Environmental Misallocation in the Copper Industry

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Abstract

We use mine-level data from the international copper industry to quantify environmental misallocation. We define this concept as the ratio between the observed carbon dioxide (CO2) emissions in the industry and the level reached by a social planner. The planner allocates the observed output across mines so as to minimize emissions, conditional on the current state of the technology and some well-defined extraction rules. We find that CO2 emissions produced from the world copper industry are reduced by 47% under the planner's allocation. We also find that the latter allocation of output would bring down production costs by 24% at the aggregate level. Our results suggest that a cleaner environment is not necessarily tied to lower levels of productive efficiency.

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1 Introduction

Climate change and global warming are issues of concern among policy makers worldwide.[1] In economies with heterogenous production units, aggregate pollution depends not only on the emission levels of the individual establishments but also on how production is allocated across those units. Concretely, two countries with exactly the same production technology could exhibit different aggregate levels of pollution if one country produces more intensively with the "cleanest" production units, whereas the other country do so with the "dirtiest" production units. The latter example illustrates a case in which a given level of aggregate output could be being produced not in the cleanest possible way, conditional on the current state of the technology. We refer to this idea as *enviromental misallocation*.

In this paper, we quantify environmental misallocation in the international copper industry. Formally, we define environmental misallocation as the ratio between the observed carbon dioxide (CO2) emissions in the industry and the level reached by a social planner that allocate the observed output across mines so as to minimize emissions, conditional on the current state of the technology and some well-defined extraction rules that the planner must respect. We estimate a value of 1.9 for the environmental misallocation indicator; that is, CO2 emissions derived from the world copper industry could be reduced by 47% if the observed yearly aggregate output is frictionlessly reallocated across mines, such that the least polluting mines are exploited first. This reduction in pollution would leave global CO2 emissions in the level observed in 1984. Furthermore, we find that the latter reallocation of production would bring down production costs by 24% at the aggregate level. These findings suggest that a cleaner environment is not necessarily tied to lower levels of productive efficiency.

We focus on the international copper industry because two reasons. First, mining and ore processing is one of the most polluting industry worldwide, as exhibited in Table 1.[2] A large number of industries depend on the mining and ore processing industry for the supply

[1] For instance, the Intergovernmental Panel on Climate Change in its AR5 Synthesis Report states: "Human influence on the climate system is clear, and recent anthropogenic emissions of greenhouse gases are the highest in history" and "Recent climate changes have had widespread impacts on human and natural systems."

[2] Table 1 ranks the ten most polluting industries in terms of the *disability-adjusted life year* (DALY).DALY is a measure of overall disease burden, expressed as the number of years lost due to ill-health, disability or early death. The DALY is becoming increasingly common in the field of public health and health impact assessment (HIA).

of minerals and metals.[3] These products occur in nature in the form of ores in rocks and must be mined and concentrated prior to use. Such processes result in the production of large volumes of waste that are often loaded with pollutants like mercury, lead, cadmium, and others. The second reason to focus on the copper industry is data availability. We collected (global) rich disaggregated information at the mine level for approximately 85% of the world copper production, which allows us to build mine-level measures of CO2 emissions and production costs.

Our analysis is inspired by the literature that studies the consequences of misallocation of factors on aggregate TFP (Restuccia and Rogerson, 2008, 2013; Hsieh and Klenow, 2009; Hopenhayn, 2014). Those studies quantify the aggregate TFP gains derived from a reallocation of inputs across production units. In the same spirit, we assess the aggregate consequence, in terms of CO2 emissions, when the output is reallocated across mines in the international industry copper. We rely on Asker et al. (2019) to build an algorithm that compares actual aggregate CO2 emissions to a counterfactual. The counterfactual scenario is defined as the level of emissions implied by an allocation of production that minimizes aggregate emissions, conditional on the observed aggregate production, the current state of technology, and some well-defined extraction criteria. The ratio between aggregate CO2 emissions and the counterfactual level is our quantification of environmental misallocation in the copper industry.

