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Full Length Articles

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

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ABSTRACT

We analyze the local effect of exogenous shocks to the value of mineral deposits on a panel of manufacturing plants in Indonesia. We introduce heterogeneity in natural resource extraction methods, which helps to explain the mixed evidence found in the 'Dutch disease' literature. In districts where mineral extraction is relatively capital intensive, mining booms cause virtually no upward pressure on manufacturing wages, and both producers of more heavily traded and relatively less-traded manufacturing goods benefit from mining booms in terms of employment. In contrast, labor-intensive mining booms drive up local wages such that heavily traded goods producers respond by reducing employment.

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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

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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 county- and firm-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 employment (Black et al., 2005; Michaels, 2011; Allcott and Keniston, 2018). For developing countries the evidence is more mixed and ranges from higher GDP per capita in Brazil (Cavalcanti et al., 2019) to more conflict in Colombia (Dube and Vargas, 2013), an increase in real income for households after a large open-pit gold mine in Peru increased local procurement (Aragón and Rud, 2013), localized negative effects on traded-sector employment 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 panel data on manufacturing plants with deposit-level data, we find that in administrative districts where mining of minerals is more *capital* intensive, mining booms cause an increase in plant-level manufacturing employment. Specifically, employment rises by 2.6% in a district with average mining intensity when world prices of local minerals increase by 100 log points and mining is relatively capital intensive. In contrast, mining booms in districts where mining is *labor* intensive reduce manufacturing employment by 1.2%. We show that this 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 a booming mining sector 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, while 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. This is consistent with oil & gas production being mostly offshore and highly capital intensive and specialized. Heterogeneity in extraction methods 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 in Indonesia is much larger than the effect of oil & gas booms on local manufacturing 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 decrease 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 resource endowments that were 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 to infer changes in the value of natural resource deposits. We employ deposit- and well-level data to compute measures of initial endowments of minerals and oil & gas at the district level. We interact these with subsequent exogenous world price shocks and, in the case of mining, with an indicator that captures the labor intensity of local extraction methods. The mining engineering literature posits that the extraction technique is determined by the exogenous geological shape of the local deposit and not by the deposits' contained minerals or local labor market characteristics (see e.g. Hartman and Mutmanský, 2002). Using three separate databases, we empirically establish that different mining techniques (such as underground versus 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 outcome variables across individual districts. Our annual manufacturing data contains detailed plant-specific information on all Indonesian manufacturing plants with 20 or more employees between 1990 and 2009. This enables us to control for plant fixed effects and four-digit industry-times-year fixed effects, which avoids selection effects and thereby improves identification. Furthermore, the richness of the data allows us to distinguish between manufacturers of relatively more-traded and relatively less-traded goods and thus analyze which of these suffer less or benefit more from mining booms.²

We contribute to a growing literature that analyzes the impact of natural resources in within-country settings. Data on counties and firms 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. Black et al. (2005) find positive employment effects on non-tradeable sectors during the 1970s coal boom in a county-level analysis across Kentucky, Ohio, Pennsylvania, and West Virginia, but no significant effects

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

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

on the manufacturing sector. A long-run study of the southern US by Michaels (2011) finds that as population increased in booming counties also local public good provision increased, with positive effects on employment in agriculture and manufacturing. 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 US manufacturing sector is also procyclical with oil & gas booms in resource-abundant counties, although there is some limited plant-level evidence that highly-traded goods producers contract. In terms of income per capita, however, busts can more than reverse the positive 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 analyzing 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 limited specialization in Indonesian manufacturing 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).

To the best of our knowledge, the effects of heterogeneity in the labor intensity of commodity extraction have only been studied in the context of conflict. Dube and Vargas (2013) 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. These effects are consistent with a model of social conflict by Dal Bó and Dal Bó (2011) in which positive shocks to labor-intensive industries diminish conflict.

We also add to a literature that has examined a range of other outcomes during natural resource booms. These include higher local household income after a rise in local procurement by a large Peruvian gold mine (Aragón and Rud, 2013), increased wage and royalty and business income after new hydrofracturing oil & gas production (Feyrer et al., 2017), a rise in reported municipal spending after oil windfalls in Brazil that is not matched by better local living standards (Caselli and Michaels, 2013), 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).

Finally, by analyzing the effects of regional shocks in local districts of Indonesia, we also relate to several recent studies that 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). In this paper we focus on the local effects of natural resource price booms on the manufacturing sector and thus abstract from a full welfare analysis. This would ideally also take natural resource-specific factors into account. These include policy at the regional and national level such as industrial policy for the development of up- and downstream industries, and macroeconomic management of resource wealth at the national level such as fiscal rules, exchange rate management, sovereign wealth funds, and redistribution.

The remainder of our paper is structured as follows. In Section 2 we develop intuition for our 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. Resource extraction methods and local Dutch disease

In this section we develop hypotheses that relate heterogeneity in resource extraction methods to local Dutch disease effects, for more- and for less-traded manufacturing plants.

Our point of departure is the observation that natural resource deposits differ in important ways. Oil & gas is typically pumped from wells and is capital-intensive. Mines that extract non-renewable natural resources from deposits (such as metals and solid minerals) vary in terms of which method they use for extraction. The most important heterogeneity is between relatively labor-intensive (underground) mining and relatively capital-intensive (open-pit) mining, which is a distinction that we describe and establish in more detail in the next section. The implication of taking into account relative labor-intensities of mining is that during a boom in world prices that increases mining output, the demand for labor by the local mining sector rises most in districts where mining is labor intensive. In districts with capital-intensive mining, less labor is required to increase production and thus the demand for workers also rises much less. In contrast, in 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) – the mining sector itself is not described as heterogeneous and always increases demand for labor during a boom in world prices. Introducing such heterogeneity in extraction methods and relative labor-intensity in mining leads to different predictions of the effect of a mining boom on the manufacturing sector.

2.1. Main effects of labor- versus capital-intensive mining

Following the intuition of a multi-region setting with imperfect labor mobility across regions, a mining boom in districts with labor-intensive mining will lead to upward wage pressure.³ In such a district, the classic Dutch disease crowding-out effects should be observed. In particular, the more-traded manufacturing sector is expected to shrink because it is a price-taker on world markets and thus cannot pass

³ In Online Appendix Table OA2 we provide Indonesia-specific empirical evidence that mines raise production as mineral prices rise, and that mining wages increase during mining booms but only where mining is labor intensive.

on the higher labor costs to consumers.⁴ However, the *less*-traded manufacturing sector is expected to contract much less, if at all: it can also raise wages and remain profitable by endogenously charging higher prices to local consumers. The sector can do so without losing much market share because it hardly faces competition from imports and because consumers earn higher wages due to the boom and thereby drive up local aggregate demand.⁵ Local aggregate demand can also rise if the national government partly redistributes taxable mining rents to producing regions, as is the case in Indonesia. Redistribution may benefit all manufacturing plants. In summary, Dutch disease effects should be most prominently observed in labor-intensive mining districts, where more-traded goods producers mostly suffer from a labor reallocation effect and reduce employment, while less-traded goods producers can pass on higher wage costs to wealthier consumers and may be able to keep employment constant.

