framework and by looking at the results on the other outcomes. More-traded plants also face an increase in the demand for their products during a mining boom, but they cannot respond by raising prices because demand can also be met through imports from elsewhere. As a consequence, more-traded goods producers are also unable to raise wages without becoming less profitable and thus choose to shed labor instead.

Since average wages at more-traded goods producers are about 15 percent higher than in other plants, it is likely that they have a different skill composition. They may shed relatively low-skilled workers at the lower end of the wage distribution, while their other workers are less perfect substitutes for miners.

Panel A also shows that more-traded goods producers benefit from a capital-intensive mining boom and then hire *more* labor, despite being more likely to sell outside of their own district. Some more-traded plants may be upstream to the mining sector, which may choose to source certain manufactured intermediate inputs locally to save on trade costs. We analyze more-traded upstream plants in Section 5.3 and find supporting evidence for this hypothesis. In addition, capital-intensive mining booms do not drive up wages, while they do generate fiscal revenue. If part of the locally redistributed mining rents are spent on infrastructure – which is suggested by our results using the KPPOD data – then especially more-traded plants that use infrastructure more intensively may benefit. Indonesian exporters in manufacturing have indicated transport infrastructure as their main constraint to global competitiveness (Winkler and Farole, 2012). The result that mining booms lead to larger public expenditure on trade and regional business development is also particularly relevant for more-traded goods producers, which further helps to explain the positive employment effect on such plants.

Panel B focuses on relatively less-traded goods producers and finds that they also benefit during capital-intensive mining booms. The magnitude of the employment effect is somewhat smaller than for more-traded goods producers, which is in line with spending on trade and infrastructure likely being less relevant for less-traded goods producers. The more important difference is when mining booms are labor intensive: less-traded goods producers do not shed employment. While they may also benefit from redistribution of mining rents, the key difference to more-traded goods producers is that they can benefit from an increase in local demand from miners and workers earning higher wages and consuming local goods. This is because they can at least partly pass on higher wage costs (caused by upward wage pressure from the mining sector) to consumers by raising prices, since their goods are harder to import and a price increase thus leads to a smaller loss in market share. Thus, less-traded goods producers do not have to shed labor to remain profitable, despite increased competition for labor due to the labor-intensive mining boom. During such booms we indeed observe a strong increase in the proxy for wages and in unit prices for less-traded plants, and the rise in unit prices also translates into a substantial rise in revenue.[31]

The classic Corden and Neary (1982) Dutch disease mechanism is thus most clearly seen for labor-intensive mining and when allowing for varying degrees of tradedness in manufacturing. More-traded goods producers mostly suffer from a labor reallocation effect and reduce employment, while less-traded goods producers benefit more from a local spending effect via stronger local demand and are able to keep employment constant.[32]

[Table 4 about here]

Total Factor Productivity

So far we have found evidence for a reallocation of employment away from relatively more-traded goods producers, but only during labor-intensive mining booms. As in Corden and Neary (1982), this reallocation effect on its own is efficient and in theory welfare-improving. However, it is often thought that a loss in learning by doing in the more-traded manufacturing sector could depress TFP and drive longer term negative aggregate effects as in van Wijnbergen (1984). Columns 1-3 of Table 5 first present the results on the contemporaneous effect of mining booms on innovations to TFP – for all plants, for more-traded plants, and for less-traded plants. While TFP is largely unchanged during capital-intensive booms, it actually increases during labor-intensive booms and most for less-traded goods producers. This is probably to a large extent driven by the large increase in revenue while keeping employment constant. To gauge potential longer-term effects we next estimate the effect on total factor productivity over a five-year period: in columns 4-6 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

31 In the Online Appendix (Table OA6) we show that the heterogeneous effect on more- versus less-traded goods producers is robust to using an alternative specification, in which we interact the more-traded goods producer dummy with the mining boom variable and restrict our sample to districts without resources and districts with labor-intensive mining. In this specification it becomes possible to include district-times-year fixed effects, but we show that these do not change the results. This implies that the set of fixed effects and trends included in our baseline specification is sufficient to absorb any remaining confounding factors at the district-year level.

32 Nominal variables increase more in areas with labor-intensive mining, but that applies only to less-traded goods producers, not to more-traded goods producers in the same districts. This speaks against general district-level inflation driving the results.

change in annual prices during the last five years. The coefficient must thus be interpreted as the effect of an increase in mineral prices by 100 log points in each year over the five-year period. We still find large positive effects of labor-intensive booms, implying that also at this time horizon we find no evidence for a loss in TFP or learning by doing. On average, labor-intensive mining booms lead to a loss in manufacturing employment, but plants appear to become more productive. This may be due to survival bias but the employment cut-off in the data of at least 20 employees does not allow us to analyze plant exit.

[Table 5 about here]

Regional spillovers and revenue sharing

The estimates of the impact of a mining boom can be interpreted as an absolute rather than merely as a relative effect if geographic spillovers are absent. In Table 6 we test for regional spillovers in two ways. In column 2 we include a variable capturing mining booms in neighboring districts.[33] In column 3 we add a variable capturing mining booms in other districts that belong to the same province. This captures potential spillovers due to redistribution of mining rents more directly, because Indonesia allocated 32% of mining royalties (but none of the land rents) to non-producing districts in the same province after decentralization in 1999.[34] The first result is that none of the spillover interactions is significant and their inclusion does not change the main results. The labor market effects are thus highly localized overall and the spillover effects may be weak. However, it is still possible that two opposing spillover mechanisms cancel each other out: a neighboring labor-intensive mining boom may draw out labor resulting in a loss of local manufacturing employment, but at the same time lead to a positive spending effect via redistribution. To disentangle these possibilities, we repeat the same specification in columns 4-6 for the years after 1999. If a spillover effect from a positive spending effect is important then it should be more visible from 2000 onwards than during 1990-1999, while the negative labor reallocation effect arguably remains equally relevant throughout. Thus, if redistribution to non-producing districts matters, the coefficients in columns 4-6 should be pushed upwards. However,

[33] We treat all neighbors as one single district and compute its 1990 mineral resources per square mile and price shock realizations analogously to the single-district computation.

[34] Since revenue sharing occurs independently of the local mining methods we do not include an interaction with the labor-intensive mining dummy in column 3.

we find that spillover effects are similarly non-existent after 1999. Although royalties were re-allocated after 1999, over time other national redistribution funds were adjusted to compensate for this, potentially resulting in a small net redistribution effect across districts.[35] In the absence of empirical evidence for spillovers, we conclude that we capture an absolute effect rather than a relative effect of local mining booms, and that crowding out and reallocation takes place between sectors as opposed to between districts.

[**Table 6 about here**]

5.3 Robustness checks

We perform a battery of robustness tests on our main results: the relevance of the labor intensity of mining, and the crowding out effect of mining booms on more-traded goods producers. We start in Table 7, with the sample of more-traded goods producers, to evaluate if the crowding out effect of labor-intensive mining booms depends on the specific degree of labor intensity of the local mining sector and whether it is different for upstream plants. Moreover, we test for any remaining selection effects.[36] We then allow for alternative clustering, market power, mineral-specific effects, decentralization effects and re-scaling in Table 8. All of these alternative estimates support our main conclusions.

Different labor intensities, upstream plants and testing for selection effects

For reference, column 1 in Table 7 repeats the baseline result for the sample of more-traded goods producers. In column 2 we distinguish between mining booms in districts where only underground methods are applied (and mining is thus most labor intensive), and booms in districts where both underground and open-pit mining take place. As we would expect, the

[35] From 2001, natural resource revenue sharing was gradually included in the formula for fiscal capacity, which determines the gap between capacity and spending needs. This then feeds into other national transfers aimed at addressing the fiscal gap, although large discrepancies still exist. See Kaiser et al. (2006) for details.

[36] We do not report average wage effects because these are insignificant in the baseline and remain so in all robustness tests.

magnitude of the crowding-out effect is strongest when mining is most labor intensive.[37] In the Online Appendix we show that also mining wages (see Table OA2) and manufacturing plants' wage bill divided by the number of workers (see Table OA5) increase most during a boom when only underground mining is applied. Column 3 evaluates if the crowding-in effect of capital-intensive mining booms is driven by plants that are upstream to the mining sector. To do so, we use US Input-Output tables to compute a variable that captures the share of sales of a plant's industry to the mining sector, and classify plants with an above-median realization as "upstream plants". We interact our mining boom variable (and its interaction with labor-intensive mining) with this upstream dummy and include year fixed effects rather than industry-year fixed effects in order to compare plants across industries, given that the upstream indicator is defined at the industry level. The results suggest that the positive effect of a capital-intensive mining boom is almost two-thirds smaller if plants are not upstream (0.013 versus 0.031), although the positive interaction term is not precisely estimated. This suggests that the positive employment effect on more-traded goods producers near capital-intensive mines is at least partly due to plants that may start to supply more capital goods to local mines during mining booms. Additional evidence in favor of an upstream effect is provided by the interactions with labor-intensive mining, where crowding out (-0.014) is turned into crowding in (0.173) if the plant is upstream to the labor-intensive mine.[38] While the local economy is not the main output market of more-traded goods producers, the effect may arise because of lower trade costs from the mining sector's perspective.

Our baseline regression controls for plant fixed effects, for industry-times-year fixed effects, and for district-specific trends. These capture a broad set of potential unobserved confounding factors, such as sector-specific shocks, local labor market trends in a particular mining district, and plant-specific time-invariant characteristics. However, our identification still relies on the assumption that there are no remaining selection effects.

First, some plants switch four-digit industry over time and may thereby change their status as more-traded goods producer, which may be due to measurement error or caused by unobserved

[37] To put the large marginal effect at the bottom of column 2 into perspective, note that the average mineral endowment in districts that only use underground methods equals $\tilde{r_k} = 0.018$; this implies that an increase in local mineral prices by 100 log points leads to a reduction in more-traded goods producers employment by 0.018 $\times$ (-3.410) $\approx$ 6.1%. In the average underground & open-pit mining district, $\tilde{r_k} = 1.844$, such that a boom makes more-traded goods producers lose 1.844 $\times$ (-0.016) $\approx$ 3% of workers.