We proceed in three steps. First, we estimate the CO2 emissions per tonne produced by each mine at each year. We rely on the Intergovernmental Panel on Climate Change (IPCC) standards for green house gas (GHG) inventories to produce this computation. Using this information, we aggregate CO2 emissions across mines and years. Then, in the second step, we rank mines from the least to the most polluting ones, within years. Using the latter rank, we estimate a counterfactual level that results from a reallocation of the yearly aggregate output across mines, exploiting first the least polluting mines. The resulting allocation is the *cleanest allocation* in the cooper industry. This computation keeps constant the observed yearly aggregate industry output and the state of the technology. Moreover, we constrain the reallocation of production to some well-defined extraction rules, but we discard any other type of frictions. In a last step, we compare the current industry-level production cost with the

[3] In 2008, the world consumption of copper was approximately 15 million tonnes, grossing 105 billion dollars in sales, and employing more than 360.000 people (US Geological survey).

one implied by the cleanest allocation. The latter analysis allows us to evaluate whether the reallocation of production implied by the cleanest allocation require a more intense input usage, or not.

Our data set include information on 333 copper mines spanning the period 1992-2010. These data represent approximately 85% of the world copper production. Our mine-level information includes the output and inputs measured in physical units, the input prices, and the geological characteristics of mines. Using these data and the procedure described above, we estimate that CO2 emission in the international copper industry could be reduced by 47%, and this action would decrease the total production cost by 24%. Thus, for the copper industry, we find that a cleaner environmental allocation does not come at the cost of reduced production efficiency.

As far as we know, this is the first paper that applies the macroeconomics notion of misallocation to compute a cleanest allocation of the output for an entire industry, as well as the cost of such action.[4] We use an *indirect approach*[5] that quantifies the amount of environmental misallocation, without digging into the underlying factors behind it. Our analysis also reveals that a cleaner allocation of output can be reached at a lower industry-level cost. This result is in contrasts to the positive costs of abatement of pollution reported in the literature (Coggins and Swinton, 1996; Hailu and Veeman, 2000; Lee, 2005; Färe et al., 2006; Lee and Zhang, 2012; Du and Mao, 2015; Tamaki et al., 2018).

The rest of this paper is organized as follows. Section 2 describes the data and the methodology to compute CO2 emissions at the mine level. Section 3 discusses the empirical approach. Section 4 presents and discuss the results. Section 5 concludes this paper.

2 Data and Preliminaries

In this section, we first present a general description of the variables included in our dataset. Then, we explain how we build two key inputs for our empirical analysis: the mine-level CO2

[4]For instance, Tombe and Winter (2015) study the effect of firm-level idiosyncratic environmental policies on aggregate TFP. Crucially difference from that study, our focus is on the consequences on aggregate emissions of a reallocation of production across units, not on aggregate productivity.

[5]This term is used in the macroeconomics literature on misallocation to group approaches that quantify the aggregate effect of distortions, without identifying the source of those distortions (Hsieh and Klenow, 2009).

emissions and the mine-level costs of production. We conclude by presenting descriptive statistics of the main variables involved in our empirical approach.

Our data were collected from the *Corporación Nacional del Cobre* (CODELCO) and include information on 333 copper mines spanning the period 1992-2010. These data represent approximately 85% of the world copper production. We have mine-level information on outputs and inputs measured in physical units, input prices, and the geological characteristics of mines.[6] Specifically, we have data on the location, the operating firm, the current status (operating or closed), the first year of production, the *in-situ* ore discoveries,[7] and the depletion rate of mines.[8] In addition, our data set contain information on the mine reserves, the ore grade,[9] the payable copper produced by each mine, and the number of workers in each mine. We also collected information on labor costs, third party services paid, energy costs, material costs, and C1 cash cost.[10]

2.1 Mine-Level CO2 Emissions

In general, there are three types of greenhouse gas (GHG) emissions. First, *scope 1 emissions* which are direct emissions from sources that are owned or controlled by the mining company; for instance, emissions from fuel combustion in owned or controlled boilers, furnaces, vehicles, and so on. Second, *scope 2 emissions* which are considered as indirect emissions from the generation of purchased electricity consumed by the company. This second type of GHG emissions are physically issued at the facility where electricity is generated but they are, in practice, allocated to the organization that owns or controls the plant or equipment where the electricity is consumed. Lastly, we have *scope 3 emissions* which are other indirect GHG emissions. Our analysis includes estimates of both direct and indirect emissions of CO2; that is, emissions included in the three scopes that we have described.

[6] All the information is disaggregated for concentrates production and SxEw (cathodes) production. A copper mine can mainly produce copper in concentrates, cathodes, or both, depending of the geological characteristics in the ore. Copper sold in form of concentrates contains between 25% and 30% of purity, whereas cathodes are 99.9% pure.

[7] Initial reserves minus stock in the previous period.

[8] Percentage of the mine already depleted at the beginning of the period.