A mining boom in districts with *capital*-intensive mining leads to much less upward pressure on wages and to much less crowding out of the manufacturing sector. However, capital-intensive mining booms are similar to labor-intensive mining booms in the sense that they also raise local aggregate demand from taxable and redistributed mining rents. Potentially, this spending effect is strong enough to overturn the small crowding-out effect and induce an *expansion* of local manufacturing. Overall, a mining boom in a capital-intensive mining district may thus be good for manufacturing. In terms of more- versus less-traded goods producers, it is unclear which would benefit more: less-traded goods producers benefit more from higher purchasing power of local consumers via redistribution (and perhaps a small rise in wages), but increased provision of public goods such as transportation infrastructure may favor more-traded goods producers relatively more.

2.2. Spillovers

The effects of a local mining boom may spill over into other districts, such as when labor mobility across districts is high. In that case some of the demand for labor in a district with labor-intensive mining can be supplied through migration. This dampens the local upward pressure on wages, while migration creates excess labor demand in non-booming districts and can drive up wages there. Second, part of the increase in local aggregate demand in mining districts may be supplied by tradeable sectors located in other districts. Third, royalties may be redistributed to non-producing districts and provinces such that higher resource rents can boost aggregate demand in other districts as well.

2.3. Other effects of mining booms

Finally, a mining boom can have several other effects. For example, it may increase demand for goods supplied by sectors that are upstream to mining, thereby potentially benefiting selected manufacturing industries even if they are traded and located in the booming district. Moreover, if the positive productivity effects of learning by doing are concentrated in the tradeable sector, then crowding out of more-traded manufacturing may also lead to a loss in total factor productivity over time.

Summarizing the effects, an exogenous increase in the returns to labor-intensive mining puts upward pressure on wages, leading the more-traded manufacturing sector to reduce employment. However, the wage effects are muted in capital-intensive mining districts where all manufacturing employment can grow through spending effects. Not taking into account 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 and construction of key variables

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.⁶ The mineral 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 Fig. 1 in the 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.⁷ These royalties are partially redistributed

⁴ 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. Less substitutability across sectors implies less scope for crowding out.

⁵ Corden and Neary (1982) refer to this latter mechanism as the 'spending effect'.

⁶ Source: Indonesia's national statistical agency *Badan Pusat Statistik* (BPS) for GDP shares; Annual census of manufacturing plants (IBS) for manufacturing export and employment shares; Indonesia's national labor force survey (SAKERNAS) for mining employment. We compute the share of the mining sector in the total workforce as the ratio of mining workers to total workers in a district. See the Online Data Appendix OA2.5 for details on this variable and 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, but from a legal perspective they are often treated as minerals.

⁷ 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>.

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 2001 non-producing districts also started to share in royalties, but 64% of land rents and 32% of royalties still go to producing districts as per Law 25/1999.⁸

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 national employment share of oil & gas was less than half the employment share of mining between 1995 and 2009.⁹ For these reasons, we always control for local occurrence of oil & gas, but focus on the mining of minerals.

3.2. Natural resources, extraction techniques and prices

3.2.1. Mineral resources

We construct a database of mining by district by combining two proprietary data sources: the *Raw Materials Data* (RMD) from S&P Global, 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 OA2.1), these sources provide us with the location, mining method in use or planned, minerals produced, the quantity of resources in the ground, year of discovery and ownership status for each deposit. RMD also provides employment per mine, but only for a small subset and for almost none of the Indonesian mines. We use the global information (as well as other data sources) 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.¹⁰ 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.

The deposits jointly contain a wide variety of minerals.¹¹ 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.¹² We use resources rather than reserves because resources more closely reflect 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 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 district's surface area in square miles such that $r_k = \sum_d R_{dk} / \text{Area}_k$, 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 $\bar{r}_k$. District-level summary statistics are reported in Appendix Table A1 and show large variation in $\bar{r}_k$.¹³

3.2.2. Mineral extraction techniques and their labor intensities

The most common extraction method 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 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 the data 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 and zero otherwise. The nine districts for which *Underground_k* equals one are spread across eight provinces and jointly contain multiple minerals, which are also mined using other techniques in other districts. Three districts only apply underground mining while in the remaining six districts all deposits are mined with both underground and open-pit techniques.

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.¹⁴ Conversely, all non-underground mining methods are classified

⁸ The decentralization laws were signed in 1999 but were implemented only on January 1, 2001 (see e.g. Suharyo, 2009). The producing district's share in royalties was 70% over 1990–1992, 64% over 1993–2000, and 32% over 2001–2009. For land rents, its share was 70% over 1990–1992 and 64% over 1993–2009. Districts in the same province as the producing district jointly accrued 32% of royalties over 2001–2009. The province of the producing district did not participate in royalties or land rents over 1990–1992 but received 16% of both over 1993–2009 (see e.g. Alisjahbana, 2005; Murniasih, 2010).

⁹ Source: Indonesia's national labor force survey (SAKERNAS).

¹⁰ 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.

¹¹ 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%).

¹² 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).

¹³ Online Appendix Table OA1 provides additional descriptive statistics on natural resource endowments by province.

¹⁴ The variables in our data are 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.

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 corroborate this classification more formally in three different ways using three different data sources that jointly cover mining activity globally and in Indonesia. In our first test we use employment data of a cross-section of mines around the world from RMD. While the full data set lists 8830 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. Data on a mine's capital input or past investment is not available. 230 of the 518 mines apply only open-pit mining, 213 only underground mining, 54 both underground and open-pit mining and 21 mines apply other (placer mining, in-situ leaching, offshore mining, tailings) or unknown mining techniques. The number of employees ranges between 13 and 10,550 and averages at 1084 employees. Only two mines in this sample are located in Indonesia, but the data allow us to control for country C_c , year of 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 mineral ore production in the same year and the mentioned fixed effects, and cluster standard errors at the country level: $\ln(\#MineEmployees)_{dt} = \delta_1 Underground_{dt} + \delta_2 \ln(MineralProduction)_{dt} + C_c + T_t + M_m + v_{dt}$. The results are reported in Appendix Table A2 and indicate that a mine that applies underground mining uses 86% 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, and that the difference between these two coefficients is statistically significant. Conditional on our controls, column 3 shows that there is no significant heterogeneity with respect to a country's level of development as measured by GDP per capita. The results are robust to replacing country and year (of 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); to excluding mines that neither apply underground nor open-pit mining (column 5); and to proxying the size of a mine by mineral resources rather than production, which increases the sample size due to data availability (column 6).