[38] The average effect is nonetheless negative as per column 1 because there are relatively few upstream plants in labor-intensive mining districts.

confounding factors. In column 4 we drop such plants, showing that the coefficients are robust to this change.

Second, including plant-specific trends instead of district-specific trends in column 5 does not change the results, implying that it is sufficient to capture trends at the industry and district level.

Third, another way to account for potential selection is to restrict our analysis to plants located in mining districts only, at the cost of sacrificing some external validity. Applying this in column 6 shows that the results are robust to this modification, despite the much smaller sample.

[**Table 7 about here**]

Alternative clustering, market power, mineral-specific effects, and decentralization

So far we always cluster by district, and column 1 in Table 8 again repeats the baseline result. In column 2 we allow for arbitrary correlation of the errors across both space and time, by clustering two-way on years and districts. This does not affect the main results and is consistent with the absence of evidence for spillovers. Following best practise (Cameron and Miller, 2015; Bertrand et al., 2004), we prefer clustering on districts because there are 19 years in the data and thus only 19 clusters in the time dimension. In that case the asymptotic requirements of clustering may no longer hold due to the small number of clusters. In column 3, inspired by Adão et al. (2019), we also cluster standard errors two-ways but at the district level and at the level of year-times-one-digit industry interactions (of which there are 57). The results are robust to this parsimonious way of accounting for correlated errors within sectors across districts.

Column 4 addresses market power that may invalidate exogeneity of mineral price shocks. Indonesia was the second-largest producer of tin and third-largest producer of nickel in 2009. We thus exclude the six districts that contain tin or nickel resources, but this has no effect on our results.

In column 5 we address the possibility that underground mining coincides with the mining of minerals with a higher price elasticity, even though all minerals that are mined underground (coal, gold, silver, copper and uranium) are also mined using other methods elsewhere, except uranium which only occurs once. If that were the case, then we may be capturing relatively easy to mine minerals rather than a different mining technique. To address this, we restrict the sample to districts that produce only coal or no mineral at all, such that all variation comes from the mining technique.[39] The estimated coefficients are similar to those of the main specification and remain statistically significant, supporting the conclusion that mining methods matter.

Column 6 controls for district times post-1999 fixed effects. The post-1999 period may be different because mineral prices started to trend upward – leading to more intense mining booms – which coincided with decentralization, giving districts more autonomy based on the belief that local public service delivery would improve. If that resulted in an improved business climate for manufacturing, then the baseline may overestimate the true effect of mining booms. However, the additional fixed effects do not alter the results.

In the last column 7, we re-scale our endowment variables by their standard deviation rather than their mean to further interpret the economic size of the effects. Re-scaling allows a direct comparison to a result in the literature based on US data (Allcott and Keniston, 2018), which is that as the oil price increases by 100 log points, manufacturing employment in a county with an additional oil and gas endowment of one standard deviation increases by 0.3%. After re-scaling, we find that a similarly defined boom in capital-intensive mining increases manufacturing employment by 7.7%. This larger result may reflect lower spillovers across space and higher labor mobility between manufacturing and other sectors as well as the pool of unemployed, due to a comparatively smaller degree of specialization of Indonesian manufacturing. In addition, the result displayed in Table 3 that oil and gas booms do not affect manufacturing employment in Indonesia reflects the minimal oil & gas revenue sharing with producing districts and weaker linkages to other sectors due to the mostly offshore nature of oil & gas production in the archipelago country.

[**Table 8 about here**]

[39] We choose to restrict to districts producing only coal as opposed to districts only producing any other specific mineral because this results in dropping the smallest number of mining districts from our sample.

6 Conclusion

We estimate the impact of local mining booms on manufacturing plants in Indonesia, exploiting detailed information on natural resource deposits and introducing the different degrees of labor and capital intensity that distinct mining methods entail. We present the novel result that only in districts where mining operations are relatively labor intensive, global resource price increases lead to crowding out of manufacturing employment. In line with a Corden and Neary (1982)-type model of factor reallocation with multiple districts, producers of less-traded goods pass on higher wage costs to local consumers by raising prices to avoid a contraction, but more-traded goods producers who compete on national or world markets are unable to do so and react by reducing employment. In contrast, mining booms in districts with capital-intensive mining lead to crowding *in* of more-traded goods producer employment, largely driven by a positive spending effect that is not accompanied by competition for labor with mines. From the perspective of manufacturing plants, mining booms can thus be good or bad, depending on the labor intensity of local extraction methods. This distinction helps to explain the mixed evidence on crowding-out effects in the literature.

Our estimated effects are much larger than in a developed economy such as the US, which arguably reflects low factor mobility across districts, limited geographic spillovers and relatively high labor mobility between manufacturing and other sectors due to a comparatively small degree of specialization. Since these are common characteristics of developing countries, and our data shows that labor-intensive mining is prevalent in many of them, our results arguably contain important lessons for other resource-rich developing countries.

Volatility in world commodity prices thus leads to frequent reallocation shocks between mines and manufacturing plants, but we do not find negative repercussions in terms of TFP: evidence for a productivity-related 'Dutch disease' remains elusive. However, volatility creates uncertainty and may itself have significantly dampened private investment into the manufacturing sector, at least in natural resource-rich districts. Exploring this potential issue is a promising avenue for future research.

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Main Tables

Table 1: Summary statistics

Variable	Sample	Mean	p(50)	s.d.	Min	Max	N (non-missing)
District-year data							
MRes90 × Δln(Mineral Price)	MRes90>0	0.040	0.000	0.775	-6.981	8.309	741
MRes90 × Δln(MPrice) × L-I Mining	MRes90>0, L-I Mining	0.044	0.000	0.925	-5.619	6.688	171
O&G Prod∼90 × Δln(Oil Price)	O&G Prod∼90 >0	0.049	0.000	0.708	-6.663	6.328	703
Mining Workers / Total Workers	MRes90>0	0.040	0.017	0.053	0	0.313	351
Oil&Gas Workers / Total Workers	O&G Prod∼90 >0	0.006	0.002	0.011	0	0.065	333
District data							
MRes90	MRes90>0	1	0.060	2.540	0.000	11.741	39
	MRes90>0, L-I Mining	1.235	0.045	3.099	0.000	9.450	9
O&G Prod∼90	O&G Prod∼90 >0	1	0.024	2.822	0.000	14.012	37
Plant-year data							
Δln(# Employees)	All	0.000	0	0.291	-4.705	5.281	261,020
	More-traded producers	0.002	0	0.319	-4.705	5.281	149,759
	Less traded producers	-0.003	0	0.247	-4.601	4.564	111,209
Δln(Wage Bill / #Employees)	All	0.130	0.096	0.573	-10.519	11.318	260,803
Δln(Unit Price)	All	0.051	0.051	1.913	-19.815	18.786	148,691
Δln(Revenue)	All	0.130	0.085	0.757	-7.634	7.883	261,017
Δln(TFP)	All	0.003	0.003	0.048	-0.972	0.958	172,504
$\Delta_5$ln(TFP)	All	0.013	0.013	0.065	-0.799	0.899	83,759
Plant data							
Upstream share in %	MRes90>0, more-tr. pr.	0.076	0.029	0.195	0	2.221	1,554
Mine data (global sample)							
ln(# Mine Employees)	n/a	5.992	5.979	1.416	1.099	10.727	464

Note: *MRes90* equals Mineral Resources 1990 scaled by the district's surface area and then by its average across districts with mineral resources. The variable corresponds to $\tilde{r}_k$ in our empirical specification. *L-I Mining* stands for labor-intensive mining and restricts to districts for which a positive fraction of resources is extracted or planned to be extracted by underground mining. O&G Prod∼90 equals the production of barrels of oil equivalent around 1990 scaled by the district's surface area and then by its average across districts with oil & gas production. The variable corresponds to $\widetilde{boe}_k$ in our empirical specification. The number of districts with *MRes90>0* is 39 as opposed to 40 since we are forced to treat Bangka and Belitung as one district; see the Online Data Appendix for details. *Unit Price* equals total revenue over units sold. $\Delta_5$ln(TFP) equals the change between year t and $t-5$. *Upstream share in %* equals the industry-specific percentage of direct and indirect sales to the local mining sector.

Table 2: Global mine-specific evidence on the labor intensity of different mining techniques

Dependent variable →	ln(# Mine Employees)				
Sample →	All Mines				Only UG &/or OP
	(1)	(2)	(3)	(4)	(5)
Underground Mining	0.646***				
	(0.122)				
100% Underground Mining		0.715***	0.854***	0.787***	0.669***
		(0.131)	(0.240)	(0.158)	(0.132)
Underground & Open-Pit Mining		0.489***	0.599***	0.456***	0.449***
		(0.139)	(0.159)	(0.151)	(0.129)
100% Underground Mining × High Income			-0.260		
			(0.312)		
Underground & Open-Pit Mining × High Income			-0.191		
			(0.250)		
ln(Mineral Resources)	0.280***	0.285***	0.279***	0.294***	0.291***
	(0.024)	(0.024)	(0.029)	(0.025)	(0.023)
Country FE	Yes	Yes	Yes	No	Yes
Year of Employment Info FE	Yes	Yes	Yes	No	Yes
Country-Year of Employment Info FE	No	No	No	Yes	No
Main Mineral FE	Yes	Yes	Yes	Yes	Yes
Observations (# Mines)	464	464	464	404	453
# Countries	39	39	39	23	38

Note: This table shows that underground mining is more labor intensive than other types of mining, using a cross-section of individual mines around the world for which we observe employment and the applied mining technique(s). The year as of which data are reported varies by mine, ranging from 2002 to 2011. The dependent variable is the log of the mine-specific number of employees. *100% Underground Mining* is a dummy that equals one if the mine is operated by underground mining only. *Underground & Open-Pit Mining* is a dummy that equals one if both underground and open-pit mining are applied. *High Income* equals one if 2011 GDP per capita of the country in which the mine is located is larger than the median GDP per capita across our sample of mines. *ln(Mineral Resources)* equals the log of mine-specific mineral resources in megatons. In column 5 we exclude tailings, placer mines and mines that use in-situ leaching, thereby restricting the sample to mines that use either underground or open-pit mining, or both. Standard errors in parentheses are clustered at the country level. ***Significant at 1% level; **Significant at 5% level; *Significant at 10% level.

