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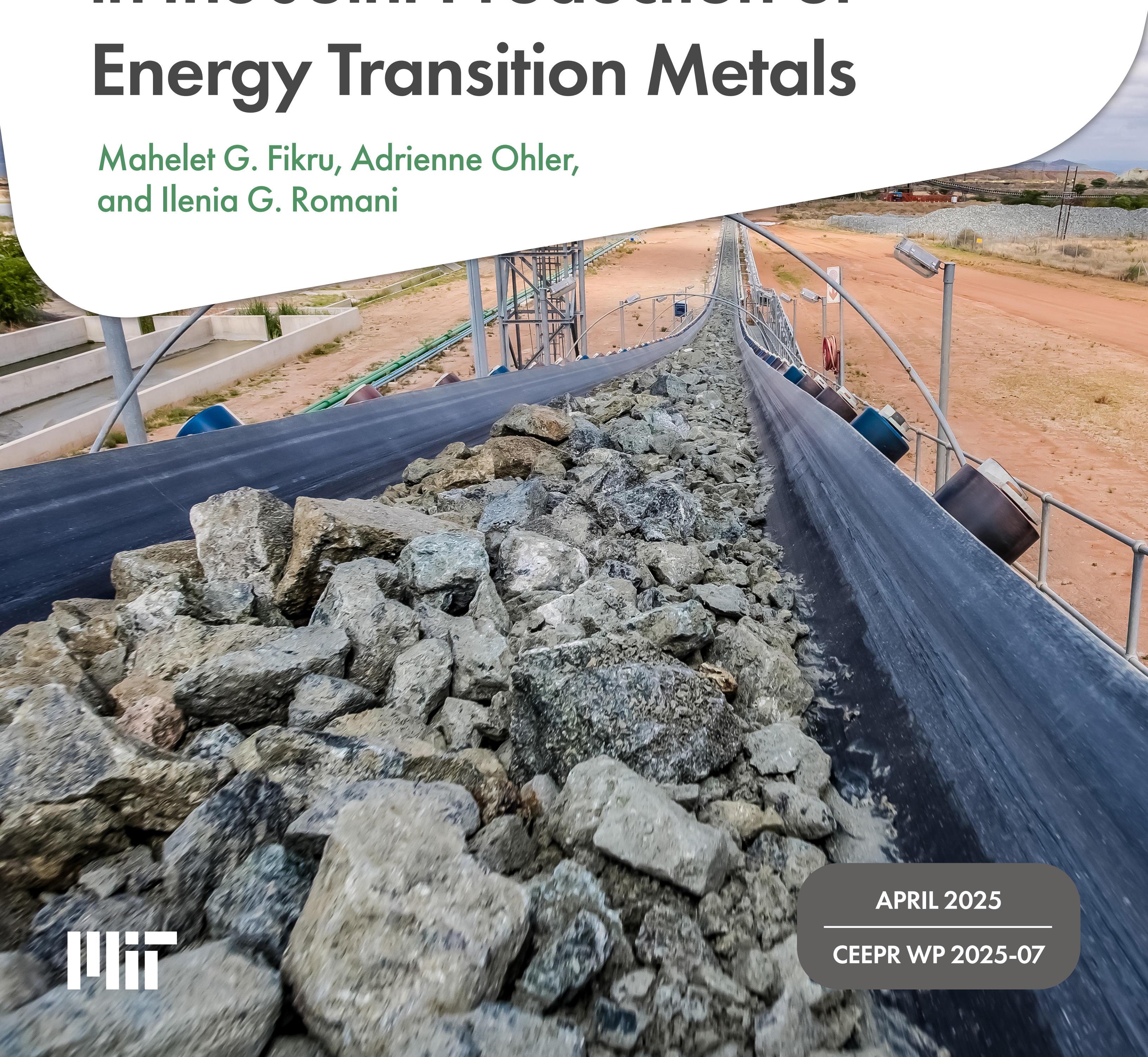

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Addressing Uncertainty in the Joint Production of Energy Transition Metals

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Abstract

An efficient and resilient supply of critical raw materials such as copper, cobalt, and nickel is essential to ensure supply chain stability and advance energy transition goals. Although prior research has examined how fluctuations in metal markets affect the energy transition, the factors that contribute to the greatest uncertainty in metal production costs, ore extraction, and investment in waste abatement remain poorly understood. Drawing on data from 114 mining projects worldwide and employing an economic model of joint metal production, this study uses Monte Carlo simulations to assess how cost, technology, and policy factors drive fluctuations in marginal cost of metal production, ore demand, and waste management. The findings reveal that, (1) marginal costs are more sensitive to output elasticity than to waste intensities and fees, (2) ore demand is more sensitive to output elasticity, waste fees, and cost of processing, while (3) the percentage of waste managed is most sensitive to waste fees and abatement costs than production parameters. These insights provide valuable guidance for stakeholders seeking to optimize metal production while managing waste and supporting the transition to sustainable energy systems.

JEL Classification: Q3, Q4, D2

Keywords: critical metals; energy transition; cobalt; copper; Monte Carlo simulation; optimization

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1 Introduction

The efficient processing and refining of ores to produce critical raw materials play a significant role in advancing global efforts to reduce carbon emissions and meet energy transition targets. With increasing demand for metals such as copper, nickel, cobalt, and other energy transition metals (ETMs), understanding the factors that affect production costs is crucial for decision making (Liang et al., 2023). As mining and metal processing firms strive to meet this rising demand, they face significant uncertainties and risks that complicate cost management and production decisions (Ku et al., 2018). Such industry-specific experiences reflect a broader economic understanding that uncertainty in cost shocks influence investment and resource allocation, while regulatory uncertainties play a critical role in shaping the abatement decision of regulated sectors (Aldy and Armitage, 2022).

Previous studies have examined the uncertainties surrounding metal prices, demand, technology, and policy, and have assesed their impact on the energy transition. For example, the prices and demand for energy transition metals are shown to fluctuate rapidly, making their markets highly volatile (Goutte and Mhadhbi, 2024). Studies estimate that changes in metal prices can lead to a 13% to 41% increase in the cost of producing clean energy technologies, potentially creating challenges in attaining energy transition goals (Leader et al., 2019). Some of this price volatility can be attributed to cost and supply uncertainties, which arise from unpredictable shifts in production expenses (e.g., exploration, development, refining) and geopolitical tensions. As these cost shocks remain uncertain, they contribute to investment delays, as companies hesitate to commit resources without clear projections of potential returns and financial viability, exacerbating shortages and supply chain risks. Other studies (Bustamante and Gaustad, 2015) suggest that high volatility in ETM markets creates significant uncertainty for both the production and consumption of clean energy technologies. Further research also suggests that technological advancements in mineral extraction and processing are highly unpredictable, in part due to uncertain market conditions

(Lundaev et al., 2023). Different technologies exhibit varying levels of efficiency, leading to a wide range of metal production volumes (Fikru and Awuah-Offei, 2022). The variability in returns from investing in new metal extraction and ore processing technologies could delay advances or cause misallocation of resources, ultimately hindering the sector's ability to support energy transition goals. Finally, evolving regulatory frameworks (Massari and Ruberti, 2013), particularly those governing environmental practices, reclamation and restoration, and waste management, could further contribute to operational complexity (Applegate, 2005). Consistent with this thesis, research has shown that increased uncertainty in environmental policy negatively affects firm-level investment in environmentally sensitive industries (Palikhe et al., 2024).

Although recent studies (Goutte and Mhadhbi, 2024) have examined the impact of uncertainties in ETM markets on the energy transition and green investments, the factors driving the largest fluctuations in metal production costs, ore extraction, and investment in waste abatement remain poorly understood. Uncertainties in ETM market parameters, policy, and technology become particularly challenging when two or more metals are produced from the same ore at a single site (Mudd et al., 2017). When a common ore is used to produce multiple ETMs, fluctuations in the market prices or demand for one metal can affect the overall cost structure and production strategy for all co-produced metals. This interdependence complicates production decisions regarding how much ore to extract and process, further amplifying uncertainties related to operational efficiency and profitability (Lewicka et al., 2021).

Despite a growing number of studies estimating the demand for ETMs in a variety of contexts (Wang et al., 2023; Fikru and Kilinc-Ata, 2024), few works comprehensively examine the interaction between technical, policy, and cost parameters in shaping cost variations as well as production and environmental outcomes for joint metal producers. In addition, the relationship between host and co-host metals is rarely studied (Watari et al., 2020), with only few studies explicitly modeling metal co-production from a common ore (Fikru and Awuah-

Offei, 2022). Our study addresses these gaps in the literature by presenting an economic model capable of capturing the impact of a variety of uncertainty sources in joint metal production.

The objective of this work is to investigate how marginal production costs, demand for ore, and waste management decisions in joint metal production are influenced by a series of factors, including cost parameters, total factor productivity, output elasticity, waste intensity of ore processing, and regulatory fees. First, we provide a descriptive analysis of data from 114 mining projects that produce joint ETMs, to justify the importance of understanding the sources of variations in the cost and volume of processed ore. These empirical insights are then used to develop an economic optimization model which analyzes the effects of key parameters, i.e., cost, technical (technology, output elasticity, waste intensity) and policy parameters (waste regulation fees), on the marginal costs of metal production, the volume of ore processed, and the percentage of waste managed. Finally, we apply Monte Carlo simulations to visualize the variation in model outputs and identify the key factors contributing to this variability. These simulations are effective in illustrating how input parameters in environmental studies propagate uncertainty in model outputs (Gillingham et al., 2018). Through this comprehensive approach, our work aims to clarify the complex dynamics that affect joint metal production.

The study is structured as follows: Section 2 presents insights on 114 mining projects focused on the joint production of ETMs. Section 3 discusses the theoretical model and its assumptions in order to characterize a generic firm that processes and refines ore to produce metals. Section 4 implements a Monte Carlo simulation to illustrate the source of uncertainty in the firm's optimal solutions, while Section 5 concludes with a summary of key insights.