In Online Appendix Section OA1.3 we provide two additional tests on the labor intensity of extraction techniques: one based on district-level data derived from Indonesia's labor force survey (SAKERNAS), and one using district-level (working-age) population data. Table OA3 shows that the number of mining workers in underground mining districts is 114% larger than in non-underground mining districts with the same mineral endowments. The result is robust to controlling for regional labor market characteristics and mining is most labor intensive in districts where only underground mining is applied. Table OA4 shows that an increase in the price of local minerals spurs working-age population growth in mining districts, but only when mining is relatively labor intensive. However, the magnitude of the coefficient suggests that labor mobility is relatively low, such that there is scope for upward wage pressure.

Based on the comprehensive evidence for this novel source of heterogeneity, we relabel the district-level dummy $Underground_k$ to *Labor - intensive Mining_k*.

3.2.3. Oil & gas endowments

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 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 remaining resources 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 6000 for natural gas to barrels-of-oil-equivalent) and divide by district size. We normalize this proxy in the same way as r_k , and denote it r_k . 37 districts spread across 14 provinces were producing oil and/or gas around 1990. Nine of these districts also contained minerals in 1990. In Online Appendix Section OA1.3 we provide evidence that oil & gas extraction is less labor intensive than minerals extraction. District-level summary statistics are reported in Appendix Table A1 and show large variation in.

3.2.4. Natural resource prices

Each district may contain several mineral deposits, and each deposit potentially contains multiple minerals. We thus construct a district-specific annual price index that captures the price level of local mineral resources that were discovered by 1990, using as weights the district-specific share of mineral m in total 1990 resources. More precisely we define:

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

where P_{mt} equals the annual average world price of mineral m in year t normalized by the price of m in 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. Fig. 2 in the Appendix plots the development of P_{mt} for all minerals in our sample and shows periods with large price swings, giving us substantial variation in the value of local mineral deposits over time.¹⁵ The definition of the mineral price index (MPI) ensures for example that the steep increase in the price of iron ore in 2005 will have no effect in districts without iron ore

¹⁵ See Online Data Appendix OA2.3 for sources and details on the specific prices.

deposits (absent spillovers), and only a substantial effect in districts where iron ore makes up a large share of endowments. Fixing weights to the base year 1990 and using only deposits that were discovered by 1990 ensures exogeneity with respect to outcomes in subsequent years, conditional on the control variables in our empirical specification (see Section 4). To capture variation in the value of local oil & gas endowment (in barrels-of-oil-equivalent), we use global oil prices.

3.3. Manufacturing census data

We use Indonesia's annual census of manufacturing plants (IBS) over the period of 1990–2009, which contains repeated observations on 59,031 manufacturing plants that employ at least 20 employees. The data are collected and compiled by Indonesia's national statistical agency *Badan Pusat Statistik* (BPS) and contain detailed information on performance indicators, including employment, investment, material inputs, revenue and exports. In addition, the data set lists the district in which the plant is located and 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 government ownership (which may be shielded from market forces) and focus on fully privately-owned plants, leaving 50,693 plants that we observe on average for six years. Appendix Table A1 presents the descriptive statistics.¹⁶

Employment equals the total number of employees reported by a plant. We do not observe individual wages nor hours worked, so as a proxy for wages we use the *total wage bill divided 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 product sales divided by the total number of product items sold, but is not available before 1998. Finally, we obtain *total factor productivity* (TFP) from Javorcik and Poelhekke (2017), which itself is based on the method by De Loecker and Warzynski (2012) and Akerberg et al. (2006). TFP is measured by the innovations to a regression of plant-year level deviations from industry-level expected value added on lagged capital and labor.¹⁷

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. The distance elasticity equals the percentage reduction in trade volume as distance increases by 1%, using industries' average shipment distance as reported in the *US Commodity Flow Survey*.¹⁸ Our sample includes 123 four-digit ISIC Rev.3.1 manufacturing industries, for which the median distance elasticity is 0.44.¹⁹ The least-traded manufacturing sector is "Manufacture of articles of concrete, cement and plaster", while five industries have an estimated distance elasticity of zero, including for example "Publishing of newspapers, journals and periodicals".²⁰ We use US elasticities because 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 is the same across the two countries.²¹ 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. 8.5% of less-traded sector employment and 7.5% of more-traded sector employment was located in mining districts.

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 a four-digit industry that sells 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 OA2.4.

4. Empirical strategy

Our main hypothesis is that the intensity of mining activity affects plant-level outcomes, and that this varies by the labor intensity of extraction techniques 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.

We 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 and across districts. $f(\cdot)$ is a function of the interactions

¹⁶ For around 6% of plants the census records 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 OA2.4 for details.

¹⁷ See the Online Data Appendix OA2.4 for details.

¹⁸ See the Online Data Appendix OA2.4 for details.

¹⁹ Our results are robust to using a cutoff of 0.8, which corresponds to an average shipment distance of around 500 miles and is used by Allcott and Keniston (2018); see Online Appendix Table OA7. The results are also robust to using only international exporter status to distinguish more- from less-traded goods producers, 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 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 5.2, our results are robust to dropping industry-switchers.

²¹ If this assumption does not hold then the resulting measurement error will make it harder to reject the null hypothesis that the effect of mining booms differs across producers of more- versus less-traded goods producers.

of normalized mineral resources per square mile in the local district, world prices of the minerals contained in local deposits MPI_{kt} , and the mining technique dummy *Labor - intensive Mining_k*:

$$\ln Y_{ijkt} = f(\tilde{r}_k, MPI_{kt}, Labor\text{-}intensive\ Mining_k) + \mu_i + \nu_{ijkt}$$

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 but not over time:

$$\Delta \ln Y_{ijkt} = \gamma_1 [\Delta \ln(MPI_{kt}) * \tilde{r}_k] + \gamma_2 [\Delta \ln(MPI_{kt}) * \tilde{r}_k * Labor\text{-}intensive Mining_k] + \eta_{ijkt}$$

captures the mining boom. The boom is larger for a larger price shock, and for a given price shock the 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.²²

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, four-digit industry-times-year fixed effects S_{jt} , and district-specific linear trends τ_{kt} to account for the possibility that shocks are persistent (Ciccone, 2011).²³ 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:

$$\Delta \ln Y_{ijkt} = \beta_1 [\Delta \ln(MPI_{kt}) * \tilde{r}_k] + \beta_2 [\Delta \ln(MPI_{kt}) * \tilde{r}_k * Labor\text{-}intensive Mining_k] + \beta_3 [\Delta \ln(OilPrice_t) * \tilde{boe}_k] + S_{jt} + \tau_{kt} + \epsilon_{ijkt} \quad (1)$$

Industry-year effects control for different industry compositions across mining and non-mining 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 depended not only on geology but also on time-invariant local labor market conditions. The district-specific trends τ_{kt} absorb trending local labor market conditions and control for different manufacturing trends in districts with labor-intensive extraction methods.