Table 3: Mining booms and plant-level manufacturing outcomes

Dependent variable →	Δln # Employees		Δln Wage Bill / #Employees		Δln Unit Price		Δln Revenue	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mineral Resources 1990 × Δln(Mineral Price)	0.015	0.026***	0.038	-0.003	0.092	0.032	0.109**	0.062*
	(0.009)	(0.005)	(0.033)	(0.021)	(0.057)	(0.044)	(0.042)	(0.036)
Mineral Resources 1990 × Δln(Mineral Price) × Labor-intensive Mining		-0.038***		0.137***		0.199***		0.158***
		(0.006)		(0.021)		(0.045)		(0.036)
Oil&Gas Production ∼1990 × Δln(Oil Price)	0.001	0.001	-0.002	-0.002	-0.012	-0.013	0.009	0.009
	(0.001)	(0.001)	(0.003)	(0.003)	(0.013)	(0.013)	(0.008)	(0.008)
Observations	261,020	261,020	260,803	260,803	148,691	148,691	261,017	261,017
# Plants	42,210	42,210	42,196	42,196	30,055	30,055	42,210	42,210
# Districts	274	274	274	274	272	272	274	274
Marginal effect of mining boom for labor-intensive mining		-0.012***		0.133***		0.230***		0.220***
		(0.002)		(0.004)		(0.010)		(0.005)

Note: All regressions control for plant fixed effects, and include four-digit industry-times-year fixed effects and district-specific linear trends. The underlying specification is equation (2). The sample contains all formal and privately-owned manufacturing plants with at least 20 employees. The sample period is 1990-2009 in columns 1-4 and 7-8, while in columns 5-6 it is 1998-2009 due to data availability. *Mineral Resources 1990* equals mineral ore resources per square mile as of 1990 in the plant's home district, scaled by its mean across all districts with positive mineral resources in 1990 ($\tilde{r}_k$ in equation (2)). We interact this variable with a time-varying, district-specific weighted mineral price shock, *Δln(Mineral Price)*; this corresponds to $\Delta ln(MPI_{kt})$ in equation (2). The weight of each mineral's price shock equals its share in total 1990 resources. *Oil&Gas 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 (2)). *Labor-intensive Mining* is a dummy that equals one if at least one of the 1990 mineral deposits in the district is operated or planned to be operated by underground mining (which typically requires more labor 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. Standard errors in parentheses are clustered at the district level. ***Significant at 1% level; **Significant at 5% level; *Significant at 10% level.

Table 4: More-traded versus less-traded goods producers

Panel A

Sample →	More-Traded Goods Producers			
Dependent variable →	Δln # Employees	Δln Wage Bill / #Employees	Δln Unit Price	Δln Revenue
	(1)	(2)	(3)	(4)
Mineral Resources 1990 × Δln(Mineral Price)	0.031**	-0.022	0.015	0.060*
	(0.015)	(0.031)	(0.059)	(0.035)
Mineral Resources 1990 × Δln(Mineral Price) × L-I Mining	-0.049***	-0.004	0.021	-0.069*
	(0.017)	(0.034)	(0.063)	(0.037)
Oil&Gas Production ∼1990 × Δln(Oil Price)	0.000	0.001	-0.009	0.010*
	(0.001)	(0.004)	(0.026)	(0.005)
Observations	149,759	149,620	82,912	149,756
# Plants	24,672	24,662	16,947	24,672
# Districts	259	259	258	259
Marginal effect of mining boom for labor-intensive mining	-0.018***			-0.009
	(0.006)			(0.011)

Panel B

Sample →	Less-Traded Goods Producers			
Dependent variable →	Δln # Employees	Δln Wage Bill / #Employees	Δln Unit Price	Δln Revenue
	(1)	(2)	(3)	(4)
Mineral Resources 1990 × Δln(Mineral Price)	0.023***	0.012	0.041	0.061
	(0.003)	(0.009)	(0.041)	(0.039)
Mineral Resources 1990 × Δln(Mineral Price) × L-I Mining	-0.025***	0.190***	0.275***	0.264***
	(0.004)	(0.011)	(0.043)	(0.040)
Oil&Gas Production ∼1990 × Δln(Oil Price)	0.002	-0.006**	-0.017**	0.008
	(0.001)	(0.003)	(0.008)	(0.012)
Observations	111,209	111,132	65,746	111,209
# Plants	19,802	19,798	14,386	19,802
# Districts	270	270	264	270
Marginal effect of mining boom for labor-intensive mining	-0.002	0.202***	0.316***	0.325***
	(0.002)	(0.006)	(0.015)	(0.008)

Note: All regressions control for plant fixed effects, and include four-digit industry-times-year fixed effects and district-specific linear trends. This table shows the effect of local mining booms on the annual change in manufacturing outcomes for producers of more-traded versus producers of less-traded goods. The underlying specification is equation (2). The sample contains formal and privately-owned manufacturing plants with at least 20 employees that are more-traded goods producers in Panel A, and those that are less-traded goods producers in Panel B. The sample period is 1990-2009 in columns 1, 2 and 4 and 1998-2009 in column 3, due to data availability. The marginal effect at the bottom of the table equals the sum of the first two coefficients in the given column. Standard errors in parentheses are clustered at the district level. ***Significant at 1% level; **Significant at 5% level; *Significant at 10% level.

Table 5: Plant-level Total Factor Productivity

Dependent variable →	Δln(TFP)			$\Delta_5$ln(TFP)		
Sample →	All Plants	More-Traded Producers	Less-Traded Producers	All Plants	More-Traded Producers	Less-Traded Producers
	(1)	(2)	(3)	(4)	(5)	(6)
Mineral Resources 1990 × Δln(Mineral Price)	-0.000	-0.003*	0.003			
	(0.002)	(0.002)	(0.004)			
Mineral Resources 1990 × Δln(Mineral Price) × Labor-intensive Mining	0.012***	0.006***	0.014***			
	(0.002)	(0.002)	(0.004)			
Mineral Resources 1990 × mean[Δln(Mineral Price)]				0.021***	0.009	0.026***
				(0.008)	(0.010)	(0.009)
Mineral Resources 1990 × mean[Δln(Mineral Price)] × Labor-intensive Mining				0.300***	0.348***	0.031
				(0.061)	(0.099)	(0.161)
Observations	172,504	97,028	75,398	83,759	47,219	36,465
Marginal effect of mining boom for labor-intensive mining	0.012***	0.003***	0.017***	0.321***	0.356***	
	(0.000)	(0.001)	(0.000)	(0.061)	(0.098)	

Note: All regressions control for plant fixed effects, and include four-digit industry-times-year fixed effects and district-specific linear trends. This table shows the effect of local mining booms on the annual change in plant-level total factor productivity (TFP). Our sample contains all formal and privately-owned manufacturing plants with at least 20 employees. In columns 1-3, the dependent variable is the change in TFP between year t and $t-1$. The underlying specification is equation (2), the sample period 1990-2009. In columns 4-6, the dependent variable is the change in TFP between year 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. The oil and gas boom variable is always included but not shown. Standard errors in parentheses are clustered at the district level. ***Significant at 1% level; **Significant at 5% level; *Significant at 10% level.

Table 6: Regional spillovers and revenue sharing

Dependent variable →	$\Delta\ln$(# Employees)					
Specification →	Baseline	Booms nearby	Booms in same province	Baseline, after 1999	Booms nearby, after 1999	Booms in same province, after 1999
	(1)	(2)	(3)	(4)	(5)	(6)
Mineral Resources 1990 × $\Delta\ln$(Mineral Price)	0.026***	0.023***	0.025***	0.026***	0.023***	0.025***
	(0.005)	(0.007)	(0.006)	(0.007)	(0.009)	(0.007)
Mineral Resources 1990 × $\Delta\ln$(Mineral Price) × Labor-intensive Mining	-0.038***	-0.036***	-0.036***	-0.044***	-0.041***	-0.043***
	(0.006)	(0.006)	(0.006)	(0.007)	(0.008)	(0.008)
Neighbors' Mineral Resources 1990 × $\Delta\ln$(Neighbors' Mineral Price)		0.022			0.024	
		(0.026)			(0.026)	
Neighbors' Mineral Resources 1990 × $\Delta\ln$(N'bors' Mineral Price) × N'bors' L-I Mining		-0.018			-0.019	
		(0.027)			(0.028)	
OthersProv Mineral Resources 1990 × $\Delta\ln$(OthersProv Mineral Price)			0.003			0.002
			(0.003)			(0.003)
Observations	261,020	259,840	261,020	152,408	151,879	152,408
Marginal effect of mining boom in labor-intensive mining...:						
...in own *district (when no neighboring mining boom (in cols. 2 & 5); when no mining boom in other districts of province (in cols. 3 & 6))*	-0.012***	-0.012***	-0.012***	-0.018***	-0.018***	-0.018***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
...in neighboring *districts (when own Mineral Resources 1990=0 or no own price shock)*		0.004			0.005	
		(0.007)			(0.009)	

Note: All regressions control for plant fixed effects, and include four-digit industry-times-year fixed effects and district-specific linear trends. In this table we study potential spillover effects of mining booms to other districts. The dependent variable is the plant-specific log yearly change in employment. Column 1 repeats the results of our baseline specification (see Table 3, column 2). In column 2 we control for mining booms/busts in neighboring districts, where we treat all Neighbors as one district and compute its mineral resources and price shock analogously to the single-district case. Since a number of districts are islands, they do not have Neighbors according to our definition. This explains why the sample size in column 2 is slightly smaller than in column 1. In column 3 we control for the average mining boom/bust in other districts of the same province. Columns 4-6 repeat the specifications of columns 1-3, estimated over the period 2000-2009. The oil and gas boom variable, as well as its adapted versions for Neighbors and districts in the same province, respectively, are always included but not shown. Standard errors in parentheses are clustered at the district level. ***Significant at 1% level; **Significant at 5% level; *Significant at 10% level.