2 Project-Level Insights on Cost and Volume Variations

Most ETMs are produced using joint production technology. A common ore is extracted and initially processed for the first metal, with additional metals recovered through further processing (Watari et al., 2020; Lewicka et al., 2021). Figure 1 illustrates a typical joint production model, where copper is the host metal and cobalt is recovered from the same ore (Fikru and Awuah-Offei, 2022; Ayres et al., 2003). Both metals are then used in various clean energy technologies.

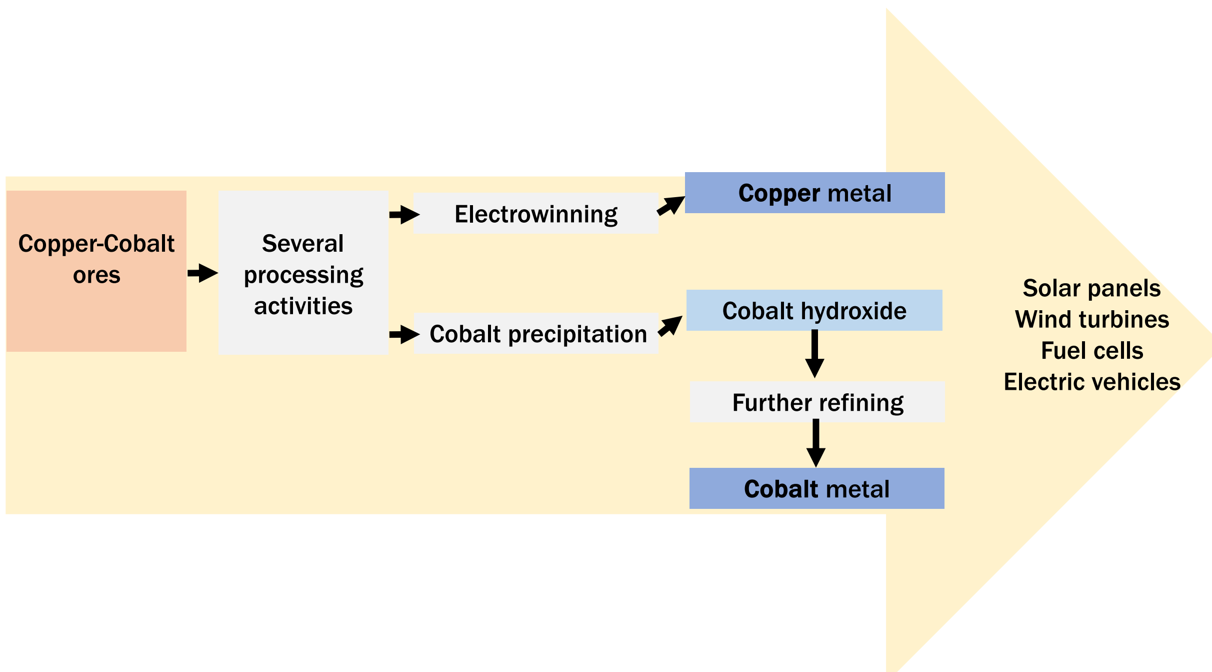

Figure 1: Joint production of copper and cobalt based on Crundwell et al. (2020)

Expanding on this simplification, different ores host several combinations of ETMs. In what follows, we aim to include as many of these combinations as possible. Using our institutional subscription to S&P Global Market Intelligence, we identify a total of 114 mining projects worldwide, referred to as *joint metal producers*. These projects process a common ore to produce different combinations of copper (Cu), cobalt (Co), nickel (Ni), molybdenum (Mo), palladium (Pd), platinum (Pt), and rhodium (Rh) as joint products at a given site. We limit our analysis to these metals because they are key inputs for energy transition technologies, difficult to substitute, and often produced jointly from a common ore. For example, Co and Ni are key battery materials, Cu is universally needed for electrical wiring, Mo for wind turbines (Henckens et al., 2018), Pd and Pt as catalysts in hydrogen fuel cells (Månberger and Stenqvist, 2018) and Rh is also used in fuel cells. In addition, these metals are often classified as critical minerals or materials for the energy transition (US Department of Energy, 2023). As shown in Table 1, most of the projects ($N = 72$) produce only two metals, while the rest of the joint production is characterized by nine different combinations of three or more metals. Moreover, most joint metal producers ($N = 96$) process copper together with at least one other critical metal.

Figure 2 shows the countries in which the 114 mining projects produce different combinations of joint metals. Most of the joint producers in the sample are located in South Africa, China, Chile, and the US. Other countries with significant joint production operations include Australia, Canada, the Democratic Republic of Congo (DRC), and Peru. The figure also shows that some countries focus on the joint production of two metals (e.g., Cu-Mo in Peru, Chile, and the US); others on the joint production of several metals (e.g., Cu-Ni-Pd-Pt-Rh in South Africa); and others are involved in multiple types of joint production operations (e.g., Canada and Zimbabwe).

Different combinations of metals can have significantly different production characteristics. To study this production variability, we analyze site-level data from S&P on two metrics: the average cash cost of processing ore (dollars per tonne of ore processed) and the total volume of ore processed at each site (kilotonnes of ore processed), in 2022. The average cash cost documents costs associated with extracting, treating, processing, and refining the ore to produce metals, hence representing the operating expenditures incurred at both the mining and processing stages. For each combination of joint products, we compute the average cash cost per tonne of ore processed, and the average volume of ore used to jointly produce two or more metals (see Table 1).

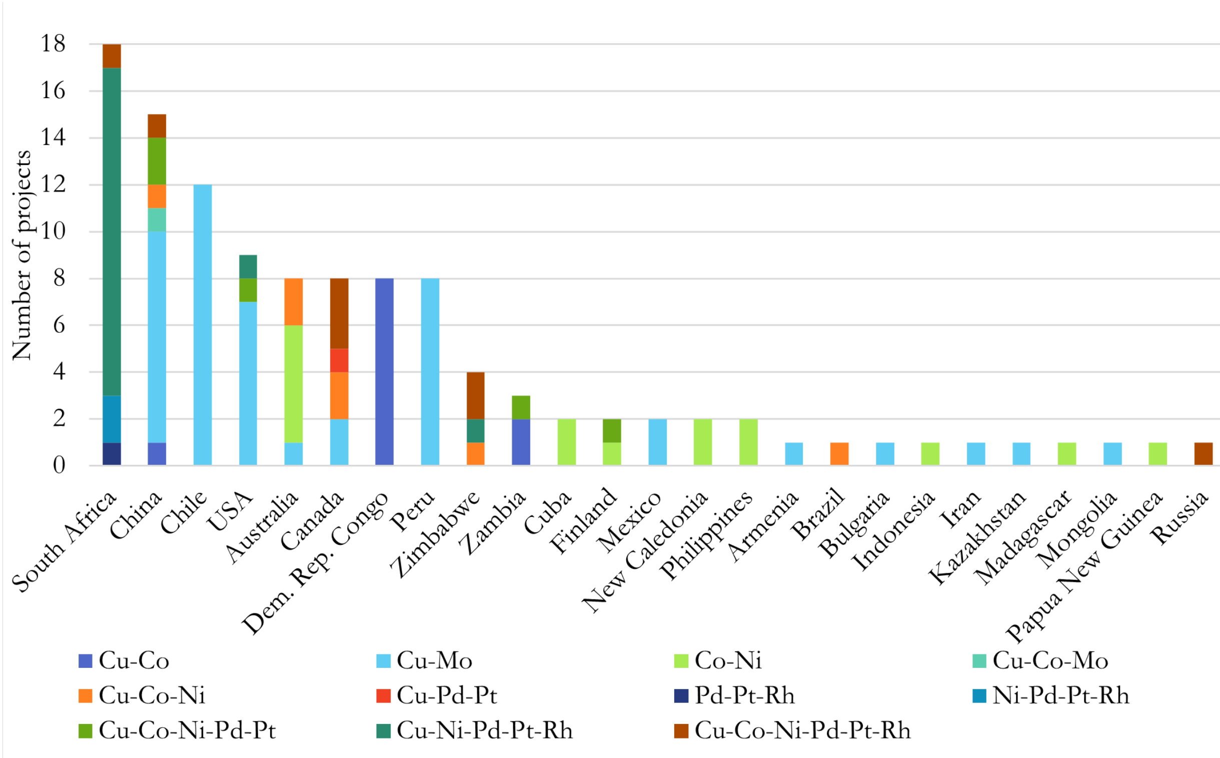

Figure 2: Country rankings based on the number of mining projects (total 114 projects).

The average cost of processing a tonne of ore varies depending on the combination of metals produced. Costs range from a minimum average of \$22.32/tonne for Cu-Mo projects, to a maximum average of \$225.36/tonne for the production of Cu-Co-Ni-Pd-Pt-Rh. Similarly, the average volume of ore processed ranges from a minimum of 165 kilotonnes for the only project that produces all seven metals, to a maximum of 35,924 kilotonnes for Cu-Mo projects. It is important to note that the dataset is unbalanced, as some joint metal categories contain just one project (e.g., Cu-Co-Mo), while others are more populated (e.g., Cu-Mo).