We estimate Eq. (1) with OLS and always cluster standard errors at the level of treatment (the districts).²⁴ 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 when *Labor - intensive Mining_k* equals one. In principle β_1 (or $\beta_1 + \beta_2$) measures a *relative* effect: the change in outcome Y relative to a plant in the same industry in the same year in a district that faces a smaller or no mining boom. In the absence of geographic spillovers, one can regard β_1 as an *absolute* effect. In Section 5 we formally test for such spillovers and find that they are not statistically different from zero.

The unbiased estimation of β_1 and β_2 rests on four identification assumptions. First, we assume that (i) global mineral prices are exogenous to district-level developments. This is very plausible and our results are robust to excluding districts containing tin and nickel, for which Indonesia has a relatively large global market share (see Section 5.2). Furthermore, we assume that conditional on our controls, (ii) changes in local manufacturing outcomes over 1990–2009 are exogenous to local mineral endowment and (iii) to local extraction techniques as of 1990. Assumption (ii) would for example be violated if there were systematic pre-1990 developments at the local level that affected resource exploration efforts and thereby 1990 resources, and these factors had lagged effects on manufacturing into the 1990s. Assumption (iii) would be violated if such time-varying factors influenced 1990 extraction methods, which is very unlikely since these are determined by a deposit's geology.²⁵ We address these potential concerns via a robustness check in which we allow for different manufacturing trends across the 1990s and the 2000s within a given district. Moreover, we estimate an alternative specification which allows us to analyze heterogeneous effects across more- versus less-traded goods producers during labor-intensive mining booms conditional on district-year fixed effects, which capture all possible confounding factors that would violate assumptions (i)–(iii). Finally, we assume that (iv) conditional on our rich fixed effects structure, there are no remaining selection effects. One such effect could be that unobserved factors that induce plants to switch industry and thereby potentially their status of being traded are correlated with our

²² Given the definition of the mineral 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 (for capital-intensive mining districts) or the coefficient on (for labor-intensive mining districts). This would suggest that the marginal effect of the price shock is non-zero for , while it is only defined for .

²³ The district-specific trends τ_{kt} absorb different trends for different values of , *Labor - intensive Mining_k* and . District fixed effects and trends also capture any systematic differences between more recent and older deposits. The industry-times-year fixed effects absorb the direct effect of a change in the price of oil or any mineral that manufacturing sectors use as input.

²⁴ 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).

²⁵ This assertion is supported by the mining engineering literature. Furthermore, it is corroborated by the fact that there is no time variation in extraction methods at the deposit level in our data, and our finding that there is no statistically significant correlation between a country's level of economic development and the labor intensity of different mining techniques in the country (see Appendix Table A2).

Table 1

Mining booms and plant-level manufacturing outcomes.

Sample → Dependent variable →	All Plants							
	Δln		Δln		Δln		Δln	
	# Employees		Wage Bill/#Employees		Unit Price		Revenue	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mineral Resources 1990 × Δln(Mineral Price) × Labor-intensive Mining	0.015 (0.009)	0.026*** (0.005) −0.038*** (0.006)	0.038 (0.033)	−0.003 (0.021) 0.137*** (0.021)	0.092 (0.057)	0.032 (0.044) 0.199*** (0.045)	0.109** (0.042)	0.062* (0.036) 0.158*** (0.036)
Oil&Gas Production ~1990 × Δln(Oil Price)	0.001 (0.001)	0.001 (0.001)	−0.002 (0.003)	−0.002 (0.003)	−0.012 (0.013)	−0.013 (0.013)	0.009 (0.008)	0.009 (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 labor-intensive mining boom		−0.012*** (0.002)		0.133*** (0.004)		0.230*** (0.010)		0.220*** (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 Eq. (1). 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 (in Eq. (1)). We interact this variable with a time-varying, district-specific weighted mineral price shock, $\Delta \ln(\text{Mineral Price})$; this corresponds to $\Delta \ln(MPI_{ikt})$ in Eq. (1). The weight of each mineral's price shock equals its share in total 1990 resources of the district. *Oil&Gas Production ~1990* equals the production of barrels of oil equivalent per square mile around the year 1990, scaled by its mean across producing districts (in Eq. (1)). *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 mining). 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.

explanatory variables. We address this particular concern via a robustness check in which we drop industry switchers and perform additional checks that address other forms of possible selection bias. Our results are robust to all these alternative samples and specifications.

5. Results

5.1. Mining heterogeneity and manufacturing outcomes

We now turn to our main results, which show that heterogeneity in the labor intensity of mining techniques can reconcile the mixed effects of mining booms on manufacturing outcomes found in the previous literature. We first distinguish the effect of labor- versus capital-intensive mining on four key manufacturing outcomes using a sample that includes both more- and less-traded goods producers (Table 1), and then study these two sub-samples separately (Table 2). For comparison, in Table 1 we start our analysis of each outcome with a specification analogous to Eq. (1) that does not distinguish by the labor intensity of mining (odd-numbered columns) and then estimate Eq. (1) (even columns). The results do not show evidence for a loss of manufacturing employment during mining booms in general: column 1 reveals that mining booms may have a positive impact on manufacturing employment, but the coefficient is not statistically significant. 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. On average, there is thus neither evidence for crowding out nor consistent evidence for positive effects of mining booms.

This conclusion changes once we allow for heterogeneity in the labor-intensity of mining extraction methods in columns 2, 4, 6, and 8. The results unveil a novel result in the literature that a mining boom has a fundamentally different effect on manufacturing if it occurs in a district where mining is labor-intensive as opposed to capital-intensive. Looking first at employment growth, we find that where *capital*-intensive mining is applied, manufacturing plants *expand* by 2.6% when the price of local minerals rises by 100 log points and local mineral endowments are equal to the average across mining districts. In sharp contrast, a mining boom of equal magnitude taking place in a district where mining is *labor*-intensive results in a *contraction* of manufacturing employment, by 1.2%, as listed in the bottom row of column 2. Labor-intensive mining booms also drive up average manufacturing wages, by 13.3%. These results are consistent with a labor reallocation effect where labor-intensive mines bid up wages to attract workers (see Online Appendix Table OA2), which leads to crowding out 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%.²⁶

²⁶ 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.