Table 7: Robustness I: Degree of labor intensity, upstream plants and testing for selection effects

Sample →	More-Traded Goods Producers					
Dependent variable →	Δln(# Employees)					
Specification →	Baseline	Different labor intensities	Upstream controls	No industry switchers	Plant-specific trends	Only mining districts
	(1)	(2)	(3)	(4)	(5)	(6)
Mineral Resources 1990 × Δln(Mineral Price)	0.031**	0.031**	0.013***	0.036**	0.031**	0.035***
	(0.015)	(0.015)	(0.004)	(0.018)	(0.013)	(0.011)
Mineral Resources 1990 × Δln(Mineral Price) × Labor-intensive Mining	-0.049***		-0.027***	-0.053***	-0.052***	-0.058***
	(0.017)		(0.005)	(0.018)	(0.014)	(0.014)
Mineral Resources 1990 × Δln(Mineral Price) × Pure labor-intensive Mining		-3.441***				
		(0.279)				
Mineral Resources 1990 × Δln(Mineral Price) × Mixed labor-intensive Mining		-0.046***				
		(0.017)				
Mineral Resources 1990 × Δln(Mineral Price) × Upstream			0.033			
			(0.026)			
Mineral Resources 1990 × Δln(Mineral Price) × Upstream × Labor-intensive Mining			0.154***			
			(0.041)			
Observations	149,759	149,759	149,858	94,922	145,884	6,510
Marginal effect of mining boom for labor-intensive mining	-0.018***	see	see	-0.017***	-0.021***	-0.022***
	(0.006)	below	below	(0.006)	(0.009)	
Marginal effect of mining boom for pure labor-intensive mining		-3.410***				
		(0.278)				
Marginal effect of mining boom for mixed labor-intensive mining		-0.016**				
		(0.006)				

*Marginal effect of mining boom on non-upstream plants for: capital-intensive mining: 0.013*** (0.004) ; labor-intensive mining: -0.014*** (0.006)*
*Marginal effect of mining boom on upstream plants for: labor-intensive mining: 0.173*** (0.033)*

Note: All regressions control for plant fixed effects, and include four-digit industry-times-year fixed effects and district-specific linear trends. This table shows the results of robustness checks on the baseline result. The dependent variable is the plant-specific log yearly change in employment. In column 2 we split labor-intensive mining districts into those in which *all* 1990 mineral resources are operated or planned to be operated by underground mines, and those in which both underground and open-pit mining are carried out or planned. In column 3 *Upstream* equals one if the share of sales of the plant's industry to the mining sector exceeds the median share across industries. Column 4 drops all plants that ever change four-digit industry. In column 5 we include a dummy for each plant into the specification, replacing the district dummies and controlling for differential linear time trends at the plant level. In column 6 we only include mining districts, i.e. those with positive mineral resources in 1990. The oil & gas boom variable is always included but not shown. Standard errors in parentheses are clustered at the district level. ***Significant at 1% level; **Significant at 5% level; *Significant at 10% level.

Table 8: Robustness II: Alternative clustering, market power, mineral-specific effects, decentralization and re-scaling

Sample →	More-Traded Goods Producers						
Dependent variable →	Δln(# Employees)						
Specification →	Baseline	Two-way clustering I	Two-way clustering II	Excluding Tin & Nickel	Same Mineral	After 1999 FE	AK2018 scaling
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mineral Resources 1990 × Δln(Mineral Price)	0.031**	0.031*	0.031*	0.031**	0.017***	0.031**	0.077**
	(0.015)	(0.015)	(0.016)	(0.016)	(0.003)	(0.015)	(0.039)
Mineral Resources 1990 × Δln(Mineral Price) × L-I Mining	-0.049***	-0.049***	-0.049***	-0.049***	-0.033***	-0.049***	-0.122***
	(0.017)	(0.014)	(0.018)	(0.017)	(0.007)	(0.017)	(0.041)
Observations	149,759	149,759	149,759	149,049	143,468	149,759	149,759
Marginal effect of mining boom for labor-intensive mining	-0.018***	-0.018**	-0.018***	-0.018***	-0.016***	-0.018***	-0.045***
	(0.006)	(0.006)	(0.002)	(0.006)	(0.006)	(0.006)	(0.014)

Note: All regressions control for plant fixed effects, and include four-digit industry-times-year fixed effects and district-specific linear trends. This table shows the results of further robustness checks and of a rescaling exercise. The dependent variable is the plant-specific log yearly change in employment. In column 2 we cluster standard errors at both the district and year and in column 3 we cluster at both the district and year × one-digit industry interactions; in all other columns, we cluster standard errors at the district level as in our main specification. In column 4 we drop the six districts that contained tin or nickel resources in 1990. In column 5 we restrict our sample to those districts that had only one type of mineral resource in 1990 (coal) and those districts that had no mineral resources in 1990. This implies dropping 33 districts from our sample. In column 6 we include a full set of district times post-1999 dummies to control for heterogeneous decentralization effects across districts. In column 7 we scale our endowment variables by their standard deviation instead of their mean to make our results comparable to those of Allcott and Keniston (2018). The oil & gas boom variable is always included but not shown. ***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

September 8, 2020

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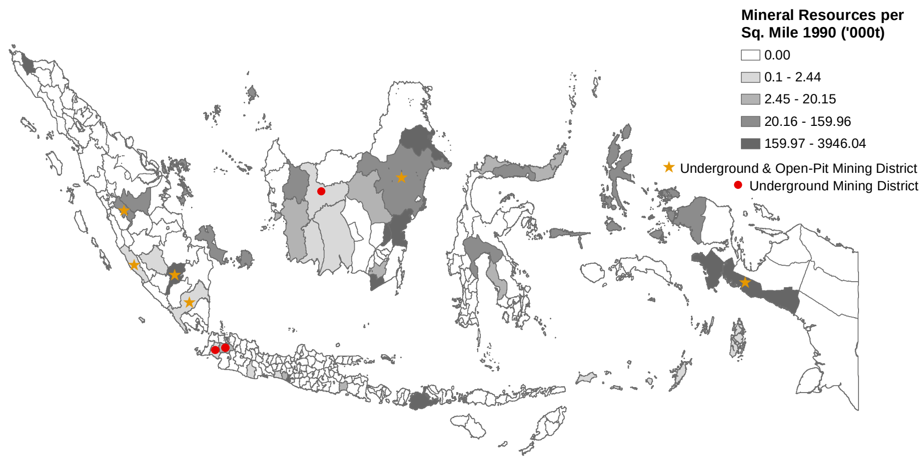
OA1 Figures and Additional Results

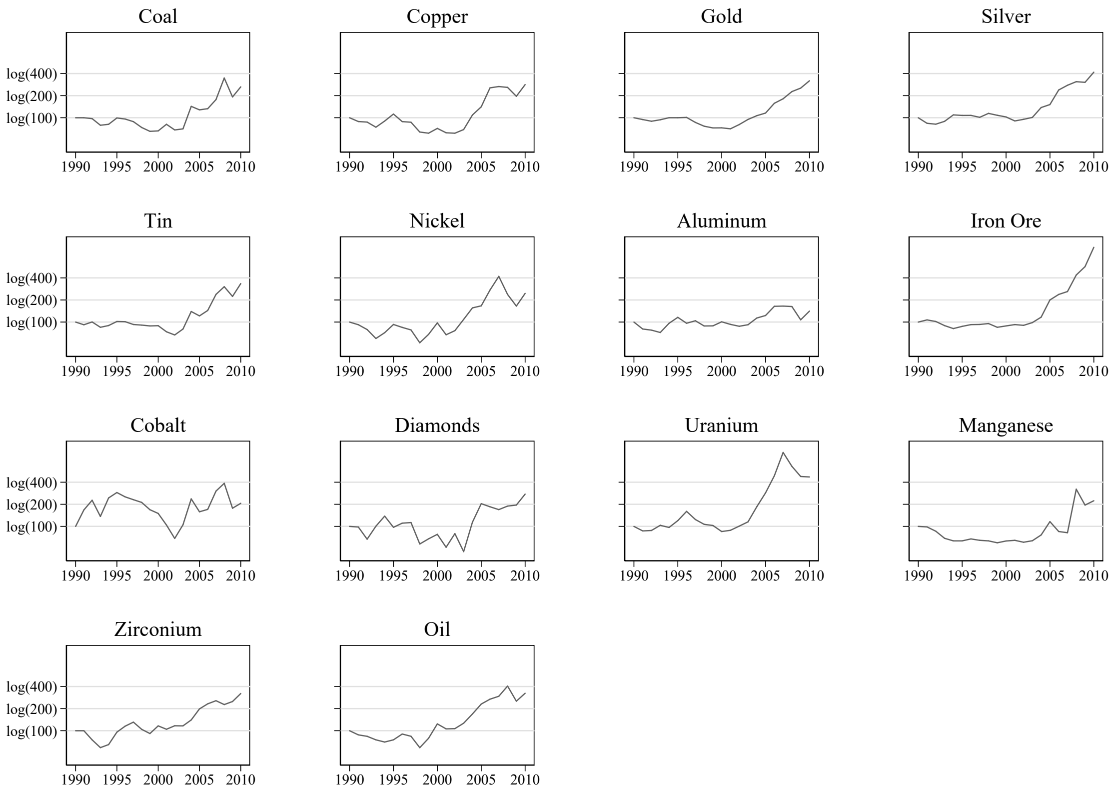
OA1.1 Figures

Figure 1: Geographic distribution of minerals, oil & gas and manufacturing plants



Note: Mineral resources and oil & gas production are organized in quartiles based on positive realizations, while plant density is organized in quintiles. Plant density is computed as simple average across the years 1990-2009.

Figure 2: Prices of Indonesian minerals and the oil price, 1990=ln(100)



Note: This figure shows the log of an indexed price series ($P_{1990} = ln(100)$) of all minerals that had been found in Indonesia by 1990, as well as the indexed oil price. Minerals are arranged from top left to bottom right based on their share in total mineral resources, and oil is displayed last. See Section OA2 for the individual price series sources.