To further understand the production variability, we analyze the distribution of these two production metrics. First, Figure 3 shows box plots of the cash cost per tonne of ore. It suggests that there is significant variation in terms of cash cost within a joint metal combination and between the different combinations of metals produced. For example, the 46 projects producing copper and molybdenum display fairly homogeneous cash cost levels,

Joint products	No. of projects	Cost per tonne of ore (project average)	Volume of ore (project average)
Cu-Co	11	118.79	4063.97
Cu-Mo	46	22.32	35924.23
Co-Ni	15	168.33	4066.02
Cu-Co-Mo	1	29.39	1827.20
Cu-Co-Ni	7	192.05	1728.69
Cu-Pd-Pt	1	80.29	3751.00
Pd-Pt-Rh	1	50.02	4320.50
Ni-Pd-Pt-Rh	2	142.24	5985.00
Cu-Co-Ni-Pd-Pt	5	101.46	2826.56
Cu-Ni-Pd-Pt-Rh	16	120.93	4819.39
Cu-Co-Ni-Pd-Pt-Rh	8	225.36	7632.53
Cu-Co-Ni-Mo-Pd-Pt-Rh	1	48.89	165.00

Table 1: Average costs and volume of ore for joint metal producers across the globe ($N = 114$)

while the 15 projects producing cobalt and nickel have more varying costs. In comparison, Figure 4 displays box plots of the volume of ore processed. The highest variation in volume is that of the copper and molybdenum projects (partly driven by an outlier, the Cerro Verde mine in Peru, which produces almost $150,000$ kilotonnes of ore), while most of the other metals' combinations exhibit homogeneous levels in terms of processed ore per project. Overall, the figures suggest that those projects that exhibit high amount of volatility in terms of costs, do not necessarily display higher variability in terms of the volume of ore processed. In other words, even when the ore volumes processed are similar between projects, their costs can vary widely; and when the volumes processed vary significantly, costs can still be homogeneous.

Thus, ore volatility alone does not appear sufficient to explain variations in production costs. For example, simply considering the geographical location of mineral projects reveals a complex relationship between ore volume and cost volatility. Figure 5 presents country rankings based on the average ore processed per project (light blue circle) and the average cash cost per project (dark blue bar), for the entire sample. The figure suggests that the cost of processing ore varies significantly between countries, with New Caledonia, Canada,

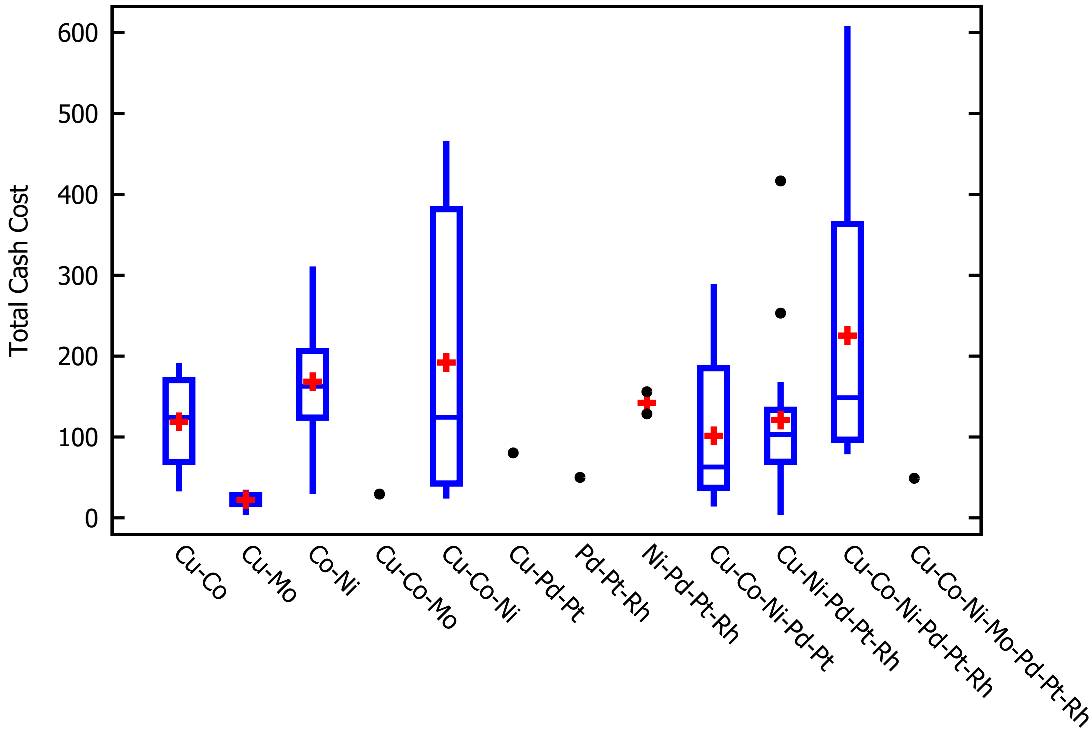

Figure 3: Total cash cost per ore processed for each group of jointly produced metals (N=114). The central box encloses the middle 50 percent of the data. The whiskers extend from each end of the box for a range equal to 1.5 times the interquartile range. Observations outside that range are represented via dots. The median is represented by the line drawn across the box. The red plus sign indicates the mean.

and Indonesia among the high-cost producers, while Finland, Mexico, and Kazakhstan are among the low-cost ones. Notably, the figure also illustrates a possible negative correlation at the country level between cost and volume processed, where countries that produce large amounts of ores tend to have lower costs (e.g., China, Peru).[1] This could be attributed to several factors, such as countries developing technological advantages that increase metal production and reduce costs, or countries imposing less stringent environmental and waste management regulations.

Two seemingly conflicting insights can be drawn from the 114 projects. On the one hand, when comparing projects across the combinations of metals produced, variations in

[1] The correlation coefficient between average cost and average ore is -0.1186 (with a 5% critical value (two-tailed) $= 0.3961$ for the 25 countries).

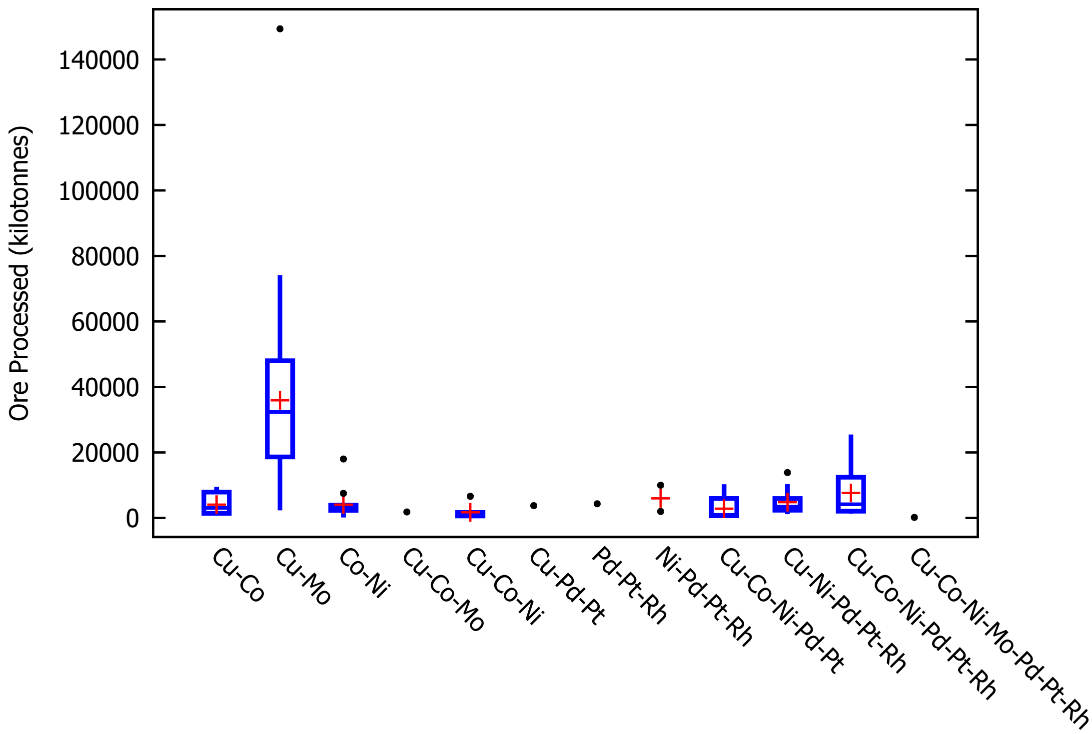

Figure 4: Ore processed (kilotonnes) for each group of jointly produced metals (N=114). The central box encloses the middle 50 percent of the data. The whiskers extend from each end of the box for a range equal to 1.5 times the interquartile range. Observations outside that range are represented via dots. The median is represented by the line drawn across the box. The red plus sign indicates the mean.

cost and in ore processed are rarely correlated. On the other hand, when comparing projects across geographical location, a negative relationship between average ore and cost emerges. This correlation between ore and cost is potentially influenced by factors such as the specific type and number of metals jointly produced, as well as the location of the project, which might, in turn, affect the quality (grade) of the ore, operational costs (e.g. extraction, refining, and processing technologies), and policy or regulatory factors that impact costs, such as via waste fees.

In this context, our work aims to shed light on the complex relationships between technical, policy and cost parameters, as well as their volatility. By presenting a theoretical framework grounded in economic principles, followed by simulations using real-world data, we

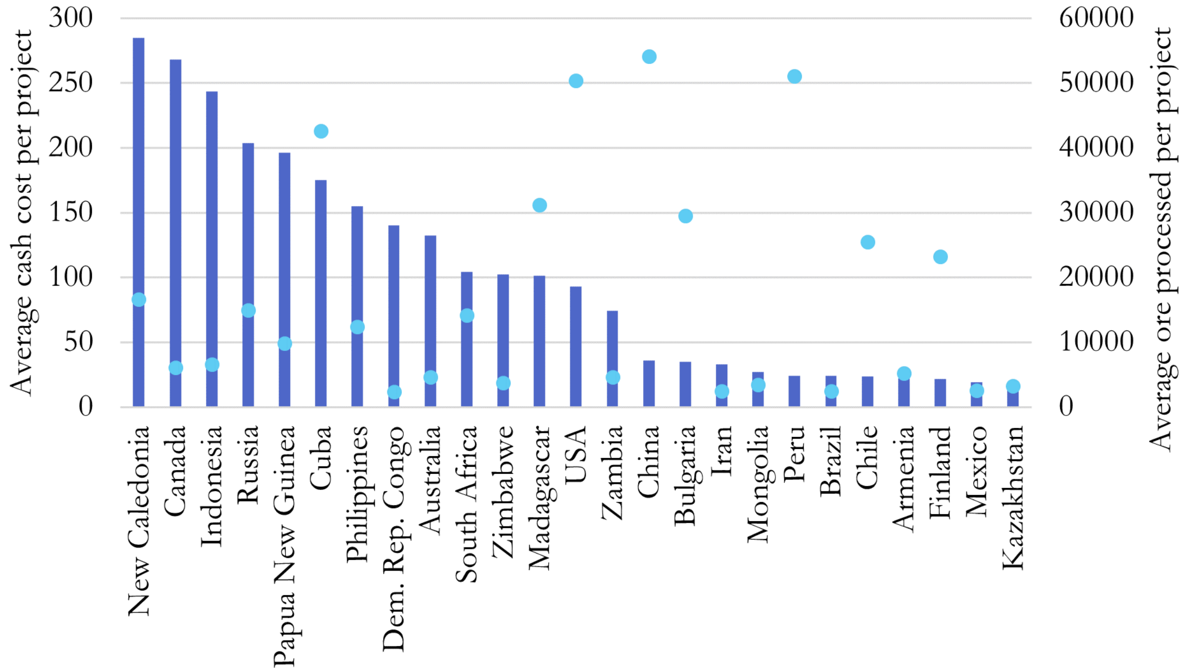

Figure 5: Country ranking according to the average project cash cost (blue histograms on the left axis) and ore processed (light blue circles on the right axis).