Table 2
More-traded versus less-traded goods producers.

Panel A				
Sample →	More-Traded Goods Producers			
Dependent variable →	$\Delta \ln$	$\Delta \ln$	$\Delta \ln$	$\Delta \ln$
	# Employees	Wage Bill/#Employees	Unit Price	Revenue
	(1)	(2)	(3)	(4)
Mineral Resources 1990 $\times \Delta \ln(\text{Mineral Price})$	0.031** (0.015)	−0.022 (0.031)	0.015 (0.059)	0.060* (0.035)
Mineral Resources 1990 $\times \Delta \ln(\text{Mineral Price}) \times \text{L-I Mining}$	−0.049*** (0.017)	−0.004 (0.034)	0.021 (0.063)	−0.069* (0.037)
Oil&Gas Production ~1990 $\times \Delta \ln(\text{Oil Price})$	0.000 (0.001)	0.001 (0.004)	−0.009 (0.026)	0.010* (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 labor-intensive mining boom	−0.018*** (0.006)	−0.026	0.036	−0.009 (0.011)
Panel B				
Sample →	Less-Traded Goods Producers			
Dependent variable →	$\Delta \ln$	$\Delta \ln$	$\Delta \ln$	$\Delta \ln$
	# Employees	Wage Bill/#Employees	Unit price	Revenue
	(1)	(2)	(3)	(4)
Mineral Resources 1990 $\times \Delta \ln(\text{Mineral Price})$	0.023*** (0.003)	0.012 (0.009)	0.041 (0.041)	0.061 (0.039)
Mineral Resources 1990 $\times \Delta \ln(\text{Mineral Price}) \times \text{L-I Mining}$	−0.025*** (0.004)	0.190*** (0.011)	0.275*** (0.043)	0.264*** (0.040)
Oil&Gas Production ~1990 $\times \Delta \ln(\text{Oil Price})$	0.002 (0.001)	−0.006** (0.003)	−0.017** (0.008)	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 labor-intensive mining boom	−0.002 (0.002)	0.202*** (0.006)	0.316*** (0.015)	0.325*** (0.008)

Note: *L-I Mining* equals *Labor-intensive mining*. 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 Eq. (1). 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.

Capital-intensive mining booms do not lead to a rise in manufacturing prices or average wages. The lack of upward wage pressure is consistent with open-pit mining requiring limited labor to raise production and explains why capital-intensive mining booms do not crowd out manufacturing. There are several plausible explanations for the result that employment, and to some extent also revenue, actually increase rather than stay constant. 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 5.2](#). On the other hand, manufacturing plants may respond to a boom in local demand for their products and/or larger public spending, which arises through redistribution of national mining revenues to the producing 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 OA6, Panel A). In addition, panel data over 2002–2004 from the Regional Autonomy Watchdog KPP0D 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 1](#) shows no evidence that oil & gas booms affect manufacturing in any way. The absence of a wage effect is consistent with the high capital intensity of oil & gas extraction and may also reflect that the sector requires workers with more specific skills that are imperfect substitutes for manufacturing workers. The result that unlike capital-intensive mining booms, oil & gas

booms do not promote manufacturing employment may be due to fiscal rules: oil & gas rents are shared much less with local districts but accrue mostly to the national government.²⁷ Alternatively, the elasticity of oil production to prices may be relatively low, as described in Anderson et al. (2018).²⁸

5.2. More-traded versus less-traded manufacturing plants

Table 2 shows results of estimating Eq. (1) for the 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. We report marginal effects of mining booms for labor-intensive mining in the bottom row.²⁹

As expected, Panel A shows stronger crowding-out effects for more-traded goods producers than for the average manufacturing plant: a labor-intensive mining boom results in a drop of employment of 1.8% (marginal effect in column 1). This is consistent with the insignificant effect on prices (column 3): more-traded plants cannot respond to rising demand 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 (column 2) without becoming less profitable. They thus choose to shed labor instead.

Panel B focuses on relatively less-traded goods producers and finds that these do *not* shed employment during labor-intensive mining booms. The key difference compared to more-traded goods producers is that less-traded goods producers can benefit from an increase in local demand from miners and workers earning higher wages and consuming local goods. This is because they can pass on higher wage costs (see bottom row of column 2) to consumers by raising prices (column 3), 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 workers to remain profitable despite increased competition for labor.

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.³⁰

Panels A and B also show that the positive effect of capital-intensive mining booms found in Table 1 holds for both more- and less-traded goods producers. While the difference in magnitude is not statistically significant, the coefficient is larger for more-traded plants. To the extent that these use infrastructure more intensively, this is consistent with our result that mining booms improve local infrastructure quality. Indonesian exporters in manufacturing have indicated transport infrastructure as their main constraint to global competitiveness (Winkler and Farole, 2012).

5.3. Total factor productivity (TFP)

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, 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 3 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 mining booms, it actually increases during labor-intensive mining booms and most for less-traded goods producers. This is probably to a large extent driven by the strong increase in revenue while keeping employment constant. To gauge potential longer-term effects we next estimate the effect on TFP 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 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 of the five years. We still find large positive effects of labor-intensive mining 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.

²⁷ 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.

²⁸ They 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 average wages only if mining is labor intensive.

²⁹ We only test the significance of marginal effects when these are meaningful, which is when the interaction term suggests that the effect of mining significantly depends on its labor intensity.

³⁰ Results are not driven by general district-level inflation: 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.

Table 3
Plant-level Total Factor Productivity.

Dependent variable → Sample →	$\Delta \ln(\text{TFP})$			$\Delta_5 \ln(\text{TFP})$		
	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 $\times \Delta \ln(\text{Mineral Price})$	−0.000 (0.002)	−0.003* (0.002)	0.003 (0.004)			
Mineral Resources 1990 $\times \Delta \ln(\text{Mineral Price}) \times \text{Labor-intensive Mining}$	0.012*** (0.002)	0.006*** (0.002)	0.014*** (0.004)			
Mineral Resources 1990 $\times \text{mean}[\Delta \ln(\text{Mineral Price})]$				0.021*** (0.008)	0.009 (0.010)	0.026*** (0.009)
Mineral Resources 1990 $\times \text{mean}[\Delta \ln(\text{Mineral Price})] \times \text{Labor-intensive Mining}$				0.300*** (0.061)	0.348*** (0.099)	0.031 (0.161)
Observations	172,504	97,028	75,398	83,759	47,219	36,465
Marginal effect of labor-intensive mining boom	0.012*** (0.000)	0.003*** (0.001)	0.017*** (0.000)	0.321*** (0.061)	0.356*** (0.098)	0.057

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 Eq. (1), 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 & gas boom measure 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.