OA1.2 Resources summary statistics by province (Table OA1)

Table OA1: Additional summary statistics: Natural resource endowments and mining 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	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				

Note: *Mining Districts* are those with positive 1990 mineral resources; *Oil & Gas Districts* are those with positive oil and/or gas production around the year 1990. *Mineral Ore Resources /Area 1990* indicates mineral ore resources per district in thousand tons per square mile in 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. *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. The indicated number of mining districts is 39 instead of 40 since we are forced to treat Bangka and Belitung as one district; see Section OA2.

OA1.3 World-price elasticity of mining output and mining wages in boom times (Table OA2)

Table OA2 analyzes how the Indonesian mining sector responds to a change in global mineral prices. In Panel A we study the mine-level elasticity of ore production to a change in the price of the produced mineral(s), using annual production figures over 1990-2009 for a sub-sample of Indonesian mines for which data are available in the *RMD* database.[40] We regress the log of one plus ore production in megatons on the log price of the produced mineral(s), control for mine and year fixed effects and cluster standard errors at the district level.[41] As in our baseline analysis, we normalize prices by the 1990-price before taking logs. The results show that mines significantly increase ore production by around 33% when the price of the produced mineral(s) rises by 100 log points. Columns 2 and 3 show that this positive effect holds across different extraction techniques that imply different labor intensities.

In Panel B we use annual data on wages paid by the Indonesian mining sector from the labor force survey SAKERNAS (see Section OA2 for details) to corroborate the claim that mining wages respond to mining booms. We regress the change in the log of the typical monthly wage received by a mining worker on the mining boom variable used in our main analysis, as well as our labor-intensity interactions. We control for year fixed effects, include district dummies to capture district-level trends, and cluster standard errors at the district level. The sample period is 2007-2015 since data are representative at the district level from 2007 onwards, and we have data until 2015. Column 2 shows that labor-intensive mines (which use underground techniques) significantly raise wages during a mining boom. In contrast, the baseline of open-pit mines, which are rather capital intensive in production, do not raise wages to increase production. Column 3 shows that the wage effect is strongest for districts in which all mines exclusively apply labor-intensive (underground) methods. Given that for the average pure labor-intensive mining district *Mineral Resources 1990* $= 0.018$, the reported marginal effect implies that mines in such districts raise the wage by $0.018 \times 15.292 \approx 27\%$ as local mineral prices rise by 100 log points.

[40] For a given mine, we only consider years that lie within the opening year and closing year (including those years) as reported in our data. We disregard mines that do not produce at all within this period.

[41] Table OA8 reports descriptive statistics. We apply a within-transformation rather than take first differences to avoid losing observations, given that the panel is unbalanced. For mines that produce multiple minerals we use a weighted price, using a mineral's share in total resources as weight; see Section OA2 for details.

Table OA2: Response of mining sector to changes in mineral prices

Panel A

Dependent variable →	ln(Ore Production + 1)		
Unit of Observation →	Mine-year		
	(1)	(2)	(3)
ln(Price of produced mineral)	0.335***	0.337***	0.346***
	(0.093)	(0.093)	(0.099)
ln(Price of produced mineral) × Labor-intensive mining		-0.190	
		(0.168)	
ln(Price of produced mineral) × Pure labor-intensive mining			0.024
			(0.135)
ln(Price of produced mineral) × Mixed labor-intensive mining			-0.300
			(0.266)
Year FE	Yes	Yes	Yes
Mine FE	Yes	Yes	Yes
Observations	533	533	533
# Districts	29	29	29
# Mines	73	73	73

Panel B

Dependent variable →	Δln(Mining Wage)		
Unit of Observation →	District-year		
	(1)	(2)	(3)
Mineral Resources 1990 × Δln(Mineral Price)	-0.001	-0.023	-0.022
	(0.021)	(0.018)	(0.017)
Mineral Resources 1990 × Δln(Mineral Price) × Labor-intensive mining		0.066***	
		(0.014)	
Mineral Resources 1990 × Δln(Mineral Price) × Pure labor-intensive mining			15.314***
			(4.083)
Mineral Resources 1990 × Δln(Mineral Price) × Mixed labor-intensive mining			0.066***
			(0.014)
Year FE	Yes	Yes	Yes
Linear district trends	Yes	Yes	Yes
Observations	260	260	260
# Districts	35	35	35
Marginal effect of mining boom for labor-intensive mining		0.042***	
		(0.011)	
Marginal effect of mining boom for pure labor-intensive mining			15.292***
			(4.087)
Marginal effect of mining boom for mixed labor-intensive mining			0.043***
			(0.011)

Note: In Panel A we regress the log of one plus mine-level annual mineral ore production in megatons on the log normalized price (P_{1990}=100) of the produced mineral(s), between 1990 and 2009. Production data are from the *RMD* database. In Panel B the dependent variable is the change in the log of annual district-specific wages paid by the mining sector, from the labor force survey SAKERNAS, observed between 2007 and 2015. *Pure labor-intensive mining* is a dummy that equals one if resources are mined with underground techniques only. *Mixed labor-intensive mining* equals one if both underground and open-pit mining are applied. The difference-in-difference specification in Panel B absorbs district fixed effects. Standard errors in parentheses are clustered at the district level. ***Significant at 1% level; **Significant at 5% level; *Significant at 10% level.

OA1.4 Labor intensity of mining techniques (Tables OA3 and OA4)

Evidence using labor force survey data

We use data from Indonesia's labor force survey (SAKERNAS) and data on district population to further test the relative labor intensity of different mining techniques, and show that underground mining is more labor intensive than other types of mining, not only on a global scale but also in Indonesia.

SAKERNAS provides an estimate of the number of mining workers in each district-year between 2007 and 2015.[42] We pool the annual data, use district-year-specific log mining employment as our dependent variable and regress it on mining technique dummy variables. In order to control for a district's mining intensity and compare districts with similarly-sized mines, we also include the district's total 1990 mineral resources, scaled by its average across districts with positive mineral endowment (but not by district size). We further include year fixed effects and cluster standard errors at the district level. The results in column 1 of Table OA3 suggest that the number of mining workers in underground mining districts is 114% larger than in non-underground mining districts with the same mining intensity. Column 2 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 occur. In column 3 we replace year fixed effects by province-year fixed effects to account for differential regional wages and other labor-market characteristics. The coefficient on underground and open-pit mining is now statistically significant (and remains positive), but the ranking in terms of labor intensity is preserved.

In column 4 we test our hypothesis that oil & gas extraction is less labor intensive than mining. The dependent variable is the log sum of the number of mining *and oil & gas* workers in a given district. We pool the annual data between 2007 and 2015, include the district's total 1990 mineral resources, and additionally include its oil & gas production around 1990. Both variables are scaled by their respective average across districts with positive realizations (but not by district size). The results suggest that a district with two times the average 1990 mineral resources employs 39% more mining and oil & gas workers than a district with average 1990 mineral resources. In contrast, a district with two times the average 1990 oil & gas production employs only 7% more mining and oil & gas workers. This smaller coefficient cannot be explained

[42] For very few district-years, SAKERNAS does not report data – see Section OA2 for details.

by a difference in the overall relevance of mining compared to oil & gas extraction: an inspection of Indonesia's national accounts reveals that the average mining district only contributed 5% more to total GDP than the average oil & gas district over 2007-2014. This corroborates that oil & gas extraction is less labor intensive than mining.

Table OA3: Indonesian district-level evidence on the labor intensity of mining methods

Dependent variable →	ln(# District Mining Workers)			ln(# District Mining and Oil & Gas Workers)
	(1)	(2)	(3)	(4)
Underground Mining	1.143**			
	(0.473)			
100% Underground Mining		2.344***	1.953***	
		(0.283)	(0.278)	
Underground & Open-Pit Mining		0.242	1.212*	
		(0.548)	(0.640)	
Total Mineral Resources 1990	0.288**	0.381***	0.169	0.387***
	(0.133)	(0.132)	(0.121)	(0.086)
Total Oil&Gas Production ∼1990				0.072***
				(0.018)
Year FE	Yes	Yes	No	Yes
Province-Year FE	No	No	Yes	No
Observations	1,207	1,207	1,196	1,484
# Districts	247	247	243	262

Note: Data come from Indonesia's labor force survey data (SAKERNAS), for the period 2007-2015. The unit of observation is a district-year. In columns 1-3 the dependent variable is the log of an approximation of the number of mining workers, while in column 4 it is the log of an approximation of the number of mining and oil & gas workers. *Underground Mining* is a dummy that equals one if at least one of the 1990 deposits in the district is operated or planned to be operated by underground mining. *100% Underground Mining* is a dummy that equals one if *all* 1990 deposits are 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 are applied or planned to be applied to extract the district's 1990 mineral resources. *Total Mineral Resources 1990* equals mineral ore resources as of 1990 scaled by its mean across all districts with positive resources (but not by the district's surface area). *Total Oil&Gas Production ∼1990* equals the production of barrels of oil equivalent around the year 1990, scaled by its mean across producing districts (but not by the district's surface area). Standard errors in parentheses are clustered at the district level. ***Significant at 1% level; **Significant at 5% level; *Significant at 10% level.

Evidence using population data

An analysis of district-specific (working-age) population data over time offers another opportunity to test whether underground mining is more labor intensive than open-pit mining. The underlying idea is that if indeed underground mining is more labor intensive, we would also expect a stronger labor force response to a booming mining sector that employs more labor, relative to other mining districts. Analyzing population data also sheds light on the overall degree of labor mobility in Indonesia following local mining booms. If labor mobility is high, then there is less scope for upward wage pressure during a boom.