provide insights into cost variations for joint metal producers from an economic perspective. These insights can help inform decisions on the extraction and processing of additional ore, and the management of increased waste, taking into account both production cost structures and resource allocation efficiency.

3 Joint Production Model Framework

3.1 General model setup

In this sub-section, we present the general model setup used to characterize a generic firm that processes and refines ores to produce metals. We follow a double optimization procedure, described in Figure 6, where the firm makes decisions in two stages: first, minimizing cost subject to a production function with a given waste fee, and then maximizing profit given the demand. The model incorporates a series of uncertain parameters widely discussed in the economics literature, such as total factor productivity (Gillingham et al., 2018), cost and (environmental) policies (Aldy and Armitage, 2022; Palikhe et al., 2024). Specifically, we distinguish between (1) production and abatement cost parameters, (2) technical parameters (total factor productivity, output elasticity, and waste intensity), and (3) waste fee as the policy parameter, all of which affect first-stage decisions.

In the first stage, the firm minimizes its expenditure subject to production constraints, to determine the volume of ore needed for processing. The decision-making in this stage also involves determining the optimal percentage of waste to manage. The model assumes that refining ores for metal production involves the generation of waste (e.g., solid waste, greenhouse gas emissions), some or all of which will be managed due to the presence of a waste release fee. In the second stage, after selecting the ore volume (i.e., the input choice), the firm maximizes its profits by determining the optimal metal production volumes. Each of these stages is discussed in detail in the remainder of this section.

Assume the firm is a joint metal producer, utilizing a common natural resource deposit, i.e. the ore. It produces two metals, x_1 and x_2, by processing and refining a common ore, x_o. To simplify the model, we limit joint production to two metals only, even though each firm may actually produce more than two, as discussed in Section 2. The first metal is a critical ETM, which might face limited technological processing capacity (e.g., cobalt), while the second is a base metal with well-developed processing technologies, such as copper. Among the projects presented in Table 1, our theoretical model might best represent the joint production of copper and cobalt (Cu-Co) metals from a common ore (e.g., copper-cobalt ore).

3.1.1 First stage decision

First, the common ore, x_o, is extracted and then processed and refined to produce the two metals using a joint production technology. Metal production is represented by production functions which include a numeraire input, x_n, where $x_1 = g(x_o, x_{n,1})$ and $x_2 = h(x_o, x_{n,2})$.

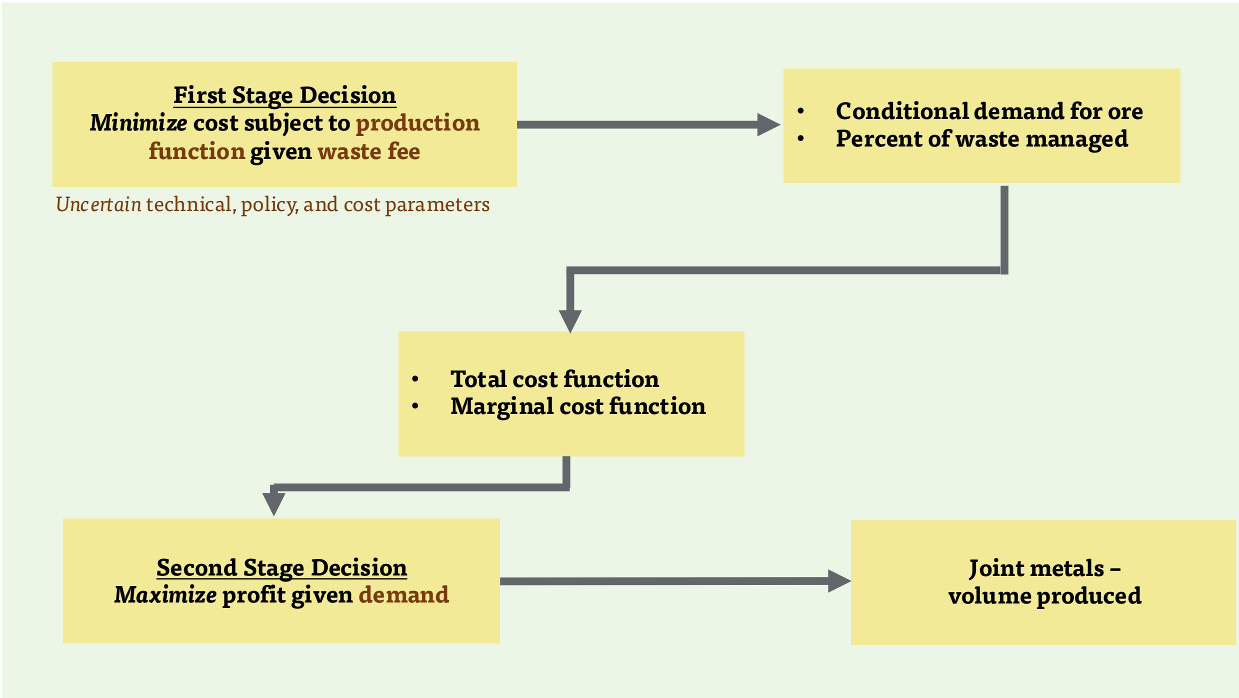

Figure 6: Double optimization framework

The two metals have different numeraire inputs because the reagents or chemicals used to refine each metal could differ. The cost of processing and refining the ore to produce the two metals is given by $c(x_o) = cx_o$, where $c > 0$. This cost also includes the cost of procuring the ore, such as buying it from a mining company. Therefore, our model is general enough to represent either an integrated mining company that extracts and processes the ore, or a metallurgical company that procures the ore from a mining company. We assume linear costs to reduce the complexity of the model.

Processing and refining ores to produce the two metals generate waste and emissions. Waste generation is generally penalized, incentivizing firms to invest in more responsible and sustainable processing practices. The generation of waste is proportional to the ore volume, $W = wx_o, w > 0$. The parameter w represents the waste generated per unit of ore, i.e., the waste intensity of ore processing for metal production. A percentage $0 \leq k \leq 1$ of total waste is managed, e.g., treated, recycled, or used in energy recovery, depending on the type of waste management technology (Eng et al., 2021). The remaining waste is subject to a waste fee $\tau > 0$, measured in dollars per tonne of waste and assumed to be exogenous to the firm (Lahiri and Ono, 2007). Therefore, the total waste fee paid by the firm is $(1-k)W\tau$. The volume of waste that is managed, kW, instead, incurs management costs (e.g., treatment cost), which are assumed to be quadratic and convex as in Fowlie and Muller (2019), $c(kW) = \epsilon(kwx_o)^2/2, \epsilon > 0$. The parameter $\epsilon > 0$ represents the slope of the marginal abatement cost function (Strandholm et al., 2023).

The firm's objective is to minimize its expenditure, subject to the production functions, by deciding the volume of input to use (ore and numeraire inputs) and the percentage of waste to abate, in order to balance abatement costs and waste penalties. The constrained optimization problem is presented as follows:

$$\begin{aligned} L(x_o, x_{n,1}, x_{n,2}, k, \lambda_1, \lambda_2) = c(x_o) + c(kW) + (1-k)W\tau + x_{n,1} + x_{n,2} \\ + \lambda_1[x_1 - g(x_o, x_{n,1})] + \lambda_2[x_2 - h(x_o, x_{n,2})] \end{aligned} \tag{1}$$

The price per unit of each numeraire input is assumed to be one. Hence, the solution is solved from the following first-order conditions:

$$\frac{\partial L}{\partial x_o} = c + \epsilon x_o(kw)^2 + (1-k)w\tau - \lambda_1\frac{dx_1}{dx_o} - \lambda_2\frac{dx_2}{dx_o} = 0 \tag{2}$$

$$\frac{\partial L}{\partial x_{n,1}} = 1 - \lambda_1\frac{dx_1}{dx_{n,1}} = 0 \tag{3}$$

$$\frac{\partial L}{\partial x_{n,2}} = 1 - \lambda_2\frac{dx_2}{dx_{n,2}} = 0 \tag{4}$$

$$\frac{\partial L}{\partial k} = \epsilon(wx_o)^2k - wx_o\tau = 0 \tag{5}$$

$$\frac{\partial L}{\partial \lambda_1} = x_1 - g(.) = 0 \tag{6}$$

$$\frac{\partial L}{\partial \lambda_2} = x_2 - h(.) = 0 \tag{7}$$

The solution provides the conditional demand for ore, $x_o^*(x_1, x_2)$, and the numeraire inputs, $x_{n,i}^*(x_1, x_2)$, where $i = 1, 2$, as well as the percentage of waste that is managed,

$k^*(x_1, x_2)$. These conditional input demands are substituted into the firm's expenditure function, where the total cost of production is calculated from $TC(x_1, x_2)$. Thus, the marginal cost of producing one metal ($MC_1 = \partial TC/\partial x_1$) depends on x_2, and vice versa, highlighting the aspect of joint production. In other words, the production of one metal can affect the marginal cost of producing the other metal (Watari et al., 2020; Lewicka et al., 2021).