5.4. Regional spillovers and revenue sharing

In Table 4 we test for regional spillovers in two ways, where we focus on employment and use the sample of all manufacturing plants. In column 2 we include a variable capturing mining booms in neighboring districts.³¹ 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 the implementation of decentralization in 2001.³² The first result is that the spillover interactions are not significant and their inclusion does not change the main results.³³ The same result holds in analogous unreported regressions that test for spillover effects on wages. However, it is still possible that two opposing spillover mechanisms cancel each other out: a neighboring labor-intensive mining boom may attract 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 2000, which is when revenue sharing increased. If a spillover effect from a positive spending effect is important then it should be more visible from 2001 onwards, 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 and may become statistically significant. However, we do not find more compelling evidence for spillover effects after 2000. A reason may be that over time other national redistribution funds were adjusted to compensate for the re-allocation of royalties after 2000, potentially resulting in a small net redistribution effect across districts.³⁴ Overall, our results provide stronger evidence in favor of local crowding out and reallocation between sectors as opposed to between districts. The result that the spillover coefficients are insignificant also suggests that our estimates come close to representing absolute effects, but we cannot draw a definite conclusion about this.

5.5. Robustness checks

We perform a battery of robustness tests, which do not change our main result that only labor-intensive mining booms crowd out relatively more-traded goods producers.

³¹ 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.

³² 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.

³³ Since the coefficients capturing neighboring mining booms in column 2 are noisily estimated, the null hypothesis of F-tests that neighboring and home district mining booms have the same effect cannot be rejected at any reasonable significance level. Spillover effects might be present, but we lack the statistical power to detect them.

³⁴ 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.

Table 4
Regional spillovers and revenue sharing.

Sample →	All Plants					
Dependent variable →	$\Delta \ln(\# \text{ Employees})$					
Specification →	Baseline	Booms nearby	Booms in Same province	Baseline, after decentralization	Booms nearby, after decentr.	Booms in same province, after decentr.
	(1)	(2)	(3)	(4)	(5)	(6)
Mineral Resources 1990 $\times \Delta \ln(\text{Mineral Price})$	0.026*** (0.005)	0.023*** (0.007)	0.025*** (0.006)	0.027*** (0.007)	0.023*** (0.009)	0.025*** (0.008)
Mineral Resources 1990 $\times \Delta \ln(\text{Mineral Price})$ $\times$ Labor-intensive Mining	−0.038*** (0.006)	−0.036*** (0.006)	−0.036*** (0.006)	−0.044*** (0.007)	−0.041*** (0.009)	−0.043*** (0.008)
Neighbors' Mineral Resources 1990 $\times \Delta \ln$ (Neighbors' Mineral Price)		0.022 (0.026)			0.027 (0.026)	
Neighbors' Mineral Resources 1990 $\times \Delta \ln(\text{N}'\text{bors'}$ Mineral Price) $\times$ N'bors' L-I Mining		−0.018 (0.027)			−0.020 (0.027)	
OthersProv Mineral Resources 1990 $\times \Delta \ln$ (OthersProv Mineral Price)			0.003 (0.003)			0.002 (0.003)
Observations	261,020	259,840	261,020	139,428	139,004	139,428
Marginal effect of labor-intensive mining boom...: ...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)) ...in neighboring districts (when own Mineral Resources 1990 = 0 or no own price shock)	−0.012*** (0.002)	−0.012*** (0.002)	−0.012*** (0.002)	−0.018*** (0.002)	−0.018*** (0.003)	−0.018*** (0.002)
		0.004			0.006	

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 1, 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 several 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 2001–2009. The oil & gas boom measure, 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.

5.6. Different labor intensities, upstream plants, market power, decentralization, and testing for selection effects

Focusing on the sample of more-traded goods producers, we start in Table 5 by evaluating the effect of the specific degree of labor intensity of local mining, and by analyzing whether mining booms are different for upstream plants. For reference, column 1 repeats the baseline result displayed in column 1 of Table 2, Panel A.

In column 2 of Table 5 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 expected, the magnitude of the crowding-out effect is strongest when mining is most labor intensive.³⁵ In Online Appendix Table OA5 we also show that manufacturing plants' wage bill divided by the number of workers increases most during a boom when only underground mining is applied.

Column 3 of Table 5 evaluates if the crowding-in effect of capital-intensive mining booms is driven by plants that are upstream to the mining sector. We interact our measure of mining booms (and its interaction with labor-intensive mining) with the *upstream plant* 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 the average effect of 0.031 in column 1), 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. 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 perspective of the mining sector. Upstream plants also benefit during labor-intensive mining booms: belonging to an upstream sector turns the crowding out of labor-intensive mining booms (−0.014) into crowding in (0.173), as shown in the two bottom rows of Table 5.³⁶

³⁵ 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 ; this implies that a price increase of local minerals 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, such that a boom makes more-traded goods producers lose $1.844 \times (-0.016) \approx 3\%$ of workers.

³⁶ The average effect is nonetheless negative as per the marginal effect in column 1 because there are relatively few upstream plants in labor-intensive mining districts.

Table 5

Robustness I: Degree of labor intensity, upstream plants, market power, decentralization and testing for selection effects.

