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Artificial Intelligence Investments Reduce Risks to Critical Mineral Supply

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Keywords

critical minerals, artificial Intelligence, risk premium

JEL Classification

Q02, Q40, Q50

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Artificial intelligence investments reduce risks to critical mineral supply

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Abstract

This paper employs insights from earth science on the financial risk of project developments to present an economic theory of critical minerals. Our theory posits that back-ended critical mineral projects that have unaddressed technical and nontechnical barriers, such as those involving lithium and cobalt, exhibit an additional risk for investors which we term the "back-ended risk premium". We show that the back-ended risk premium increases the cost of capital and, therefore, has the potential to reduce investment in the sector. We posit that the back-ended risk premium may also reduce the gains in productivity expected from artificial intelligence (AI) technologies in the mining sector. Progress in AI may, however, lessen the back-ended risk premium itself through shortening the duration of mining projects and the required rate of investment through reducing the associated risk. We conclude that the best way to reduce the costs associated with energy transition is for governments to invest heavily in AI mining technologies and research.

Keywords: Critical Minerals, Artificial Intelligence, Risk Premium

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1. Introduction

Unlike traditional energy sources, such as oil, coal, and gas, clean energy production and storage requires an unprecedented amount of critical minerals, such as copper, lithium, nickel, zinc, cobalt and rare earth minerals (Nature Editorial, 2023). Consequently, the supply shortage of critical minerals that is needed to achieve global net zero targets by 2050 has gained significant attention (see eg. Nature Editorial, 2023). Recently, the International Energy Agency (IEA) (2021) estimated that the investment that will be required in critical minerals between 2022 to 2030 to realize global net zero by 2050 is around 360 to 450 USD billion, while the anticipated supply is between 180 to 220 USD billion, implying a shortfall of 180 to 230 USD billion.

A key issue in meeting this shortfall is that there is a considerable time lag between investment and production. According to the IEA (2021) it can take as much as 12.5 years between exploration and the start of production for some critical minerals. One potential way to increase critical mineral production is via technological progress through artificial intelligence (AI), which can be used at all stages of the mining process.[1] Sganzerla et al. (2016) argue that the mining industry is poised to reap the rewards of AI and data-driven approaches as it deals with a complex integrated value chain of exploration, extraction and refining that has a history of integrating high-technology systems in order to increase productivity. Noriega and Pourrahimian (2022) argue that applying AI to mining databases may be useful in developing operations for decision-making support. Hyder et al (2019) argue that automatization using AI provides significant economic benefits for the mining industry through cost reduction, efficiency and improving productivity.

This paper uses insights from earth science about the financial risk of project developments for some key critical minerals to develop a theory which provides a less sanguine view of the potential for AI to address the shortfall in investment in critical minerals, at least in the short-to-medium term. Sykes et al. (2014), Trench and Packey (2012) and Trench et al. (2014) observed that some key critical minerals have lower value to investors during the initial stages of project development, due to both technical and non-technical risks. This type of risk is called back-ended risk and contrasts with front-ended risk, which is present in more traditional mining projects in which investors place a high value on the project in very early stages, reducing the cost of capital. Taking this observation as a starting point, we develop an economic theory of what we call the back-ended risk premium. This theory states that for minerals that exhibit back-ended risk, the required rate of return by investors is higher than for front-ended risk mineral projects, leading to a back-ended risk premium.[2] We show that the increase in the cost of capital due to this risk premium leads to a theoretical slowdown in technological progress. In the infancy of the AI revolution in the mining sector, the back-ended risk premium has the potential to reduce some of the expected gains from AI-inspired technologies. The extent to which this

[1] A comprehensive review of the literature on AI in the mining industry can be found in Gomez-Flores et al. (2022).
[2] The required rate of return is defined as “the minimum amount an investor or company seeks, or will receive, when they embark on an investment or project” (Drake and Fabozzi, 2009).

occurs will depend on whether, and to what extent, progress in AI can reduce the back-ended risk premium through shortening the duration of mining projects and lowering the required rate of investment.

This paper proceeds as follows. In Section 2, we develop a theory of the back-ended risk premium and provide conservative estimates of the value of the back-ended risk premium under two different scenarios proposed by the IEA for progress in meeting climate change mitigation objectives. In Section 3, we discuss the economic implications of the back-ended risk premium for expectations that the shortfall in critical mineral production will be overcome by AI development in mining. In section 4 we conclude.