3.1.2 Second stage decision

After optimally choosing input volumes, the metal producer maximizes its profit by deciding its production volume. The price of each metal is p_1 and p_2. We assume a linear demand for the metals, represented by $p_1 = a_1 - b_1 \sum_j x_1$ and $p_2 = a_2 - b_2 \sum_j x_2$, where $j = 1, 2, ..., n$ is the number of companies in the market, $a_i > 0$, with $i = 1, 2$, is an indicator of market size and $b_i > 0$ is the slope of the metal demand line.

The joint producer's objective is to maximize profits as follows:

$$\max_{x_1, x_2} \Pi = p_1 x_1 + p_2 x_2 - TC(x_1, x_2) \tag{8}$$

The first-order profit maximizing conditions are:

$$p_1 + x_1 \frac{\partial p_1}{\partial x_1} - \frac{\partial TC(x_1, x_2)}{\partial x_1} = 0 \tag{9}$$

$$p_2 + x_2 \frac{\partial p_2}{\partial x_2} - \frac{\partial TC(x_1, x_2)}{\partial x_2} = 0 \tag{10}$$

The final equilibrium solutions per firm are x_1^* and x_2^*. Under a symmetric equilibrium assumption, the industry supply is simply given by nx_1^* and nx_2^*. The equilibrium metal prices are calculated using the equilibrium production levels. The solutions are derived from:

$$x_1 = \frac{a_1 - MC_1}{b_1(n + 1)} \tag{11}$$

$$x_2 = \frac{a_2 - MC_2}{b_2(n + 1)} \tag{12}$$

3.2 Model and simulation assumptions

3.2.1 Model assumptions

To solve the model, we introduce a series of simplifying assumptions. First, the production functions are assumed to be Cobb-Douglas, as in Fikru and Awuah-Offei (2022). They are defined as $x_1 = A_1 x_o^{\alpha} x_{n,1}^{\beta}$ and $x_2 = A_2 x_o^{\theta} x_{n,1}^{\eta}$. The parameters A_1, A_2 represent total factor productivity in processing ore into metals (e.g., scaling factor). Technologies that produce more metal per ore result in a higher efficiency frontier, while constrained metal production due to inefficient technologies leads to a lower A. The returns to scale in metal production are given by $\alpha + \beta$ for the critical ETM, x_1, and $\theta + \eta$ for the base metal, x_2.

Second, we assume increasing returns to scale in the production of the base metal, x_2, where $\theta = \eta = 1$, resulting in $\theta + \eta = 2$. This reflects the fact that base metals, such as copper, zinc, and aluminium are generally produced from ores with fewer productivity or technology related challenges (Aydin, 2020; Boulamanti and Moya, 2016). In contrast, for the critical ETM, x_1, we assume constant or decreasing returns to scale, $\alpha + \beta \leq 1$, reflecting the technological and/or scaling challenges associated with their production, which result in non-declining marginal costs (Rosenau-Tornow et al., 2009; Dutta, 2017). In fact, the complex processing methods currently used for producing ETMs could limit economies of scale (Humphries, 2013; Jaskula, 2019). In addition, for simplicity, we assume $\alpha = \beta$, implying that the output elasticity of the critical metal production is identical for the ore and the numeraire input.

3.2.2 Initial values and simulation assumptions

As highlighted in Section 3.1, our theoretical model is best suited for ETMs such as Cu-Co projects, where copper has an established and more efficient processing technology than cobalt. For this reason, the simulation focuses on joint producers of Cu-Co. We first collect the most current data on metal production volumes in the US from the USGS-Copper

Report and USGS-Cobalt Report, which we use as proxies for cobalt production, x_1, (U.S. Geological Survey, 2024a) and copper production, x_2 (U.S. Geological Survey, 2024b). Then we assume that the values for the model parameters $(c, \epsilon, \tau, w, \alpha, A_i)$ are drawn from uniform distributions with minimum and maximum values, $U(min, max)$ as indicated in Table 2. Through 1,000 random draws, we simulate the marginal cost of producing the critical ETM of interest, i.e., cobalt, (MC_1), and the base metal, i.e., copper, (MC_2), and use the same procedure to calculate the optimized volume of ore demanded, x_o^*. We also restrict the percentage of waste managed $k^* \leq 1$ and present results for its optimum level. Since data of metal production volumes are taken from the real world, these are assumed to represent optimized solutions (x_1^*, x_2^*) resulting from fully solving the second stage.

Parameters	Units	Values	Source/Assumptions
Cost parameters			
c	USD per kilotonne of ore	$U(75, 150)$	Figure 3
ϵ	USD per waste tonne	$U(0.85, 0.99)$	Values represent a plausible range
Policy parameter			
τ	USD per waste tonne	$U(25, 100)$	Losurdo (2024), California Department of Toxic Substances Control (2024), Missouri Department of Natural Resources (2024)
Technical parameters			
$\alpha = \beta$	Unit free	$U(0.45, 0.5)$	< 0.5 for decreasing returns; > 0.45 for plausible range for non-negative MC_2
A_1	Unit free	$U(0.7, 0.9)$	Values represent a plausible range
A_2	Unit free	$U(\mathrm{A}_1,\ 1)$	$A_1 < A_2$
w	waste tonne per kilotonne of ore	$U(0.8, 0.99)$	Values represent a plausible range
Optimal metal production volumes			
x_1^* (Cobalt)	metric tonnes	500	U.S. Geological Survey (2024a)
x_2^* (Copper)	metric tonnes	1,230,000	U.S. Geological Survey (2024b)

Table 2: Assumptions and initial values

4 Results and Discussions

4.1 Model solutions

Given the model framework and the simplifying assumptions, we now present solutions for the first and second stages. The equations below represent the conditional demand for ore (Eq.13), the optimal rate of waste management (Eq.14), and the numeraire inputs (Eq.15-

16).

$$x_o^* = \left\{ \frac{1}{c+\tau w} \left[\alpha \left(\frac{x_1}{A_1} \right)^{\frac{1}{\alpha}} + \frac{x_2}{A_2} \right] \right\}^{\frac{1}{2}} \tag{13}$$

$$k^* = \frac{\tau}{\epsilon w x_o^*} \tag{14}$$

$$x_{n,1}^* = \left[\frac{x_1}{A_1 x_o^{*\alpha}} \right]^{\frac{1}{\alpha}} \tag{15}$$

$$x_{n,2}^* = \frac{x_2}{A_2 x_o^*} \tag{16}$$

We find that demand for the common ore decreases with factors that increase its cost of production (e.g., the unit cost of processing the ore, c, its waste intensity, w, and the waste fee, τ) and increases with demand for metals, x_1, x_2. Moreover, a technically efficient production leads to lower volumes of ore being demanded, $dx_o/dA < 0$. Similarly, we find that under the assumptions given, improvements in the output elasticity of the critical ETM reduce demand for ore, $dx_o/d\alpha < 0$.

The solutions also imply that the firm will treat a higher percentage of the waste it generates if the penalty, τ, is high. This positive relationship occurs both directly through increases in τ and indirectly as higher τ decreases conditional ore demand x_o^*. Waste intensity also influences the percentage of waste managed both directly, as increases in waste intensity decrease k^*, and indirectly through ore demand, leading to an overall negative effect ($dk^*/dw < 0$). Similarly, a higher unit cost of processing of the ore, c, leads to a lower demand for the ore, x_o^*, which in turn increases the percentage of processed waste, k^*. Finally, Equation 14 hypothesizes that a high marginal cost of abatement, ϵ, will lead to a lower percentage of waste managed. Improvements in technical efficiency ($A_i, i = 1, 2$) and improvements in ETM output elasticity (α) will also indirectly increase the percentage of waste managed, through decreases in ore demand.

The solutions presented in Equations 13-16 are plugged into the firm's total cost function to obtain the total optimized expenditure (as a function of both metals) and to derive the marginal cost of metal production. The total cost of metal production is calculated as:

$$TC(x_1, x_2) = (\left\{ \frac{1}{c + \tau w} \left[\alpha \left(\frac{x_1}{A_1} \right)^{\frac{1}{\alpha}} + \frac{x_2}{A_2} \right] \right\}^{\frac{1}{2}} (c + \tau w) + \frac{(x_1/A_1)^{\frac{1}{\alpha}} + (x_2/A_2)}{x_o^*} - 0.5\tau^2 \epsilon^{-1} \tag{17}$$

The last term in the above equation is negative, showing the abatement effect where firms save on waste fee by abating a higher percentage of their waste (Lahiri and Ono, 2007). Marginal costs are also important for production decisions and are calculated from:

$$MC_1(x_1, x_2) = \frac{x_1^{\frac{1}{\alpha}} \sqrt{c + \tau w}}{x_1 A_1^{\frac{1}{\alpha}} \sqrt{\nu}} \left[\frac{(\alpha - 1) x_1^{\frac{1}{\alpha}}}{2 A_1^{\frac{1}{\alpha}} \nu} + \alpha^{-1} \right] \tag{18}$$

$$MC_2(x_1, x_2) = \frac{\sqrt{c + \tau w}}{2 A_2 \nu^{3/2}} \left[\frac{x_1^{1/\alpha} (3\alpha - 2)}{A_1^{\frac{1}{\alpha}}} + \frac{x_2}{A_2} \right] \tag{19}$$

The parameter ν is a function of both metal production volumes, $\nu = \alpha(x_1/A_1)^{1/\alpha} + x_2/A_2 > 0$. The base metal, x_2, is produced with increasing returns to scale. Therefore, it is less likely that its production will require additional technical efficiency or productivity gains. Moreover, due to the base metal's increasing returns to scale, marginal cost, MC_2, declines with increased demand, x_2, whereas this is not the case for critical ETM production, x_1 (i.e,., MC_1 is increasing in x_1 with decreasing returns). For the critical ETM to exhibit declining returns to scale $\alpha < 0.5$ must hold, while for constant returns to scale, $\alpha = 0.5$.