Sample →	More-Traded Goods Producers							
Dependent variable →	$\Delta \ln(\# \text{ Employees})$							
Specification →	Baseline	Different labor intensities	Upstream controls	Excluding Tin&Nickel	District × After de-centr. FE	Excluding industry switchers	Plant-specific trends	Only mining districts
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mineral Resources 1990 × $\Delta \ln(\text{Mineral Price})$	0.031** (0.015)	0.031** (0.015)	0.013*** (0.004)	0.031** (0.016)	0.038** (0.019)	0.036** (0.018)	0.031** (0.013)	0.035*** (0.011)
Mineral Resources 1990 × $\Delta \ln(\text{Mineral Price})$ × Labor-intensive Mining	−0.049*** (0.017)		−0.027*** (0.005)	−0.049*** (0.017)	−0.055*** (0.020)	−0.053*** (0.018)	−0.052*** (0.014)	−0.058*** (0.014)
Mineral Resources 1990 × $\Delta \ln(\text{Mineral Price})$ × Pure labor-int. Mining		−3.441*** (0.279)						
Mineral Resources 1990 × $\Delta \ln(\text{Mineral Price})$ × Mixed labor-int. Mining		−0.046*** (0.017)						
Mineral Resources 1990 × $\Delta \ln(\text{Mineral Price})$ × Upstream			0.033 (0.026)					
Mineral Resources 1990 × $\Delta \ln(\text{Mineral Price})$ × Upstream × L-I Mining			0.154*** (0.041)					
Observations	149,759	149,759	149,858	149,049	149,753	94,922	145,884	6510
Marginal effect of labor-intensive mining boom	−0.018*** (0.006)	see	see	−0.018*** (0.006)	−0.017*** (0.005)	−0.017*** (0.006)	−0.021*** (0.006)	−0.022** (0.009)
Marginal effect of pure labor-intensive mining boom		below −3.410*** (0.278)						
Marginal effect of mixed labor-intensive mining boom		−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: capital-intensive mining: 0.046; 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 using the sample of more-traded goods producers. 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 mines that only use underground methods, 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. *Upstream* and its interaction with *Labor-intensive Mining* are included separately in column 3 but not shown. In column 4 we drop the six districts that contained tin or nickel resources in 1990. In column 5 we include a full set of district times post-2000 dummies to control for heterogeneous decentralization effects across districts. Column 6 drops all plants that ever change four-digit industry. In column 7 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 8 we only include districts with positive mineral resources in 1990. The oil & gas boom measure 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.

Column 4 addresses market power that may invalidate exogeneity of mineral price shocks. Indonesia was the world's 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.

Column 5 controls for different district trends after decentralization. The post-2000 period may be different because mineral prices started to trend upward, and because the decentralization to districts that started in that period may have improved the local business climate for manufacturing. The baseline might therefore overestimate the true effect of mining booms. However, including district-times-post-2000 fixed effects (which also addresses potential concerns regarding identification assumptions ii) and iii) discussed in Section 4) does not alter the results.

Despite our rich fixed effects structure, there may still be unobserved selection effects. Therefore, in column 6 we drop plants that switch four-digit industry over time and may thereby change their status as more-traded goods producer (which may also be due to measurement error), but the coefficients are robust to this change. Moreover, including plant-specific trends instead of

Table 6

Robustness II: Alternative clustering, mineral-specific effects and mine ownership.

Sample →	More-Traded Goods Producers					
Dependent variable →	$\Delta \ln(\# \text{ Employees})$					
Specification →	Baseline	Two-way clustering I	Two-way clustering II	Same Mineral	Excl. state-owned mining	AK2018 scaling
	(1)	(2)	(3)	(4)	(5)	(6)
Mineral Resources 1990 $\times \Delta \ln(\text{Mineral Price})$	0.031** (0.015)	0.031* (0.015)	0.031* (0.016)	0.017*** (0.003)	0.016*** (0.004)	0.077** (0.039)
Mineral Resources 1990 $\times \Delta \ln(\text{Mineral Price}) \times$ Labor-intensive Mining	−0.049*** (0.017)	−0.049*** (0.014)	−0.049*** (0.018)	−0.033*** (0.007)	−0.034*** (0.007)	−0.122*** (0.041)
Observations	149,759	149,759	149,759	143,468	147,432	149,759
Marginal effect of labor-intensive mining boom	−0.018*** (0.006)	−0.018** (0.006)	−0.018*** (0.002)	−0.016*** (0.006)	−0.019*** (0.006)	−0.045*** (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 re-scaling 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-times-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 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 5 we exclude the 12 districts in which all 1990 mineral deposits are majority state-owned. In column 6 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 measure is always included but not shown. ***Significant at 1% level; **Significant at 5% level; *Significant at 10% level.

district-specific trends in column 7 does not change the results, implying that it is sufficient to capture trends at the industry and district level. Finally, in column 8 we restrict our analysis to plants located in mining districts only, at the cost of sacrificing some external validity. The results are robust to this modification, despite the much smaller sample.

5.7. Clustering, mineral-specific effects, deposit ownership, and re-scaling

So far we always cluster by district, and column 1 in Table 6 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 compelling evidence for spillovers. Following best practise (Cameron and Miller, 2015; Bertrand et al., 2004) we prefer clustering on districts, because that is the level of treatment, and because also clustering on years may violate the asymptotic requirements of clustering: with 19 years of data there are only 19 clusters in the time dimension. In column 3, inspired by Adão et al. (2019), we also cluster standard errors two-way 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 across districts and within sectors.

In column 4 we address the possibility that labor-intensive mining coincides with the mining of minerals with a higher price elasticity, such that the results could reflect the impact of relatively easy-to-mine minerals rather than different mining methods. This is unlikely, however, because 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. Nevertheless, to make sure that all variation comes from the mining method we restrict the sample to districts that produce only coal or no mineral at all.³⁷ The estimated coefficients are similar to those of the main specification and remain statistically significant, supporting the conclusion that mining methods matter.

In column 5 we address the potential concern that state-owned mining has a different effect on local manufacturing. We do so by dropping the 12 districts in which the state of Indonesia owns more than 50% of every 1990 mineral deposit. The results are robust to this change. This is consistent with the finding in Online Appendix Table OA2 that majority state-owned mines are no different from the other mines in their output response to global mineral price shocks.

In the last column 6, we re-scale the resource endowment variables by their standard deviation rather than their mean to allow a direct comparison of the magnitude to a result in the literature based on US data (Allcott and Keniston, 2018). They find that as the oil price increases by 100 log points, manufacturing employment in a county with an additional oil & 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 labor mobility and spillovers across space and higher labor mobility between manufacturing and other sectors due to a comparatively smaller degree of specialization of Indonesian manufacturing. In addition, the result displayed in Table 1 that oil & 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.

³⁷ 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.

Table 7

Robustness III: Controlling for district-year fixed effects: labor-intensive mining versus no mining.

Sample → Dependent variable →	All plants in districts with labor-intensive mining or no mining							
	Δln		Δln Wage Bill/ #Employees		Δln		Δln	
	#Employees		#Employees		Unit Price		Revenue	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mineral Resources 1990 × Δln(Mineral Price)	0.003 (0.002)		0.205*** (0.006)		0.317*** (0.012)		0.331*** (0.007)	
MinRes90 × Δln(MPrice) × More-Traded Goods Producers	−0.046*** (0.007)	−0.037*** (0.008)	−0.216*** (0.015)	−0.213*** (0.013)	−0.255*** (0.019)	−0.255*** (0.020)	−0.352*** (0.012)	−0.372*** (0.016)
Linear district trends	Yes	No	Yes	No	Yes	No	Yes	No
District-Year FE	No	Yes	No	Yes	No	Yes	No	Yes
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 (0.002)		0.205*** (0.006)		0.317*** (0.012)		0.331*** (0.007)	
...more-traded goods producers	−0.043*** (0.006)		−0.011 (0.012)		0.062*** (0.018)		−0.021** (0.010)	

Note: In this table we use an alternative specification which makes it possible to analyze the effect of labor-intensive mining booms on more- versus less-traded goods producers conditional on district-times-year fixed effects. 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* × *Δln(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. The oil & gas boom measure, as well as the dummy *More-Traded Goods Producers* as separate variable, 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.