District-level population over time is available from the IPUMS-International database of the *Minnesota Population Center* (MPC).[43] It includes the micro-data from the 2000 and the 2010 Indonesian population census, as well as the 1995 and 2005 SUPAS inter-census population surveys, from Indonesia's national statistical agency (BPS).[44] We use these data to compute total population and working-age population (age 15-65) for the 1990-districts. Since population data are only collected every five years we study the change in log population during four periods: 1990-1995, 1995-2000, 2000-2005, and 2005-2010. In columns 1 and 2 of Table OA4 we focus on total population while in column 3 we look at the working-age population, which is unaffected by changes in fertility and less affected by changes in mortality. We regress the dependent variables on the mining boom variable and the labor-intensity interactions, with the difference that the change in mineral prices is computed as the simple average of all five annual price changes. We control for year fixed effects, initial population, differential trends across districts with varying mining intensity and districts with heterogeneous oil and gas intensity, and (in columns 2-3) differential trends across districts with varying labor intensity in the mining sector. Standard errors are clustered at the district level.

The results suggest that while mining booms spur immigration overall, labor mobility dur-

[43] See: `https://international.ipums.org/international/`

[44] While annual population data would be preferred and is also reported by 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 and are not corrected ex-post using census or inter-census data. The IPUMS 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 in 2004. For 1995, data are missing for 12 provinces: 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 Papua) (2), and Maluku (2). For 1990, population data are missing for one district.

ing mining booms clearly depends on local extraction methods. When mining is more capital intensive, booms do not affect population, and nor do oil & gas booms. When mining is more labor intensive, population significantly increases in boom times, although the magnitude of the estimates suggests that labor mobility across districts as a response to mining booms is not large. Specifically, the marginal effect at the bottom of column 2 indicates that if local mineral prices rise by 100 log points in each year over a period of five years, then district population increases by 6%, in the district with average mineral resources and where underground mining occurs. Column 3 shows that working-age population rises by 4.8% during such a sustained labor-intensive mining boom. The results confirm that underground mining is most labor intensive.

Table OA4: Mining booms and population growth

Dependent variable →	$\Delta_5$ln(Population)		$\Delta_5$ln(Working-age Population)
	(1)	(2)	(3)
Mineral Resources 1990 × mean[Δln(Mineral Price)]	0.040**	-0.006	-0.006
	(0.020)	(0.033)	(0.030)
Mineral Resources 1990 × mean[Δln(Mineral Price)] × L-I Mining		0.066*	0.054*
		(0.033)	(0.030)
Oil&Gas Production ~1990 × mean[Δln(Oil Price)]	-0.027	-0.029	-0.030
	(0.038)	(0.038)	(0.042)
ln(Population 1990)	-0.026***	-0.027***	
	(0.009)	(0.009)	
ln(Working-age Population 1990)			-0.026***
			(0.009)
Observations	941	941	941
# Districts	280	280	280
Marginal effect of mining boom for labor-intensive mining=1		0.060***	0.048***
		(0.017)	(0.017)

Note: *L-I Mining* equals *Labor-intensive mining*. *mean[Δln(Mineral Price)]* equals the simple average of the five annual log price shocks. The unit of observation is a district-period, and the dependent variable is the change in log population across the periods 1990-1995, 1995-2000, 2000-2005 and 2005-2010. In columns 1-2 we analyze changes in total population, while in column 3 we focus on changes in working-age population. All specifications contain dummies for the years 2000, 2005 and 2010, and the difference-in-difference specification absorbs district fixed effects. We also include the linear trend controls *Mineral Resources 1990*, *Oil&Gas Production ~1990* and (in columns 2-3) *Labor-intensive Mining*$_k$ and [*Mineral Resources 1990* × *Labor-intensive Mining*$_k$], but do not show their coefficients. Standard errors in parentheses are clustered at the district level. ***Significant at 1% level; **Significant at 5% level; *Significant at 10% level.

OA1.5 Splitting labor-intensive mining into pure underground and mixed mining (Table OA5)

Sections 5.1 and OA1.4 showed that underground mining is more labor intensive than other methods, and that mining is most labor intensive in districts in which all mines only use underground methods. In Table OA5 we repeat Table 3 using the same sample of all plants and add separate interactions for pure and mixed labor-intensive mining methods, to gauge whether this finer distinction also translates into different effects on manufacturing-plant outcomes. The first row still captures the effect of capital-intensive mining booms and is thus identical to the even-numbered columns in the first row in Table 3. We find indeed that all interaction coefficients are much larger in absolute magnitude for pure labor-intensive mining. While these coefficients seem very large, they represent the effects for an endowment of *Mineral Resources 1990* $= 1$, while the average pure labor-intensive mining district has *Mineral Resources 1990* $= 0.018$. The key take-away is that if pure underground mines were as big as the average mine, then the labor market effects would be much larger as well.

Table OA5: Pure labor-intensive mining versus mixed labor-intensive mining

Dependent variable →	Δln # Employees	Δln Wage Bill / #Employees	Δln Unit Price	Δln Revenue
	(1)	(2)	(3)	(4)
MinRes 1990 × Δln(Mineral Price)	0.026***	-0.003	0.032	0.062*
	(0.005)	(0.021)	(0.044)	(0.036)
MinRes 1990 × Δln(Mineral Price) × Pure L-I mining	-2.079***	1.361**	15.246***	0.985
	(0.185)	(0.536)	(2.494)	(0.716)
MinRes 1990 × Δln(Mineral Price) × Mixed L-I mining	-0.037***	0.136***	0.196***	0.158***
	(0.006)	(0.021)	(0.044)	(0.036)
Observations	261,020	260,803	148,691	261,017
Marginal effect of pure labor-intensive mining boom	-2.053***	1.357**	15.278***	
	(0.185)	(0.536)	(2.494)	
Marginal effect of mixed labor-intensive mining boom	-0.011***	0.133***	0.228***	0.220***
	(0.002)	(0.004)	(0.009)	(0.005)

Note: *MinRes 1990* equals *Mineral Resources 1990*. *L-I mining* equals *labor-intensive mining*. All regressions control for plant fixed effects, four-digit industry-times-year fixed effects, and district-specific linear trends. *Pure labor-intensive mining* equals one for districts where only underground methods are used or planned in all deposits in 1990. *Mixed labor-intensive mining* equals one for districts where both underground and open-pit methods are used or planned in 1990. The sample contains all privately-owned manufacturing plants with 20 or more employees, over 1990-2009. The oil & gas boom variable is included but not shown. Standard errors in parentheses are clustered at the district level. ***Significant at 1% level; **Significant at 5% level; *Significant at 10% level.

OA1.6 Interacting with more-traded goods producer dummy (Table OA6)

As a robustness check on the results of Table 4, we restrict the sample to districts without mineral resources and districts with labor-intensive mining, and interact our mining boom dummy with the more-traded goods producer dummy. This allows a more direct test of the effect of labor-intensive mining booms on more- versus less-traded good producers without including a four-tuple interaction term. The downside of this specification is that it loses some external validity compared to the estimate of Table 4, but the benefit is that we can control for district-times-year fixed effects, and thus control for all observed and unobserved effects that are district-year specific (such as the state of the local labor market).

Since we thus drop capital-intensive mining districts, the coefficient on *Mineral Resources 1990* $\times$ Δ*ln(Mineral Price)* now indicates the effect of a *labor*-intensive mining boom, for *less*-traded goods producers. The odd-numbered columns of the first row in Table OA6 are thus comparable to the last row of Panel B in Table 4 (the row with the marginal effects), and indeed show nearly identical coefficients. Similarly, the coefficient sums in the odd-numbered columns in Table OA6 are comparable to the last row in Panel A of Table 4. The latter comparison shows that the crowding-out effect is stronger when restricting the sample by dropping capital-intensive mining districts, despite finding some upward pressure on prices.

Adding district-times-year fixed effects in the even-numbered columns, the results show that, compared to less-traded goods producers, a mining boom results in less employment growth, less average wage growth, less price and less output growth for more-traded goods producers. The similarity between the coefficients in the odd- and even-numbered columns suggests that the set of fixed effects and trends included in our baseline specification is sufficient to absorb confounding factors at the district-year level.

Table OA6: Interacting with more-traded goods producers in a sample of labor-intensive and non-mining districts

Sample →	Districts with underground mining or no mining							
Dependent variable →	Δln #Employees		Δln Wage Bill / #Employees		Δln Unit Price		Δln Revenue	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mineral Resources 1990 × Δln(Mineral Price)	0.003		0.205***		0.317***		0.331***	
	(0.002)		(0.006)		(0.012)		(0.007)	
Mineral Resources 1990 × Δln(Mineral Price) × More-Traded Goods Producers	-0.046***	-0.037***	-0.216***	-0.213***	-0.255***	-0.255***	-0.352***	-0.372***
	(0.007)	(0.008)	(0.015)	(0.013)	(0.019)	(0.020)	(0.012)	(0.016)
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Linear district trends	Yes	No	Yes	No	Yes	No	Yes	No
District-Year FE	No	Yes	No	Yes	Yes	No	Yes	No
Observations	250,952	250,646	250,751	250,445	143,052	142,882	250,949	250,643
Marginal effect of labor-intensive *mining boom for:*								
...less-traded goods producers	0.003		0.205***		0.317***		0.331***	
	(0.002)		(0.006)		(0.012)		(0.007)	
...more-traded goods producers	-0.043***		-0.011		0.062***		-0.021**	
	(0.006)		(0.012)		(0.018)		(0.010)	

Note: In this table we use an alternative specification which allows a more direct test of the differential effect of labor-intensive mining booms on more-traded versus less-traded goods producers: We restrict the sample to districts with either no mineral resources or mining districts in which labor-intensive techniques are applied, as of 1990. In other words, we drop capital-intensive mining districts such that the coefficient on *Mineral Resources 1990* × Δ*ln(Mineral Price)* now indicates the effect of a labor-intensive mining boom. All regressions control for plant fixed effects and include four-digit industry-times-year fixed effects. Columns 1, 3, 5 and 7 also include district dummies capturing differential district-specific linear trends; in columns 2, 4, 6 and 8 we replace these by a full set of district-year dummies, which control for time-varying and district-specific factors that affect the state of manufacturing outcomes relative to the previous year. Standard errors in parentheses are clustered at the district level. ***Significant at 1% level; **Significant at 5% level; *Significant at 10% level.