The characterization of costs shows that, while total and average costs (Eq. 17) are directly affected by the slope of the marginal waste abatement cost, ϵ, marginal costs (Equations 18-19) are not. This is due to the endogenous choice of k, where a higher ϵ lowers k^*. However, we find that waste intensity, cost of ore processing, and waste penalty positively and directly affect marginal costs. Equations 18-19 also suggest that production parameters ($A_i, i = 1, 2$ and α) influence marginal cost of production in a non-linear way.

For instance, A_1 affects MC_1 directly (productivity lowers marginal costs) and indirectly, since it lowers the volume of ore demanded (captured by ν), while A_2 affects MC_1 indirectly through ν.

The main analytical findings are summarized in the following proposition.

Proposition 4.1. *(1) A higher cost of processing ore, c, a higher waste fee, τ, and a higher waste intensity, w, increase marginal costs. (2) The conditional demand for ore decreases with total factor productivity, A, output elasticity, α, and with the parameters that increase costs, i.e., c, w, τ. (3) The optimal percentage of waste managed increases with the waste fee and cost of processing, decreases with the slope of the marginal cost of abatement, and waste intensity. Improvements in technical efficiency and output elasticity will also increase the percentage of waste managed, indirectly through decreases in ore demand.*

4.2 Variability in cost, ore, and waste managed

Building on the theoretical model outlined above, we now examine the variation in the three model outputs (i.e., marginal cost, optimized demand for ore, and waste management) to identify which parameters have the strongest effect on the uncertainty in joint metal production – specifically through their impact on ore demand and marginal cost of production.

The effect of the technical parameters A_i, α, w, the waste fee, τ, and the cost parameter, c, on the marginal cost of producing cobalt, MC_1, and copper, MC_2 is presented in Figures 7 to 9. Figure 7 suggests that as the value of A_1 increases, the median and spread of cobalt's marginal cost appear to decline (top left panel), indicating that as technical efficiency improves cobalt's production costs could start to fall and become less variable (although this effect is not particularly strong). Hence, enhanced efficiency has the potential to improve not only cost reduction, but also cost predictability for cobalt. For copper (bottom right panel) this effect is much less pronounced likely due to increasing returns which make copper's marginal costs less sensitive to additional technical efficiency gains. The figure also illustrates that the cross-impacts of one metal's technical efficiency on the marginal cost of the other are negligible.

Figure 8 suggests that as the output elasticity of cobalt production (α) increases, the marginal cost of cobalt production (both median and spread) decreases significantly, becoming less variable and more stable, with very few outliers (top-left panel). However, a higher output elasticity of cobalt production increases the level of copper's marginal production costs (top-right panel). The figure (bottom panels) also shows that the marginal costs of both cobalt and copper remain relatively consistent across different levels of waste intensity, with no clear increase in the median or spread of costs, though some outliers are present at certain levels of w. This suggests that, in the simulations, waste intensity is not a dominant driver of variability in marginal cost. Similar results are observed for the impact of cost, c, and waste fee, τ, on the variation of marginal costs, as shown in Figure 9.

The effect of the model parameters on the optimized demand for ore, x_o^*, and the percentage of managed waste, k^*, are presented in Figures 10 and 11, respectively. Figure 10 suggests that α, c, and τ are the three main factors driving the reduction in both the level and spread of ore processed. This indicates that higher output elasticity of cobalt production is associated with lower and less volatile volumes of ore processed, while a similar effect is observed for the waste fee and cost of processing. Technical efficiency indicators, A_1 and A_2, also seem to play a role, though there are several outliers. Figure 11 shows that a higher τ increases both the level and variability of k^*, suggesting that while a higher waste fee increases waste management, it also increases variability up to a certain threshold.

We also asses the influence of the slope of the marginal abatement cost (ϵ) on the percentage of waste managed. Figure 12 illustrates the relationships between ϵ, and k^*, suggesting that the waste fee and abatement cost parameter have a larger impact on the percentage of waste managed than the production parameters.