5.8. Controlling for district-year fixed effects: labor-intensive mining versus no mining

In Table 7 we restrict the sample to districts without mineral resources and districts with labor-intensive mining, and interact our measure of mining booms with the more-traded goods producer dummy. This makes it possible to analyze the effect of labor-intensive mining booms on more- versus less-traded goods producers conditional on district-times-year fixed effects, which control for any potential confounding factors that are district-year specific (such as local labor market conditions). The downside of this specification is that it does not include all districts and provides no information on the effect of capital-intensive mining booms.

Since we thus drop capital-intensive mining districts, the coefficient on *Mineral Resources 1990* × *Δln(Mineral Price)* now indicates the effect of a labor-intensive mining boom, for less-traded goods producers. The coefficients in the odd-numbered columns in the first row of Table 7 are thus comparable to the marginal effects in the last row of Panel B in Table 2, and they are indeed nearly identical. Similarly, the coefficient sums in the odd-numbered columns in Table 7 are comparable to the last row in Panel A of Table 2. 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.

We add district-times-year fixed effects in the even-numbered columns of Table 7. 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.

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 global resource price increases only lead to crowding out of manufacturing employment in districts where mining operations are relatively labor intensive, and only for more-traded goods producers. 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 employment for more-traded (as well as less-traded) goods producers, 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 because our

data show that labor-intensive mining is prevalent in many of them, our results 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 total factor productivity: evidence for a productivity-related 'Dutch disease' remains elusive. However, volatility creates uncertainty and may itself significantly dampen private investment into the manufacturing sector, at least in natural resource-rich districts. Exploring this potential issue is a promising avenue for future research.

Declaration of Competing Interest

None.

Appendix A

Fig. 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.

Fig. 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 were discovered 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 the Online Data Appendix OA2.3 for the individual price series sources.

Table A1
Summary statistics.

Variable	Sample	Mean	p(50)	s.d.	Min	Max	N (non-missing)
<i>District data</i>							
: 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
<i>District-year data</i>							
MRes90 × $\Delta \ln(\text{Mineral Price})$	MRes90>0	0.040	0.000	0.775	−6.981	8.309	741
MRes90 × $\Delta \ln(\text{MPrice}) \times \text{L-I Mining}$	MRes90>0, L-I Mining	0.044	0.000	0.925	−5.619	6.688	171
O&G Prod-90 × $\Delta \ln(\text{Oil Price})$	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
<i>Plant-year data</i>							
$\Delta \ln(\# \text{ Employees})$	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
$\Delta \ln(\text{Wage Bill}/\# \text{ Employees})$	All	0.130	0.096	0.573	−10.519	11.318	260,803
$\Delta \ln(\text{Unit Price})$	All	0.051	0.051	1.913	−19.815	18.786	148,691
$\Delta \ln(\text{Revenue})$	All	0.130	0.085	0.757	−7.634	7.883	261,017
$\Delta \ln(\text{TFP})$	All	0.003	0.003	0.048	−0.972	0.958	172,504
$\Delta_5 \ln(\text{TFP})$	All	0.013	0.013	0.065	−0.799	0.899	83,759
<i>Plant data</i>							
Upstream share in %	MRes90>0, more-tr. pr.	0.076	0.029	0.195	0	2.221	1554
<i>Mine data (global sample)</i>							
$\ln(\# \text{ Mine Employees})$	n/a	5.992	5.979	1.416	1.099	10.727	464

Note: *MRes90* equals mineral ore resource endowment per square mile in 1990, scaled by the average of this variable across districts with positive endowments. The variable corresponds to $\ln$ in Eq. (1). *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 production of barrels of oil equivalent around 1990 per square mile, scaled by the average across districts that produce oil & gas. The variable corresponds to $\ln$ in Eq. (1). 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 OA2.1 for details. *Unit Price* equals total revenue over units sold. $\Delta_5 \ln(\text{TFP})$ 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 A2
Global mine-specific evidence on the labor intensity of different mining techniques. max width = tw.

Dependent variable →	$\ln(\# \text{ Mine Employees})$					
Sample →	All Mines				Only UG &/or OP	All Mines
	(1)	(2)	(3)	(4)	(5)	(6)
Underground Mining	0.863*** (0.184)					
% Underground Mining		0.959*** (0.182)	1.136*** (0.327)	0.974*** (0.217)	0.867*** (0.155)	0.715*** (0.131)
Underground & Open-Pit Mining		0.652*** (0.183)	0.813*** (0.267)	0.659*** (0.176)	0.580*** (0.183)	0.489*** (0.139)
$\ln(\text{Mineral Production})$	0.431*** (0.055)	0.444*** (0.053)	0.423*** (0.069)	0.444*** (0.065)	0.447*** (0.055)	
$\ln(\text{Mineral Resources})$						0.285*** (0.024)
% Underground Mining × High Income			−0.436 (0.465)			
Underground & Open-Pit Mining × High Income			−0.334 (0.395)			
Country FE	Yes	Yes	Yes	No	Yes	Yes
Year of Information FE	Yes	Yes	Yes	No	Yes	Yes
Country-Year of Information FE	No	No	No	Yes	No	No
Main Mineral FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations (# Mines)	308	308	308	277	303	464
# Countries	27	27	27	22	27	39
p-value F-test $\beta_{(100\% \text{ UG Mining})} = \beta_{(\text{UG\&OP Mining})}$		0.003		0.009	0.003	0.096

Note: This table shows that underground mining is more labor intensive than other types of mining, and that pure underground mining is more labor intensive than a combination of underground and open-pit mining. The data are a cross-section of individual mines around the world for which we observe employment, the applied mining technique(s), and mineral production (columns 1–5) or mineral resources (column 6). 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. *Mineral Production* and *Mineral Resources* are measured in terms of megatons of ore and in the same year as employment. *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. 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. The sample size in columns 1–5 is smaller than in column 6 because of lower data availability on production. Standard errors in parentheses are clustered at the country level. ***Significant at 1% level; **Significant at 5% level; *Significant at 10% level.

Appendix B. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.jinteco.2021.103457>.

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