[9] Ore grade is the percentage of copper content in the ore body. Alternatively, this concept is also named the "law of the mineral."

[10] C1 cash cost represents the cost incurred at each processing stage, from mining through to recoverable metal delivered to market, less net by-product credits (if any) in cents per pound.

We estimate CO2 emissions at the mine level according to the IPCC standards for GHG inventories as follows. Fuel data comes from diesel consumption. CO2 emissions from diesel combustion in all mining processes were calculated using the following equation:

$$CO2_{i,t}^{fuel} = F_{i,t} \times d \times NCV \times CEF \times FCO \times MoR, \tag{1}$$

where $F_{i,t}$ is is fuel consumption in liters in mine i at period t, d is the diesel density (CO2/kg), NCV represents the Net Caloric Value for diesel (TJ/10^3ton), CEF is the carbon emission factor for diesel (kg/Gj), FCO is the fraction of carbon oxidised (equal to 1 for diesel), and MoR is the molecular weight ratio of Carbon Dioxide to Carbon C (44/12).

In addition, electricity consumption is calculated as the KWh consumed. CO2 emissions from electricity is calculated using data on electricity emissions factor for each country's national grid as follows:

$$CO2_{i,t}^{electricity} = E_{i,t} \times EEF_c, \tag{2}$$

where $E_{i,t}$ is is the electricity consumption in KWh in mine i at period t, and EEF_c is the country specific electricity emission factor CO2 kg/ KWh.[11]

We then aggregate the CO2 emissions from fuel and electricity to get an aggregate measure of CO2 emissions for each mine in kilograms. In addition, our dataset also allow us to estimate the tonnes of copper production and the total metal production accounting for by-products or *equivalent output*. We use the latter output to compute the mine-level coefficient emission.

2.2 Mine-Level Cost of Production

We define the mine-level variable cost as:

$$VC_{i,t} = p_{i,t}^l l_{i,t} + p_{i,t}^e e_{i,t} + p_{i,t}^f f_{i,t} + M_{i,t} + S_{i,t}, \tag{3}$$

where $p_{i,t}^l$ is the unit price of labor (wage) in mine i at period t, $l_{i,t}$ is the number of workers, $p_{i,t}^e$ is the unit price of electricity, $e_{i,t}$ is the electricity consumption measured in units, $p_{i,t}^f$ is

[11] Given the restricted access to the data, yearly data on emission factors is available only for Chile, China, Indonesia, Peru, Poland, Russia and Zambia. For the rest (33 countries), emission factors are based on 1996 country's national grid, collected from the International Energy Agency.

the unit price of fuel, $f_{i,t}$ is the fuel consumption measured in units, $M_{i,t}$ is total expenses in materials, and S_{it} is total expenses in services.

We next use information on the each input's rate of use per unit of output to express equation (3) as:

$$VC_{i,t} = p^l_{i,t}\left(R^l_{i,t} \times q_{i,t}\right) + p^e_{i,t}\left(R^e_{i,t} \times q_{i,t}\right) + p^f_{i,t}\left(R^f_{i,t} \times q_{i,t}\right) + p^M_{i,t}\left(R^M_{i,t} \times q_{i,t}\right) + p^S_{i,t}\left(R^S_{i,t} \times q_{i,t}\right), \quad (4)$$

where $R^z_{i,t}$ is the input's z rate of use per unit of output and q is the quantity produced.

Our dataset does not contain information to disaggregate total expenses in materials and services into prices and quantity. Then, we use information on the total expenses on materials and services and the quantity produced to get an expression for value of the rate of use of these inputs, per unit of output: $p^M_{i,t}R^M_{i,t} = M_{i,t}/q_{i,t}$ and $p^S_{i,t}R^S_{i,t} = S_{i,t}/q_{i,t}$. Thus, we can express equation (4) simply as:

$$VC_{i,t} = p^l_{i,t}\left(R^l_{i,t} \times q_{i,t}\right) + p^e_{i,t}\left(R^e_{i,t} \times q_{i,t}\right) + p^f_{i,t}\left(R^f_{i,t} \times q_{i,t}\right) + M_{i,t} + S_{i,t}. \quad (5)$$