OA1.7 Mining booms and local expenditure and infrastructure (Table OA7)

In Table OA7 we study the impact of a mining boom on local public expenditure and infrastructure. In Panel A we use district-level expenditure data provided by Indonesia's Ministry of Finance. Expenditure is indicated in current million Rupiahs and reported in two main categories: routine expenditure and development expenditure. We focus on the latter as well as its three most important sub-categories from the perspective of (more-traded) manufacturing plants, namely expenditure on: "Industry Sectors"; "Trade, Regional Business Development, Regional Finance and Cooperatives"; and the "Transportation Sector". We regress the change in the log of these variables on our standard mining boom variable, control for year fixed effects and differential trends across districts with varying mining intensity, and cluster standard errors at the district level. The sample period is 2000-2004 since before 2000 the reporting period was April 1 – March 31 and after 2004 a new reporting scheme was used.[45] We restrict the sample to districts that did not split over 1990-2005 such that we can meaningfully use the variable *Mineral Resources 1990*. The results show that an increase in mineral prices by 100 log points in the mining district with average endowments leads to an increase in overall development expenditure by 11%, expenditure on industry sectors by 27% and expenses in the category trade, regional business development, regional finance and cooperatives by 37%.[46] These developments clearly benefit manufacturing plants, and in particular more-traded goods producers.

In Panel B we use a data set of district-level scores on the availability and quality of local infrastructure taken directly from the Indonesian Regional Autonomy Watchdog *KPPOD*. A given score partly represents the results of a survey of the local business community and partly concrete and measurable indicators; see `https://www.kppod.org/` for details. We focus on the panel dimension of the data, which is available for 2002-2004. We restrict the sample to districts that did not split over 1990-2004 such that we can meaningfully use the variable *Mineral Resources 1990*. In column 1 we look at the total state of infrastructure, which captures both availability and quality, while in columns 2-3 we separate the two. We regress the change in the

[45] The use of the new reporting scheme became mandatory as of 2006, but districts could volunteer to use it already before 2006. As a consequence, the number of districts with available data decreases over time from 2000-2005, and in fact equals zero for 2005.

[46] Since for some district-years expenditure on one or more of the sub-categories is zero, the number of observations differs across columns. The results are highly robust to accounting for zero expenditure by taking the log of one plus expenditure rather than the log of expenditure when computing the dependent variable.

log of these variables on our mining boom variable, control for year fixed effects and differential trends across districts with varying mining intensity, and cluster standard errors at the district level. Column 1 shows that a rise in mineral prices by 100 log points in the mining district with average endowments leads to an improvement of local infrastructure by 5.5%. Columns 2 and 3 show that this effect is driven by an improvement in infrastructure quality, which is intuitive given the annual horizon of our analysis. In column 4 we look at a more specific variable which is particularly important for more-traded goods producers given the geography of Indonesia, namely the quality of the local seaport, and again find a positive effect of a local mining boom.

Table OA7: Mining booms and local expenditure and infrastructure

Panel A

Dependent variable →	Δln Total Development Expenditure	Δln Dev-Ex Industry Sectors	Δln Dev-Ex TradeBusFin Sector	Δln Dev-Ex Transport Sector
	(1)	(2)	(3)	(4)
Mineral Resources 1990 × Δln(Mineral Price)	0.108***	0.274**	0.374***	0.108
	(0.037)	(0.106)	(0.111)	(0.164)
Year FE	Yes	Yes	Yes	Yes
Observations	412	363	404	411
# Districts	182	169	181	182

Panel B

Dependent variable →	Δln Infra-str.	Δln Infra: Avail.	Δln Infra: Qual.	Δln Infra:Q. Seaport
	(1)	(2)	(3)	(4)
Mineral Resources 1990 × Δln(Mineral Price)	0.055***	0.009	0.103***	0.142*
	(0.017)	(0.018)	(0.017)	(0.085)
Year FE	Yes	Yes	Yes	Yes
Observations	190	190	190	190
# Districts	117	117	117	117

Note: In Panel A we use district-level expenditure data provided by Indonesia's Ministry of Finance. The sample period is 2000-2004. *TradeBusFin* stands for Trade, Regional Business Development, Regional Finance and Cooperatives. In Panel B we use district-level data on local infrastructure from the Regional Autonomy Watchdog *KPPOD*. The sample period is 2002-2004. We always include *Mineral Resources 1990* separately to capture differential linear trends across districts with varying mining intensity, but do not show the coefficient. The difference-in-difference specifications absorb district fixed effects. Standard errors in parentheses are clustered at the district level. ***Significant at 1% level; **Significant at 5% level; *Significant at 10% level.

OA1.8 Additional summary statistics (Table OA8)

Table OA8: Additional summary statistics

Variable	Sample is districts with:	Mean	p(50)	s.d.	Min	Max	N (non-missing)
District-year data							
ln(Mining Workers)	All	7.446	7.301	1.584	3.503	12.104	1,207
ln(Mining and Oil&Gas Workers)	All	7.512	7.432	1.549	3.553	12.104	1,484
$\Delta_5$ln(Population)	All	0.068	0.057	0.160	-2.224	1.088	941
	MRes90>0	0.105	0.097	0.116	-0.161	0.690	109
	MRes90>0, L-I Mining	0.115	0.092	0.156	-0.161	0.690	30
Δln(Mining Wage)	All	0.066	0.048	0.369	-1.669	1.352	260
Δln(Development Expenditure)	All	0.566	0.450	0.865	-3.128	7.762	412
Δln(Dev-Ex on Industry Sectors)	All	0.537	0.420	1.353	-4.535	8.550	363
Δln(Dev-Ex on TradeBusFin Sector)	All	0.745	0.607	1.228	-2.482	9.651	404
Δln(Dev-Ex on Transport Sector)	All	0.514	0.417	1.100	-4.080	8.464	411
Δln(Infrastructure)	All	0.068	0.065	0.340	-0.820	0.799	190
Δln(Infra: Availability)	All	0.057	0.067	0.369	-0.928	1.112	190
Δln(Infra: Quality)	All	0.092	0.063	0.412	-0.841	1.156	190
Δln(Infra: Quality of Seaport)	All	0.151	0	0.698	-1.642	2.335	190
District data							
Total Mineral Resources 1990	MRes90>0	1	0.048	2.103	0.000	9.601	39
	MRes90>0, L-I Mining	2.308	0.017	3.632	0.001	9.601	9
Total Oil&Gas Production ∼1990	O&G Prod∼90 >0	1	0.013	4.204	0.000	25.717	37
Mine-year data							
ln(Ore Production in Mt + 1)	n/a	1.574	1.232	1.269	0	5.017	561

Note: This table provides summary statistics for variables that are only used in the Online Appendix. *MRes90* equals a district's mineral resources as of 1990 scaled by the district's surface area and then by its average across districts with mineral resources. *L-I Mining* stands for labor-intensive mining. O&G Prod∼90 equals the production of barrels of oil equivalent scaled by the district's surface area and then by its average across districts with oil & gas production. *TradeBusFin* stands for Trade, Regional Business Development, Regional Finance and Cooperatives. *Total Mineral Resources 1990* equals mineral ore resources in 1990 scaled by its mean across districts with positive resources (but not by the district's surface area). *Total Oil&Gas Production ∼1990* equals the production of barrels of oil equivalent around 1990 scaled by its mean across districts with positive production (but not by surface area).

OA2 Online Data Appendix

OA2.1 Mining

Combining RMD *and* MinEx *data*

The data sources we use to compute district-specific mineral resources as of 1990 are *Raw Materials Data* (*RMD*) and *MinEx Consulting* (*MinEx*). Both data sets claim full coverage, and the majority of deposits are indeed listed in both. We double-checked the reported deposits with public data from the *Mineral Resources Data System* (MRDS) of the *United States Geological Survey* (USGS), which however lists fewer deposits. To build a complete data set we match deposits across sources using a deposit's name. For each unmatched deposit, we use additional variables such as location and ore resources to verify if it corresponds to a deposit in the other data set. We identify 82 mineral deposits with positive mineral resources in 1990. 49 of these are listed in both sources, while the remaining 33 are only listed in one. These 33 deposits have statistically significantly lower 1990 mineral resources than the deposits listed in both data sets. 24 of the 33 deposits are unique to *MinEx* and nine are unique to *RMD*. For matched deposits we use the *MinEx* data because we are more confident about its accuracy, based on a test in Google Earth revealing that the *MinEx* location data are more precise.

Location of mineral deposits

Both *RMD* and *MinEx* report the location of a deposit in terms of latitude and longitude. For the set of deposits that are operated by a mine over our sample period and for which different latitude and longitude data are reported by *MinEx* and *RMD*, we entered the location data into Google Earth and regard the location displaying a mine as the correct one. For three deposits, our sources do not provide location data; we retrieved these via Internet search (sources are available on request). Using latitude and longitude, we identify the home district of the deposit as of 2016 using Google Maps. We then identify the corresponding 1990-district, using district proliferation tables provided by the BPS and information provided by Bazzi and Gudgeon (2020).

Time of discovery of deposits

Only *MinEx* reports the year of discovery, which refers to "when the deposit was recognized as having significant value". Data are missing for around one third of deposits. Since we are only interested in whether the discovery took place before 1990, for several of these deposits we use the fact that production started before 1990. For all remaining deposits we carried out an Internet search. We found the discovery year for 42 deposits, mostly through annual reports of the companies operating the deposits or via mining information websites such as *mining-atlas.com*.[47] For some remaining deposits, we infer that the discovery took place after 1990 if in 2016 (the vintage of the *MinEx* data) the deposit's status is either "Advanced Exploration", "Emerging Project" or different categories containing the term "Feasibility Study". For all deposits that are only listed in the *RMD* data, 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. Regarding the 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 data sets with missing discovery date, we infer the year of discovery as the year of production start-up minus the median difference between discovery year and production start-up year across all deposits for which we have information on both variables, which is eight years.[48]

Inferring missing ore resources data

Ore resources data are missing for some deposits. We infer ore resources as ore *reserves* times the mineral-specific average ratio of resources and reserves.[49] 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 resources data are missing for a given deposit, we retrieve data using Internet search. There are no deposits that were discovered by 1990 for which we were unable to retrieve resources data.