To further examine the relationship between the model parameters and the three

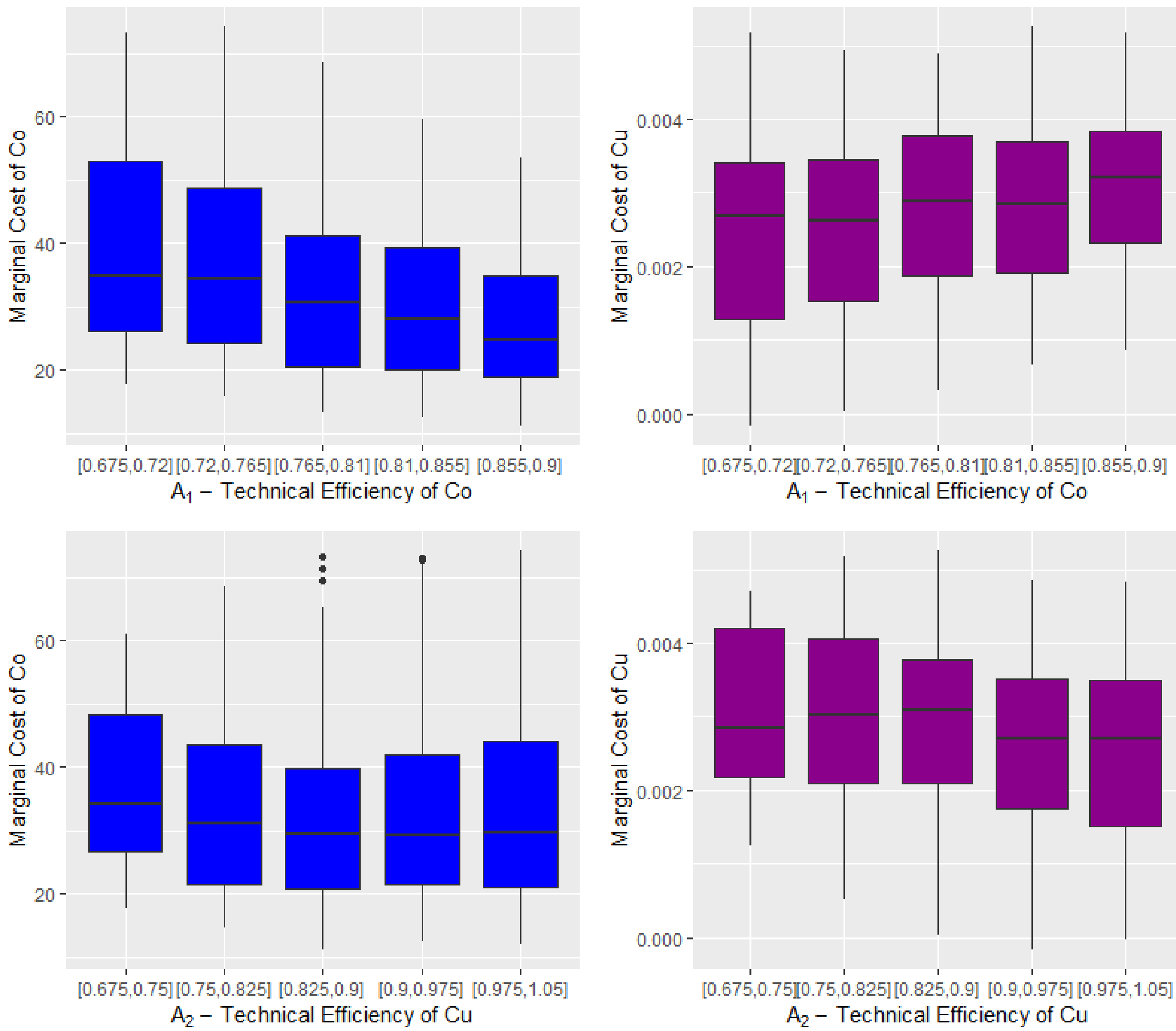

Figure 7: Impact of technical efficiency (A) on marginal costs

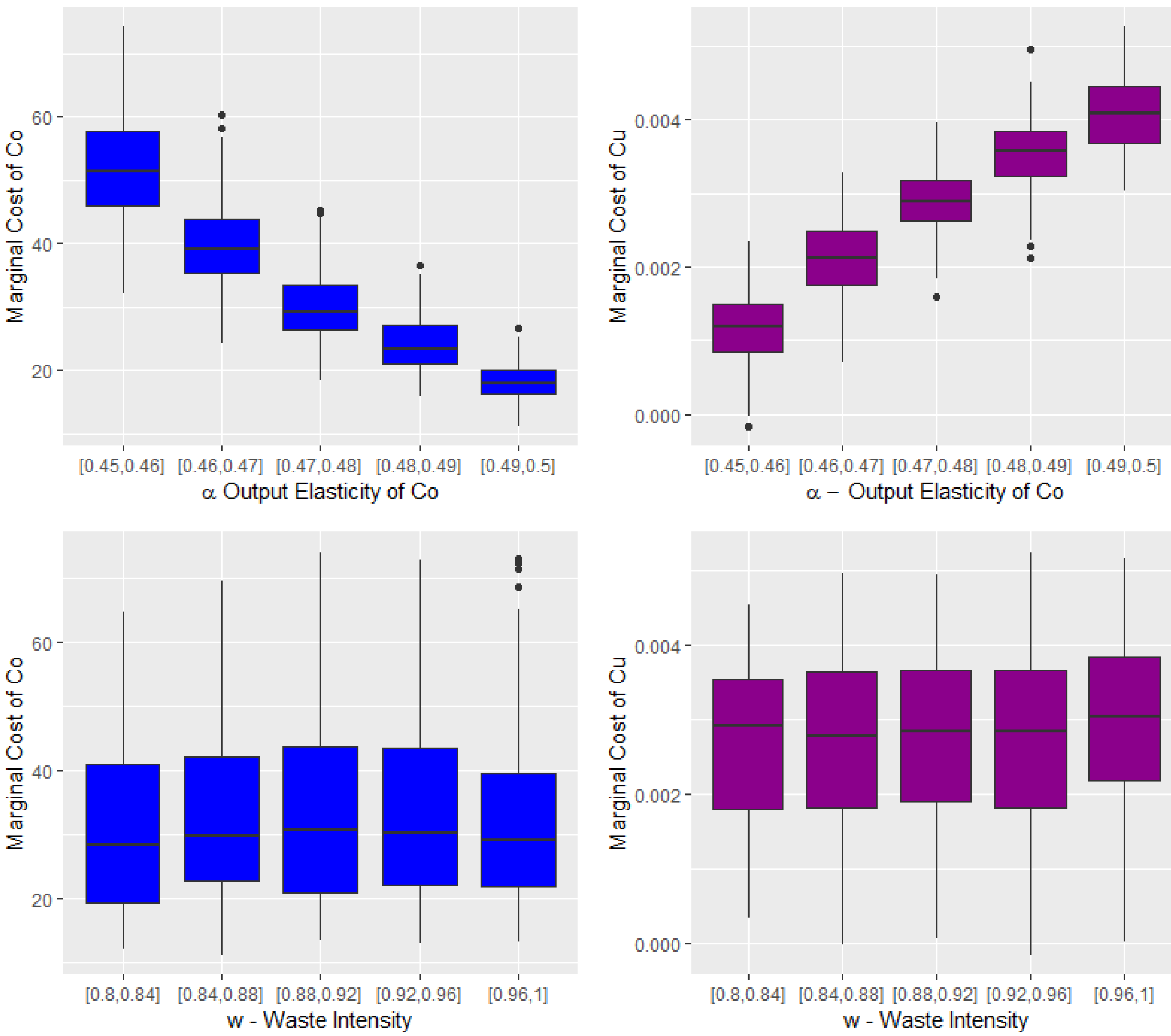

Figure 8: Impact of output elasticity (α) and waste intensity (w) on marginal costs.

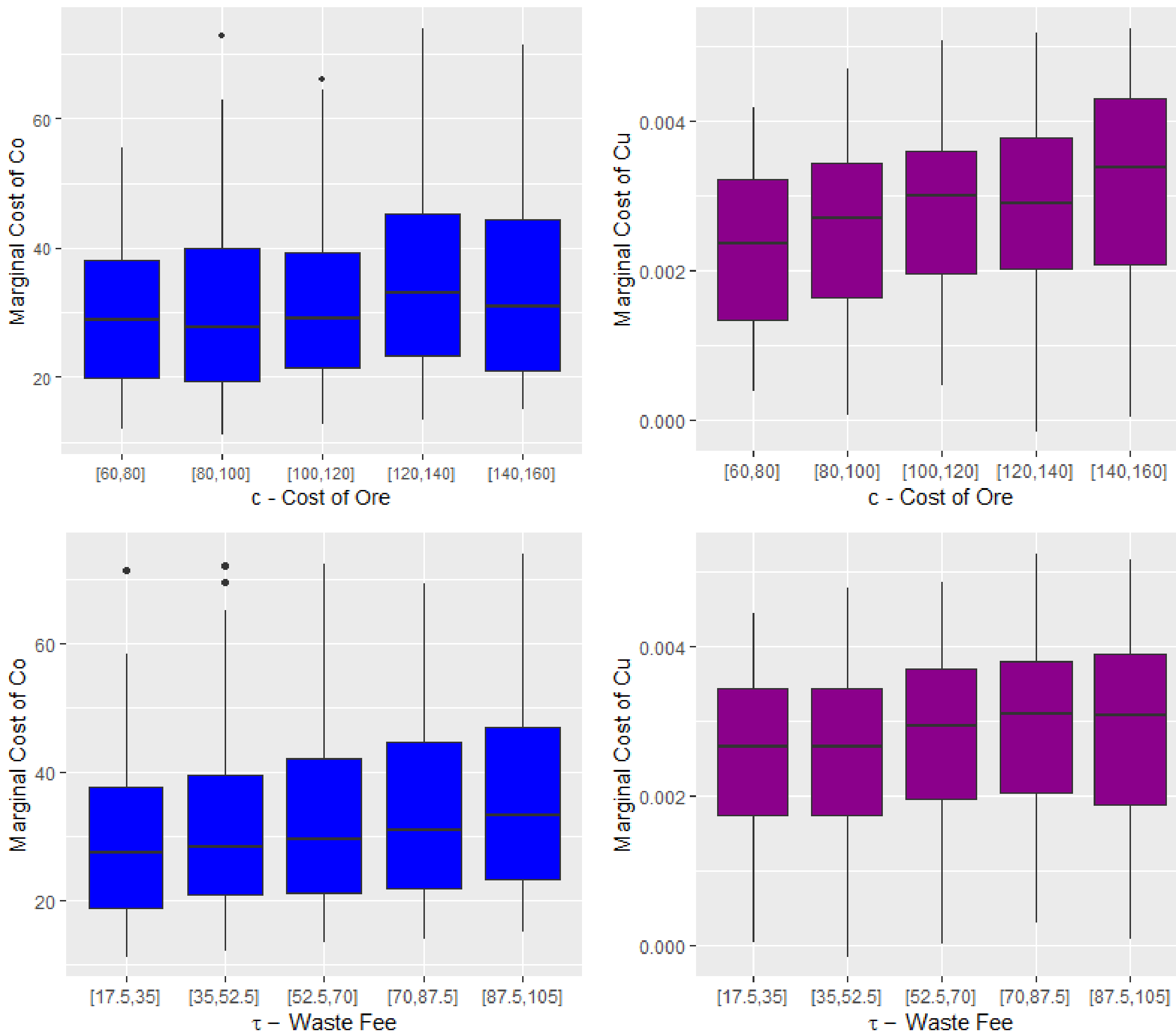

Figure 9: Impact of cost (c) and waste fee (τ) on marginal costs

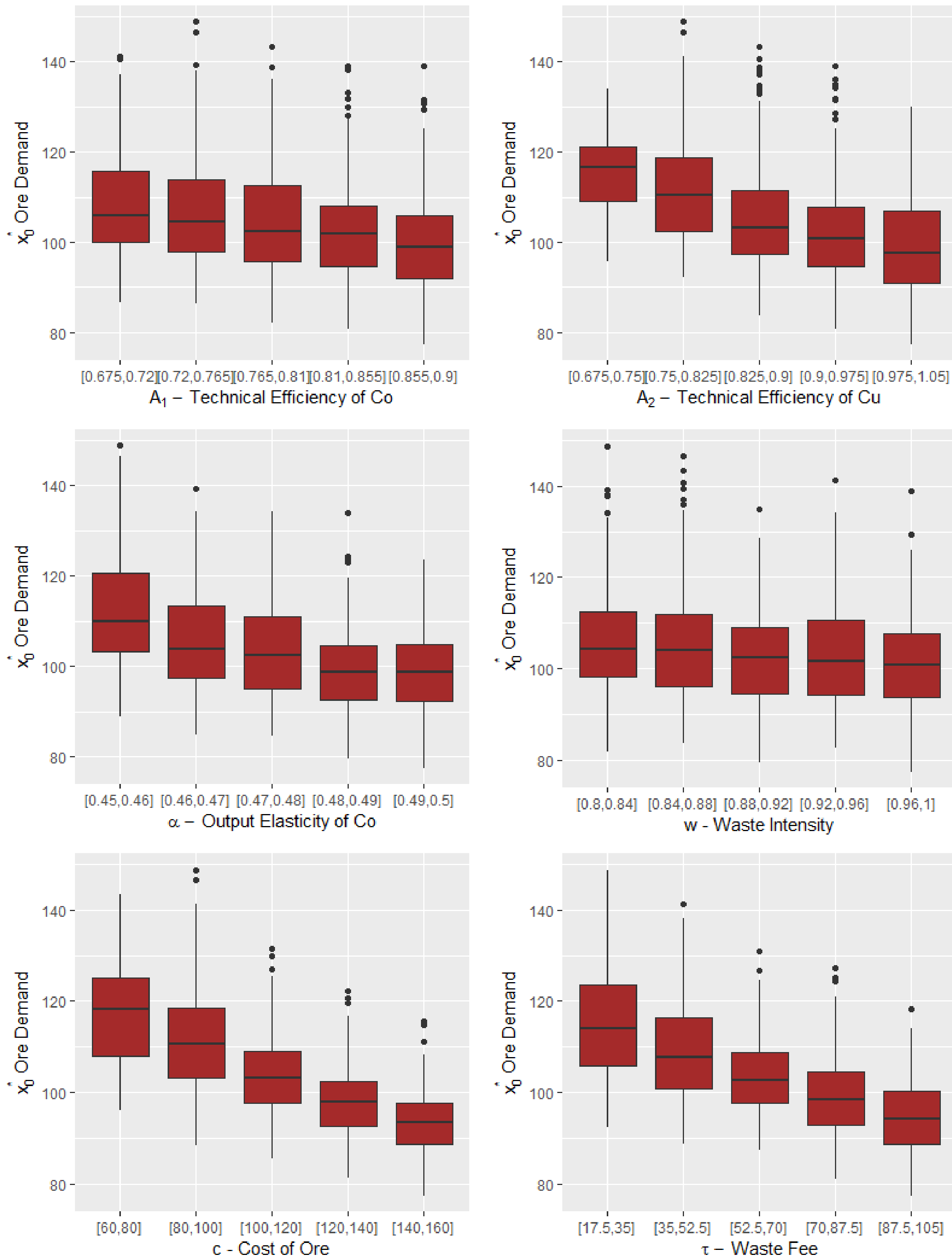

Figure 10: Impact of model parameters on ore processed (x_o^*)