Our next step is to estimate a variable cost function.[12] We impose a Cobb-Douglas functional form on inputs prices and output. In addition, we model a transition rule for ore grades, which is motivated by the fact that ore grades are decreasing in lagged output. This latter property is the *depletion effect* documented by Aguirregabiria and Luengo (2016). Hence, we estimate the following system of equations:

$$\ln VC_{i,t} = \beta_0 + \beta_q \ln q_{i,t} + \beta_\ell \ln p^\ell_{i,t} + \beta_e \ln p^e_{i,t} + \beta_f \ln p^f_{i,t} + \beta_M \ln p^M_{i,t} + \beta_s \ln p^S_{i,t} + \beta_g g_{i,t} + \eta_i + d_t + \varepsilon_{i,t}, \quad (6)$$

$$g_{i,t} = \beta_u g_{i,t-1} + \delta_q \ln(1 + q_{i,t-1}) + \eta_i + d_t + \xi_{i,t}. \quad (7)$$

where $p^M_{i,t}$ is the unit price of materials, $p^S_{i,t}$ is the unit price of services, g_{it} is the ore grade, d_t is a time variable accounting for technological shocks that are common across mines, η_i is an efficiency level of the mine which we assume it is constant over time, and $\varepsilon_{i,t}$ and $\xi_{i,t}$ are i.i.d error terms. Note that, in equation (7), δ_q is a measure of the depletion effect and β_u is

[12]Fixed cost are not relevant for the analysis because, in our approach, the planner allocate production respecting the productive capacity of each mine.

a change in ore grades due to other mine activities, i.e., updates in ore grades.[13] Furthermore, as explained above, we do not have information on unit prices for material and services. Thus, we use the following approximation to build theses prices: $p^M_{i,t} = M_{i,t}/q_{i,t}$ and $p^S_{i,t} = S_{i,t}/q_{i,t}$.

Tables 4 and 5 presents the estimates of equations (6) and (7). For a comparison purpose, we present OLS and fixed effects models. However, we rely on the fixed-effects model for the analysis in Section 4. We observe, as expected, a positive relation between prices and variables costs. Moreover, the technology estimated by equation (6) implies positive marginal variables costs. Lastly, we observe that the a higher ore grade is negatively correlated with the variable costs. The latter is consistent with the fact that, when a mine has a high grade, it takes relatively less effort to extract a tonne of mineral from the ground and less ore has to be dug out, which reduces input costs for the mining company.

In addition, we observe in Table 5 a negative relation between lagged production and the ore grade, which confirms the existence of a depletion effect, as documented by Aguirregabiria and Luengo (2016). Furthermore, there is a positive relation between the current and the past ore grade, which reflects that the ore garde exhibits persistence over time. We use, in Section 4, the fixed effect specification in equations (6) and (7) to estimate the variable cost of each mine that is implied by different allocation of the aggregate industry output.

2.3 Descriptive Statistics

Table 2 presents descriptive statistics of our data set. First, we observe that electricity or indirect emissions are the main source of GHG emissions: this type of emissions represents, on average, 76% of the total CO2 emissions, whereas fuel or direct emissions accounts for the 24% of emissions in this industry. We also observe a large heterogeneity in emission coefficients across mines, which is the amount kilograms of CO2 emitted per tonne of output. Concretely, the emission coefficient per output in the most polluting mines (those at the $99th$ percentile) is 120 times the one in the least polluting mines (those at the $1st$ percentile). In addition, we also observe heterogeneity regarding the marginal variable cost of production. Table 2 shows that the most efficient mines exhibit a marginal cost that is around 70% lower than the least efficient mines.

[13]This parameter is set equal to one in case that no activities are performed

Overall, we observe a a large heterogeneity across mines in the CO2 emissions per output. We also observe heterogeneity in the average variable cost of production across mines. Both facts suggest that a reallocation of production across mines has the potential to reduce the aggregate CO2 emissions in the copper industry, but that this re-allocation could be costly. We formally explore these issues in the next section.

3 Empirical Approach

In this section, we discuss our approach to quantify the extent of environmental misallocation in the international copper industry. We define environmental misallocation as the ratio between current aggregate CO2 emissions and the emission level reached by a social planner that allocates the observed output to minimize pollution, conditional on the current state of technology and some well-defined extraction criteria that the planner must respect. We refer to the planner's allocation as the cleanest allocation.

Our approach is inspired by Asker et al. (2019), who measure the misallocation of production in the oil market. The authors develop an iterative procedure in which the observed aggregate oil production is obtained by exploiting the low-cost fields first, and then, the high-cost fields. They use the latter algorithm to get the production plan that minimizes the net present value of costs subject to satisfying an aggregate production path. In the same spirit, we compare actual aggregate CO2 emissions in the copper industry to a counterfactual scenario, which is the one implied by the cleanest allocation.