Ore reserves and resources data are missing for all tin deposits in both *RMD* and *MinEx*.

[47] 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 is after 1990, this turns out to be equivalent to dropping the deposits from our sample.

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

[49] 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). The ratios of resources and reserves are obtained from *RMD*, since *MinEx* only reports ore resources.

We retrieved the missing data via Internet search. Since we could not obtain resources data at the deposit level, 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 megatons of tin in 2008, according to the annual report of PT Timah of that year. We were unable to retrieve ore resources 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 spatial distribution of tin resources across Indonesia, we infer the share of the different 1990-districts using annual production data from *Indonesia's Department of Mines and Energy*. While data on annual aggregate tin production in Indonesia are available from 1949-2008, data at the sub-national level are only available for the period 1978-1988 (Wu, 1989), thus we compute the production shares using the data from this period. Since with these data we cannot attribute tin deposits that are located 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 deposits located in the Bangka-Belitung archipelago between 1978-1988. We thus infer the tin resources of Bangka-Belitung as this percentage times our measure of total tin resources as of 1990. The remaining 9% of tin production over 1978-1988 took place in deposits in the Riau archipelago; we thus inferred 1990 tin resources of the 1990-district Riau as 9% of total 1990 tin resources.

Computation of district-specific 1990 ore resources

With the exception of tin, we first compute mineral ore resources as of 1990 for each deposit. We then sum 1990 resources across all deposits in a district.

If a deposit was discovered before 1990 but did not start production before that year, the deposit's 1990 resources 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. For all deposits contained in *RMD*, this is done using annual production data whenever available. Since *MinEx* does not report production data, for all deposits unique to *MinEx* annual production data are unknown. For these deposits we infer total production before 1990 as *average* annual production times the number of production years before 1990, both of which can be inferred using *MinEx*.[50]

In the *RMD* data, for some deposits pre-1990 production is only reported in terms of metal rather than ore. In these cases we compute the average ratio of ore and metal production of the specific deposit and metal for each year in which both are available, and use this ratio to infer pre-1990 ore production. If ore production is not available for any year, we use the mine- and metal-specific *grade* to infer ore production from metal production. If the grade is not reported, we retrieve it via Internet search. For five deposits in which production started before 1990, pre-1990 production data are entirely unavailable. In these cases, we infer pre-1990 production as the average yearly (post-1990) production across years in which production data are reported, multiplied by the number of pre-1990 production years. In one case we do not have any information on production, and therefore infer 1990 ore resources as initial resources.

Multi-mineral deposits

RMD reports deposits' annual production figures per extracted mineral, with maximum coverage 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 is operating and production data are available. When production is only reported in terms of metal rather than ore output, we infer ore production using the average mine-specific ratio of metal to ore production across all years for which the ratio can be computed, and otherwise with the use of mine-metal-specific grade data. In the 11 districts that contain at least one multi-mineral deposit with positive resources in

[50] *MinEx* reports both "initial resources", the year of production commencement and "current resources". The year as of which current resources are reported varies by deposit. 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.

1990, we incorporate the inferred mineral shares in multi-mineral deposits into our computation of the mineral price index (MPI) of the district.

MinEx only lists the *main* mineral of a given deposit, thus for deposits unique to *MinEx* we have to assume that the main mineral is the only mineral. Given the low occurrence of multi-mineral deposits in *RMD* and the fact that deposits only listed in *MinEx* have small ore resources, we do not expect this to affect our results.

OA2.2 Oil & Gas

The *Indonesia Oil and Gas Atlas* is divided into six volumes, each of which covers a certain geographic 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 1990-district using data on the field's latitude and longitude provided in the data source. If a field is located offshore, we assign it to the closest district in terms of geographic distance.

OA2.3 Prices

Prices are global benchmarks rather than the prices of specific Indonesian blends. While differences in quality across Indonesian blends and the blends we work with may imply that their prices are not equivalent, we claim that the (percentage) *change* in the global price is a good proxy for the (percentage) change in revenue accrued by the producer of the respective mineral in Indonesia, in a given year. The prices we use are those of the respective metal rather than the ore/rock, since ore prices heavily depend on the metal content and are therefore not comparable across ores of different grades. For all prices, we compute and use annual averages.

We use prices reported by Platts Metals Week and the USGS for: copper (U.S. producer cathode, 99.99-percent-pure copper), nickel (London Metal Exchange cash price for primary nickel of minimum 99.80% purity), tin (New York composite), aluminum (99.7-percent-pure aluminum ingot, U.S. market spot price) and cobalt (99.8-percent cobalt cathode, U.S. spot price).[51] For gold and silver, we use the prices determined on the London Bullion Market, which is a wholesale over-the-counter market.[52] Due to availability and data quality, the prices we use

[51] Source: USGS.
[52] Source: London Bullion Market Authority (LBMA).

for manganese, diamonds, chromium, zirconium and uranium are those paid domestically in the United States.[53] 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 imported metric ton on average in a given year, since China is a geographically close and important importer of iron ore.[54] For coal, we use the price of Australian coal instead of other coal types, due to data quality and given that price changes are likely most aligned with Indonesian coal, since China is a key importer of both Australian and Indonesian coal.[55] For crude oil, we use the price of West Texas Intermediate (WTI), which is a benchmark for the prices of other crude oil sorts.[56] We do not account for natural gas prices separately, both in order to follow the tradition of the literature and because the development of natural gas prices and the development of crude oil prices over time are in any case highly correlated.

OA2.4 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.[57] We drop six plants that have a district ID that does not correspond to any of the district IDs in the BPS list. Around 6% of plants are reported to operate in different (two or more) 1990-districts in different years. This could be due to changes in district borders that are not explained by district splits, by the plant actually moving to another district or, arguably most likely, by measurement error. The plant fixed effects that we control for only nest district-specific fixed effects if plants are always recorded as in the same 1990-district. We therefore keep the plant's district-years of the 1990-district that is reported for the longest consecutive period.

Defining more- versus less-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

[53] Uranium prices are from the IMF, all other prices from the USGS.
[54] Source: IMF, `http://www.imf.org/external/np/res/commod/index.aspx`
[55] Source: IMF, `http://www.imf.org/external/np/res/commod/index.aspx`
[56] Source: Energy Information Administration (EIA).
[57] Consistent with the plant-size threshold of 20 employees, only for a few plants the data reports less than 20 employees, which we treat as typos.

the percentage change in trade volume as distance increases by one percent. Trade is based on the 1997 *U.S. Commodity Flow Survey* (CFS), which documents the destination, product classification, weight and value of a broad sample of shipments. Holmes and Stevens (2014) estimate the distance elasticity via a standard log-log specification. 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. 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 Indonesian manufacturing plants into more- versus less-traded goods producers, using the four-digit sector of each plant, as defined by 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 assign to each KBLI 2000 industry code its corresponding ISIC Rev.3.1 code. 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 four-digit (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 industry.

Defining upstream plants

We use the 2007 U.S. Input-Output tables of the *Bureau of Economic Analysis* (BEA) to identify upstream plants. These tables distinguish more sectors than any Indonesian Input-Output table does, which thus allows a finer evaluation of an industry's linkage to the mining sector. Because formal mining is done in a very standard way across the globe, we can confidently use Input-Output tables of another country for the mining sector.

The tables distinguish three mining industries which we together refer to as the "the mining sector": *Coal mining*; *Iron, gold, silver and other metal ore mining*; and *Copper, nickel, lead and zinc mining*. Details on the concordance of the ISIC Rev.3.1 codes inferred from 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:

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

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 equals the total 1990 mineral resources in district k. $Upstream_{jk}$ takes into account which minerals are found locally, which makes it industry- and district-specific rather than only industry-specific. For example, if industry j is only upstream to the coal mining sector and there are no coal deposits but only gold deposits in 1990 in district k, then we do not classify plants in industry j in district k as upstream ($Upstream_{jk} = 0$). 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 more so if the coal mining sector is in district k is more important.

We first walk from the BEA Input-Output table 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.* In the census data, 133 four-digit ISIC Rev.3.1 manufacturing industries are represented, while the BEA tables report 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.

Total Factor Productivity (TFP)

The calulation of TFP is based on the method by De Loecker and 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, labor, 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 labor input where current labor is instrumented with lagged labor 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, labor with the number of employees. All variables are expressed in Indonesian rupiahs, deflated using five-digit industry producer price indices.

OA2.5 SAKERNAS Labor Force Survey

We use the August round of the survey for the years 2007-2015, because these are representative at the district level, unlike other rounds or the years 1976-2006. This sample of SAKERNAS covers all 1990-districts except in 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.[58] This implies a coverage of between 0.2 and 0.4%.

In Table OA2 we use annual district-level mining wage data from SAKERNAS. The variable is computed as a weighted average of the typical monthly wage across the sectors *Coal Mining and Peat Excavation*; *Uranium and Thorium Mining*; and *Metal Mining* in a given 1990-district and year, using the sample weight assigned to an individual respondent in the data.

For our analysis in Table OA3 we approximate the number of workers employed in the mining sector and the number of workers employed in the combined mining and oil & gas sectors in a given 1990-district and year. To compute the latter variable, we first compute the weighted *share* of surveyed individuals who reported to work in the mining or oil & gas sector. The numerator of this share is the weighted number of respondents in the district-year who state that their main

[58] 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.

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 & Gas*. The denominator is the weighted number of respondents in the district-year. We then multiply the ratio by the most recent available population figure from a given year's perspective.[59] To approximate the number of mining workers, we repeat the above exercise, but exclude oil & gas workers from the share's numerator.

For illustrative purposes (see Section 3.1), in Table 1 we report descriptive statistics on the fraction of mining workers to total workers across district-years (based on districts with mineral resources as of 1990) and the fraction of oil & gas workers to total workers (based on districts with oil&gas production around 1990), over 2007-2015. For a given district and year, the computation of the numerators of these shares is done as described above, conceptually. The denominator of both shares is the weighted number of surveyed individuals who state that their main activity in the past week was working.

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[59] See Section OA1.4 for details on population data. 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.