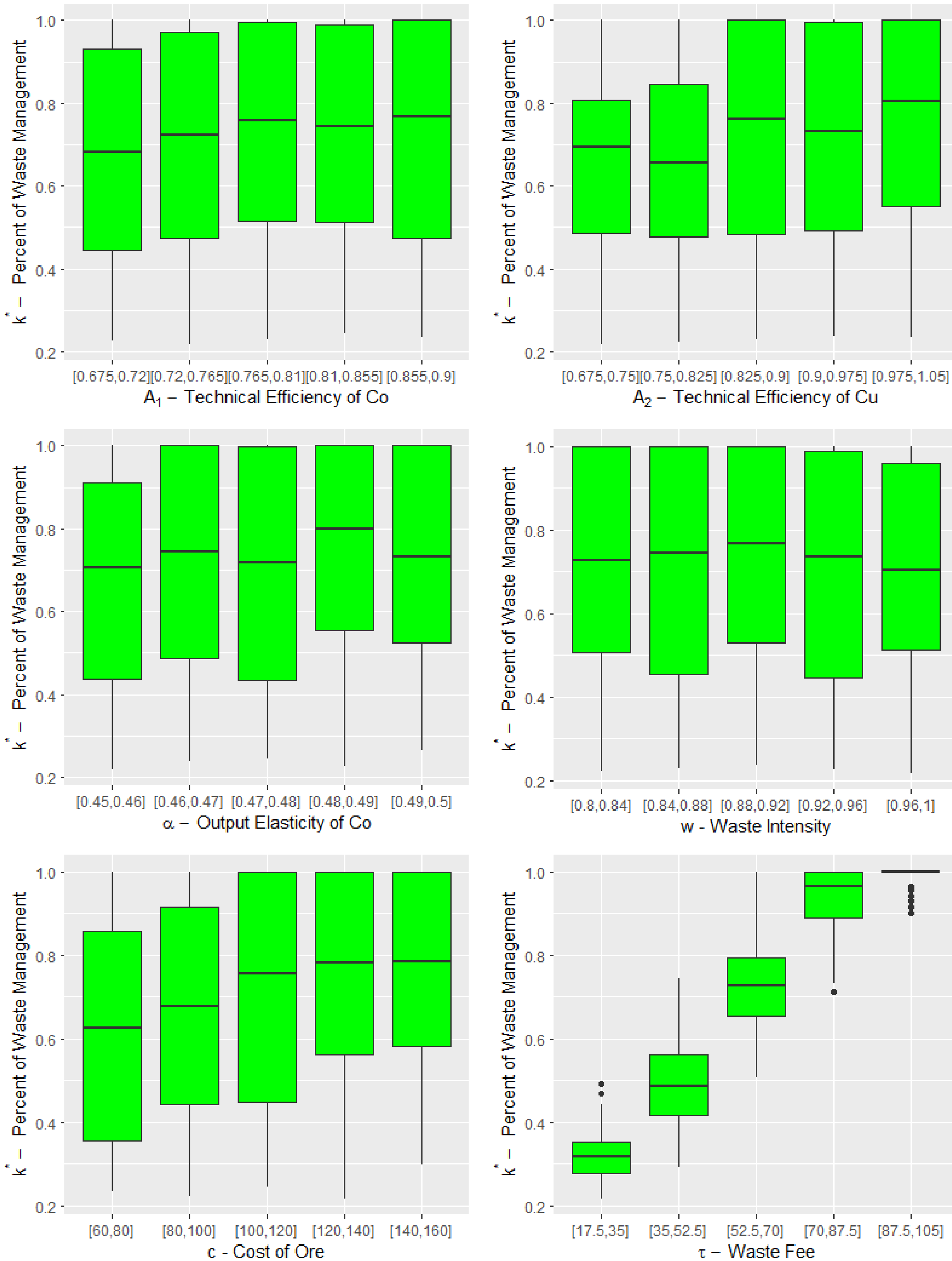

Figure 11: Impact of model parameters on the percentage of managed waste (k^*)

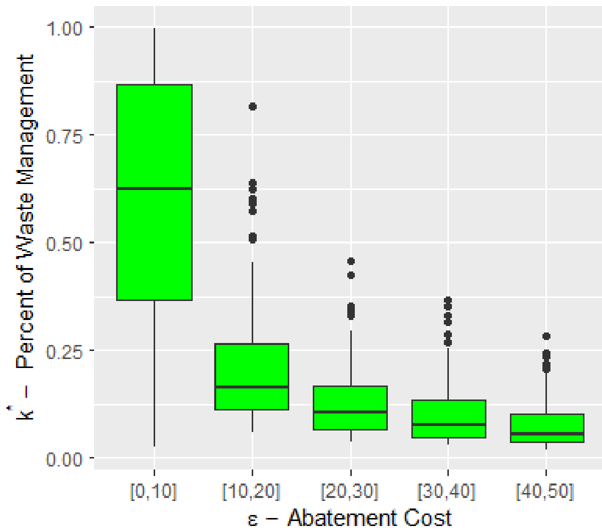

Figure 12: Impact of ϵ on the percentage of managed waste (k^*)

model outputs (marginal cost, ore demand, and percentage of waste managed), we analyze the correlation coefficients in Table 3. These statistics further highlight the strong influence of α on marginal costs and ore demand, and the strong impact of waste fee on waste management. The technical efficiency parameters A_1 and A_2 are also correlated with marginal costs even though to a lesser extent. The waste fee, τ, and the cost of processing ore, c, parameters are correlated with waste managed. Both costs increase the percentage of waste managed, for c this occurs indirectly through decreasing the ore demand, x_o^*, and τ increases the percentage of waste managed both directly and indirectly through ore demand, explaining why the correlation is much stronger for the waste fee than the processing cost parameter.

5 Conclusion

The efficient processing and refining of ores to produce critical energy transition metals (ETMs) is essential for advancing global efforts to reduce carbon emissions and achieve clean energy targets. As demand for metals such as copper, nickel and cobalt continues to increase, understanding the factors influencing production cost uncertainty becomes increasingly important (Liang et al., 2023; Romani and Casoli, 2024). These uncertainties may arise

Table 3: Correlation between model's parameters and outputs. P-value represented in the parenthesis. *, ** and *** indicate significance at the 0.1, 0.05 and 0.01 levels.

	Co	Cu	Ore demand	Waste managed
Parameters	MC_1	MC_2	x_0^*	k^*
c	0.145***	0.177***	-0.623***	0.163***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)
τ	0.155***	0.136***	-0.576***	0.958***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)
w	0.034	0.053*	-0.186	-0.027
	(0.285)	(0.091)	(<0.001)	(0.396)
α	-0.904***	0.923***	-0.419***	0.087***
	(<0.001)	(<0.001)	(<0.001)	(0.006)
A_1	-0.294***	0.197***	-0.231***	0.043
	(<0.001)	(<0.001)	(<0.001)	(0.175)
A_2	-0.045	-0.128***	-0.335***	0.105***
	(0.160)	(<0.001)	(<0.001)	(<0.001)

from a variety and combination of sources, including technical factors (e.g., extraction and processing efficiency), policy changes (e.g., evolving regulations and frameworks), and market conditions (e.g., fluctuating demand). Such factors can affect resource allocation decisions in the extractive industries, potentially leading to delayed or reduced investments, and ultimately hindering production. In fact, metal production is often constrained by technical challenges and high processing costs, which affects the overall cost of the energy transition and the adoption of new energy technologies.

In particular, when multiple products are derived from a common ore, the production of joint metals faces heightened uncertainty for several reasons. First, the economic viability of extracting and processing one metal can be significantly affected by the market dynamics of another metal produced from the same ore. Second, joint metals are often produced at the same site, where varying technical requirements for processing different metals can introduce operational complexities. Each metal may require distinct technologies, processes, and methods, increasing the likelihood of technical challenges that could disrupt production timelines and escalate costs. This is especially true for critical minerals such as cobalt, which face greater technological uncertainties compared to base metals like copper. Lastly, regulatory changes could further amplify these uncertainties. For these reasons, understanding the economic and environmental dynamics of joint metal production is crucial for optimizing resource use, minimizing waste, and enhancing the sustainability of metal production processes.

Drawing from empirical trends observed from 114 mining projects worldwide, and theoretical insights from an economic model of joint metal production, this study uses a Monte Carlo simulation to assess the impact of technical, policy, and cost parameters on fluctuations in the marginal cost of joint metal production and ore demand. The key findings reveal that marginal costs are more sensitive to production function parameters (e.g., output elasticity) than to waste intensities and fees, that ore demand is more sensitive to output elasticity, waste fees and cost of processing than total factor productivity, while the percentage of waste managed is most sensitive to waste fees and abatement costs.

These results suggest that improving production parameters can significantly enhance the economic viability of joint metal production by lowering marginal costs. This also emphasizes the need for mining firms to prioritize investments in technology and innovations to better navigate uncertainties and improve overall production outcomes in the rapidly evolving landscape of ETMs. Finally, the fact that the percentage of waste managed is more sensitive to the waste fee than to cost and production parameters underscores the need for ongoing investment in technological advancements and robust environmental policy frameworks to optimize production while minimizing environmental impacts.

In connection with this point, we propose extending the current model as a potential avenue for future research to explore the economic impacts of material recycling. For example, while most materials in lithium-ion batteries can theoretically be recycled, the high cost of material recovery currently hinders large-scale recycling efforts (Compagnoni et al., 2024). Standardizing batteries, materials, and cell design could improve recycling efficiency and cost-effectiveness, potentially generating spillover effects on joint metal production and recycling.

The economic model can also be expanded to accommodate more complex and dynamic scenarios. For example, future research could relax simplifying assumptions such as constant marginal costs, linear demand, and the static structure. Moreover, incorporating a broader set of technological advancements and evolving regulatory frameworks would provide a more nuanced understanding of the uncertainties facing the ETM sector. Finally, future studies could explore how external factors such as geopolitical risks and environmental considerations contribute to uncertainty in production and investment decisions within the extraction industry.

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