We start with three preliminary computations. Let $I = \{1, ..., M\}$ be the set of all the mines observed in our data set. We denote by i the typical element of set I. Time is discrete and indexed by $t \in \{1992, ..., 2010\}$. First, we directly extract information from our database on the amount of reserves for each mine at each year t. We denote by $K_{i,t}$ the reserves of mine i at period t. Second, we compute the yearly extraction rate of each mine, defined as the ratio between production and reserves. Then, we order each mine-year observation of the extraction rate in a descending way. We get that the extraction rate of the mine at the $99th$ percentile is 10%, which we hereafter call the *maximal extraction rate of the industry.* Third, we compute the maximal historical yearly production of each mine, $\overline{q}_i$, and define mine-i *production capacity* as $1.25 \times \overline{q}_i$. We scale up multiplicatively the term $\overline{q}_i$ because it is commonly considered that copper mines usually produce at 80% of their total production capacity. For future discussion, we will refer to the parameter 1.25 as the *production capacity parameter.* Fourth, we compute the mines' yearly emission coefficient scaled by the output, and denote it by $ec_{i,t}$.

We then use the previous inputs to feed the following algorithm. First, we fix the year-mine observations of the emission coefficient. Then, we use the emission coefficients to rank mines, within each year, in an ascending order. Let $n_t(i) \in \mathbb{N}^+$ be the position of mine i at period t in the latter rank. Then, $n_t(i) < n_t(j)$ if, and only if, $ec_{i,t} < ec_{j,t}$. Let $i_{p,t}$ be the mine in the position p of the rank at period t. Then, $n_t(i_{p,t}) = p$.[14] Next, we fix $t = 1992$. We assign to mine $i_{1,t}$ an output $\tilde{q}_{i_{1,t},t}$ that is equal to the minimum value between the maximal extraction level and the production capacity of the mine. That is, $\tilde{q}_{i_{1,t},t} = \min\{0.1 \times K_{i_{1,t},t}, 1.25 \times \overline{q}_{i_{1,t}}\}$. Let Q_t be the aggregate output at period t. If $\tilde{q}_{i_{1,t},t} \geq Q_t$, then we re-assign an output $\tilde{q}_{i_{1,t},t} = Q_t$ to mine $i_{1,t}$. We then update the reserves level of mine $i_{1,t}$ such that $K_{i_{1,t},t+1} = K_{i_{1,t},t} - \tilde{q}_{i_{1,t},t}$ and we start an analogous process for $t = 1993$. If $\tilde{q}_{i_{1,t},t} < Q_t$, then we proceed with mine $i_{2,t}$ following a process analogous to that for mine $i_{1,t}$. If $\tilde{q}_{i_{1,t},t} + \tilde{q}_{i_{2,t},t} \geq Q_t$ we assign $\tilde{q}_{i_{2,t},t} = Q_t - \tilde{q}_{i_{1,t},t}$ and proceed for $t = 1993$. If $\tilde{q}_{i_{1,t},t} + \tilde{q}_{i_{2,t},t} < Q_t$, , then we proceed analogously with mine $i_{3,t}$.

The output of this algorithm is the cleanest allocation. We then compute the aggregate CO2 emission implied by the cleanest allocation and compare it to the observed emissions of the industry. This gap results in a quantification of environmental misallocation in the copper industry. Formally, $\tilde{q}_{it}$ is the output allocated to mine i at period t under the cleanest allocation. Denote by τ the magnitude of environmental misallocation. Then,

$$\tau = \frac{\sum_i \sum_t q_{i,t} \times ec_{i,t}}{\sum_i \sum_t \tilde{q}_{i,t} \times ec_{i,t}}. \tag{8}$$

Then, notice that $\tau \geq 1$. Hence, $\tau > 1 (\tau = 1)$ implies that the observed output in the copper industry was not (was) produced in the cleanest possible way, conditional on the state of the technology and well-defined extraction rules for the planner.

Our last step of the analysis consists on an assessment of the cost of reaching the cleanest allocation. First, we estimate the observed total variable cost for each mine and each year using

[14] Thus, mine $i_{1,t}$ is the one with the lowest emission coefficient at period t, mine $i_{2,t}$ is the one with the second lowest, and so on.

equation (5). Denote this cost by $c_{i,t}$. Then, we use the estimated system of equations (6) and (7) to compute the counterfactual cost under the cleanest allocation. To do so, we impute the observed mine's input prices and the mine's output implied by the cleanest allocation into the system (6) and (7) to estimate a counterfactual mine-level variable cost:

$$\widehat{\ln VC_{i,t}} = \hat{\beta}_0 + \hat{\beta}_q \ln \tilde{q}_{i,t} + \hat{\beta}_\ell \ln p^\ell_{i,t} + \hat{\beta}_e \ln p^e_{i,t} + \hat{\beta}_f \ln p^f_{i,t} + \hat{\beta}_M \ln p^M_{i,t} + \hat{\beta}_s \ln p^S_{i,t} + \hat{\beta}_g \hat{g}_{i,t} + \hat{\eta}_i + \hat{d}_t, \quad (9)$$

$$\hat{g}_{i,t} = \hat{\beta}_u g_{i,t-1} + \hat{\delta}_q \ln(1 + \tilde{q}_{i,t-1}) + \hat{\eta}_i + \hat{d}_t. \quad (10)$$

Define $\tilde{c}_{it} = \exp\left(\widehat{\ln VC_{i,t}}\right)$. Then, $\tilde{c}_{it}$ are the total variable cost for mine i at period t that is implied by the cleanest allocation. Then, we compute the gap between the observed cost and the counterfactual cost as follows:

$$\gamma = \frac{\sum_i \sum_t c_{i,t}}{\sum_i \sum_t \tilde{c}_{i,t}}. \quad (11)$$

Therefore, $\gamma > 1$ ($\gamma < 1$) implies that the cleanest allocation result in strictly lower (higher) production costs. Next section presents our estimates of τ and γ.

4 Results

We use the approach described in Section 3 to estimate the environmental misallocation in the copper industry. We estimate an amount of environmental misallocation, τ, of 1.9. This estimate implies that total CO2 emissions in the international copper industry could be reduced by near 47% if the observed yearly aggregate output is frictionlessly reallocated across mines, such that the least polluting mines are exploited first.[15] Consider the world annual CO2 tonnes of emissions exhibited in Figure 1. The amount of environmental misallocation that we estimate is equivalent to the observed change in the global CO2 emissions during the past 20 years (1984-2017).

The cleanest allocation is reached by distributing the observed output across mines under well-defined extraction rules; each mine cannot produce more than the minimum value between the maximal extraction level and the production capacity of the mine, which is given by the

[15] As discussed in Section 3, this reallocation can be understood as the choice of a planner who aims to minimize pollution, and is constrained by the current state of the technology and well-defined extraction rules.

expression $\min\{0.1 \times K_{i,t}, 1.25 \times \overline{q}_i\}$.[16] Let call *production constraint* to the latter expression and denote it by $\theta_{i,t}$. Then, the reduction in CO2 emissions under the cleanest allocation would be null if the the least polluting mines do not exhibit room to absorb the production from other mines. The latter is a case in which $\theta_{i,t} = q_{i,t}$ at the least polluting mines, for all t; that is, in the least polluting mines, the production capacity is equal to the observed output. Thus, our main result implies that the mines with the lowest emission coefficient indeed exhibit available capacity to absorbe an additional amount of the yearly observed output.

Our next step is to quantify the cost of reaching the cleanest allocation, that is, the parameter γ. Relying on the approach described in Section 3, we estimate $\gamma = 1.3$. Hence, the observed allocation is produced with an aggregate variable cost that is 30% higher than the cost implied by the cleanest allocation. In order to understand the latter result, notice that there are two effects involved. The first effect is triggered by the heterogeneity in production costs across mines. The cleanest allocation moves production from the most to the least polluting mines. Hence, a within-year negative correlation between the CO2 emissions and the production costs of mines implies that the cleanest allocation produces a given output at a lower production cost than the current cost observed in the data. The opposite conclusion is reached when CO2 emissions and production costs are positively correlated. This is an extensive margin effect and its sign is ambiguous. The second effect is triggered by the depletion effect documented in Aguirregabiria and Luengo (2016). A more intensive production of a mine reduces its ore grade, which raises the input costs to extract a tonne of mineral from the ground. This is an intensive margin effect and it unambigously leads to a greater production cost under the cleanest allocation. Then, our result of $\gamma > 1$ implies that the extensive margin effect leads to smaller costs under the cleanest allocation and this effect overcomes the intensive margin effect.

We perform in Table 5 a sensitivity analysis regarding the production capacity parameter. We observe that a release in the mines' production capacity makes more pronounced the fall in both CO2 emissions and production costs of the industry implied by the cleanest allocation. This results is consistent with our previous discussion: more production capacity implies that the cleanest allocation moves a bigger share of the yearly industry output to the least polluting mines, which in turn, are those that exhibit the lower production costs.[17]

[16] $K_{i,t}$ is the amount of reserves of mine i at time t and $\overline{q}_i$ is the the maximal historical yearly production of mine i.

[17] The sensitivity analysis is carried out by exclusively moving the production capacity parameter since the

Overall, we find that producing the aggregate output path with less CO2 emissions would not imply higher aggregate costs. This results is in contrast with to the positive costs of abatement of pollution reported in the literature (Coggins and Swinton, 1996; Hailu and Veeman, 2000; Lee, 2005; Färe et al., 2006; Lee and Zhang, 2012; Du and Mao, 2015; Tamaki et al., 2018). Our findings also (indirectly) reveal the existence of misallocation of inputs in the copper industry. We show the same yearly output in the copper industry can be produced at a lower cost when it is re-allocated across mines. The other side of the coin is that more output could be produced with the same input usage. The latter is the concept of input misallocation used in the macro literature (Restuccia and Rogerson, 2008, 2013; Hsieh and Klenow, 2009; Hopenhayn, 2014). Thus, our results open the research question for the macro literature on input misallocation regarding the frictions that are preventing an efficient input allocation in the copper industry. We will explore the latter issue in future research.

5 Conclusions

This paper introduces the concept of environmental misallocation as the ratio between the observed carbon dioxide (CO2) emissions in the industry and the level reached by a social planner that allocate the observed output across mines so as to minimize emissions, conditional on the current state of the technology and some well-defined extraction rules. In order to compute this parameter, we used mine-level data for the international copper industry and an iterative algorithm that allocates the observed yearly aggregate across mines, such that the least polluting mines are exploited first. We find that CO2 emissions derived from the world copper industry could be reduced by 47% under the latter allocation, which we called the "cleanest allocation." Furthermore, we use reduced-form cost regressions to estimate the industry-level cost that is implied by the cleanest allocation and compared it with the observed cost. We find that the cleanest allocation would bring down production costs by 24% at the aggregate level.

Therefore, our findings suggest that a cleaner environment is not necessarily tied to lower levels of productive efficiency. In the particular case of the copper industry, this result is driven by the (theoretical) excess of capacity of the least polluting mines to absorb output from

maximal extraction rate parameter is infrequently binding.

other mines, and the fact that those mines are also which exhibit a lower cost of production. Hence, indirectly, our paper opens the research question of what frictions are preventing the international copper industry from reaching the highest level of efficiency. The latter is a question that can be framed in the macro literature on input misallocation, which we plan to explore in the future.

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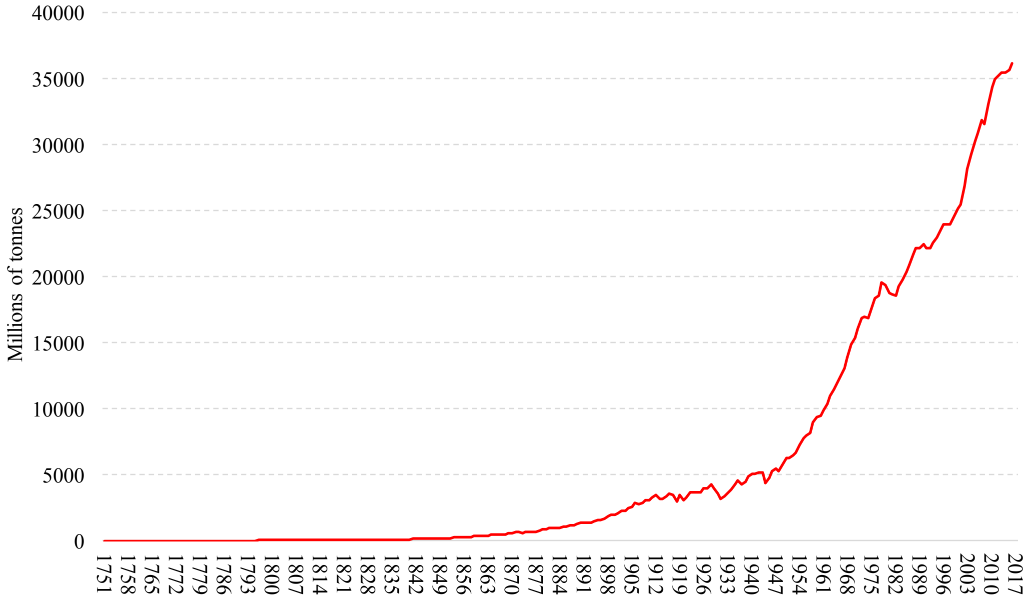
Figures

Figure 1: Global CO2 Emissions, 1751-2017



Source: Ritchie and Roser (2019).

Tables

Table 1: The World's Most Polluting Industries, 2016

Ranking	Industry	DALY
1	Used Lead-Acid Batteries (ULAB)	2,000,000 - 4,800,000
2	Mining and Ore Processing	450,000 - 2,600,000
3	Lead Smelting	1,000,000 - 2,500,000
4	Tanneries	1,200,000 - 2,000,000
5	Artisanal and Small Scale Gold Mining (ASGM)	600,000 - 1,600,000
6	Industrial Dumpsites	370,000 - 1,200,000
7	Industrial Estates	370,000 - 1,200,000
8	Chemical Manufacturing	300,000 - 750,000
9	Product Manufacturing	400,000 - 700,000
10	Dye Industry	220,000 - 430,000

Source: Pure Earth.

Table 2: Production, CO2 Emissions, and Costs in the Copper Mining Industry 1992 - 2010

	Reserves	Output	CO2 elect.	CO2 fuel	CO2 total	EC	Marginal cost (2010)
	mt	kt	kt	kt	kt	kg/ton	USD
p1	129	0.1	0.3	0.1	1.0	83.5	526.3
p5	738	0.4	1.9	0.4	3.5	254.0	751.0
p10	1,699	0.8	3.6	0.8	5.5	354.8	905.0
p25	5,298	4.4	11.1	2.0	15.2	665.6	1,186.5
p50	24,200	19.3	35.6	5.9	47.3	1,379.9	1,604.4
p75	211,036	69.8	137.7	31.9	177.7	2,611.9	2,171.0
p90	747,000	167.1	377.9	97.5	467.1	4,473.1	2,909.7
p95	1,287,800	298.5	627.6	174.2	801.9	5,752.9	3,592.7
p99	2,500,000	623.7	1,408.9	635.5	1,904.1	10,053.6	5,341.5
Mean	240,762	64.5	141.7	41.5	185.1	2,040.9	1,817.4
Std. Dev.	506,840	122.3	319.5	126.5	407.7	2,381.2	1,068.2
Min	9	0.0	0.1	0.0	0.2	47.2	271.5
Max	5,730,149	1,443.5	6,393.2	2,948.6	6,655.6	29,163.3	19,683.9
Obs	3,286	3,286.0	3,004.0	3,258.0	2,996.0	2,996.0	2,996.0

Source: Codelco and International Energy Agency. Note: (a) *ton* denotes metric tonnes (1,000 kg), *kt* denotes thousand of metric tonnes, *mt* denotes million of metric tonnes, and *EC* denotes Emission Coefficient.

Table 3: Equation for Variable Costs

	OLS	FE
Ln output	0.902***	0.805***
	(0.0108)	(0.0164)
Ln wage	0.112***	0.171***
	(0.0148)	(0.0203)
Ln electricity price	0.121***	0.111***
	(0.0298)	(0.0346)
Ln fuel price	0.0499	0.0862***
	(0.0311)	(0.0242)
Ln materials price	0.407***	0.349***
	(0.0408)	(0.0392)
Ln services price	0.222***	0.176***
	(0.0266)	(0.0167)
Ore grade	-0.0392***	-0.0697***
	(0.0090)	(0.0129)
Constant	10.44***	10.78***
	(0.3030)	(0.4120)
Mine dummies	No	Yes
Time dummies	Yes	Yes
Observations	2,972	2,972

Table 4: Equation for Ore Grades

	OLS	FE
Ln output (lagged)	-0.0341***	-0.0687**
	(0.0078)	(0.0271)
Ore grade (lagged)	0.961***	0.542***
	(0.0096)	(0.0566)
Constant	0.193***	1.073***
	(0.0413)	(0.1070)
Mine dummies	No	Yes
Time dummies	Yes	Yes
Observations	2,919	2,919

Table 5: Robustness for Different Values of the Production Capacity Parameter

Prod. capacity	τ	γ
1	1.475	1.207
1.25	1.899	1.311
1.5	2.232	1.357