2. The Back-ended Risk Premium

Figure 1 presents the medium-term 2025-2035 supply risks of 50 minerals, based on an assessment of the U.S. Department of Energy (2023).[3] The vertical axis represents their importance to the energy transition, while the horizontal axis represents the supply risk. Minerals considered critical are in red; those in yellow are near critical, while those in green are not critical.

Sykes et al. (2014), Trench and Packey (2012) and Trench et al. (2014) made the empirical observation that many of the minerals considered critical for energy transition exhibit back-ended risk in project development caused by technical and non-technical risks occurring in the later stages of the project (six-eight years after the exploration starts). [4] The existence of such back-ended risk means that investment is insufficient for these minerals to increase production in response to an increase in demand. This contrasts with the risk faced by other minerals - so called front-ended risk minerals - such as gold, copper, and iron ore for which the value of the project increases rapidly during the exploration stage. For these minerals, most of the investment needed for production occurs in the early stages of project in response to an increase in demand.

In Figure 2, we illustrate back-ended and front-ended risk project development and show how this is related to our proposed concept of the back-ended risk premium. The vertical axis represents the valuation (or share price) that the market places on the mineral project. The horizontal axis displays the different stages of development of the mining project (exploration, scoping, feasibility, development, and mining). At time T_1 the valuation (or share price) of front-ended risk minerals is V_2 , which is much higher than the valuation of back-ended risk minerals (V_1). Figure 2 shows that the valuations of back-ended and front-ended risk projects eventually converge after the development stage. The back-ended risk premium can be seen as the

[3] Critical minerals are defined by the U.S. Department of Energy (2023) as "any non-fuel mineral, element, substance, or material that the Secretary of Energy determines: (i) has a high risk of supply chain disruption; and (ii) serves an essential function in one or more energy technologies, including technologies that produce, transmit, store, and conserve energy". The 50 critical minerals are aluminium, antimony, arsenic, barite, beryllium, bismuth, cerium, cesium, chromium, cobalt, dysprosium, erbium, europium, fluorspar, gadolinium, gallium, germanium, graphite, hafnium, holmium, indium, iridium, lanthanum, lithium, lutetium, magnesium, manganese, neodymium, nickel, niobium, palladium, platinum, praseodymium, rhodium, rubidium, ruthenium, samarium, scandium, tantalum, tellurium, terbium, thulium, tin, titanium, tungsten, vanadium, ytterbium, yttrium, zinc, and zirconium.

[4] These studies offer as examples of critical minerals that exhibit back-ended risk: bauxite, cobalt, lithium, graphite, niobium, nickel laterite, tungsten, scandium, rare earth, vanadium, and zinc.

relative additional rate of return required by investors for back-ended minerals project, relative to front-ended minerals projects and in Figure 2 is denoted by the grey-shaded area.

Figure 2 suggests that for back-ended critical minerals the value to shareholders only accrues in the latter stages of the project development, meaning that investment (and production) will be lower than the market equilibrium requires. Figure 3 illustrates the difference in risk premium between front-ended and back-ended risk projects or the additional risk that investors would incur investing in back-ended minerals compared to from-ended minerals. The vertical axis represents the required rate of return by investors and the horizontal axis denotes the time between T_1 and T_2 from Figure 2. From this figure, we can infer the following:

- Investors require a relatively larger return to be compensated by the back-ended risk premium.
- The back-ended risk premium decreases as a function of time.
- The back-ended risk premium is equal to the risk of front-ended minerals after T_2 .

2.1. Measuring Non-technical and Technical Risk Premiums

In this section we develop measures of the non-technical and technical risks premium and use these to compare the non-technical and technical risks of the main critical minerals.

2.1.1 Non-technical risk premium

We construct indexes for the non-technical risk premium for 16 major critical minerals and a benchmark index, consisting of the average for coal, iron ore and gold, which are three representative non-critical front-ended minerals (Trench & Packey, 2012). These 16 critical minerals account for more than 90% of the market value of the 50 critical minerals, defined by the U.S. Department of Energy (2023).[5] The indexes are the product of the investment attractiveness index from the Annual Survey of Mining Companies (Fraser Institute, 2022), weighted by country proven reserves of each individual mineral from the United States Geological Survey (USGS) (2022) and the BP Statistical Review of World Energy (2022).

Formally,

$$Non - technical\ risk = \sum_{i}^{n} w_{c,m} * s_c \tag{1}$$

$w_{c,cm}$ is the proven reserves of critical mineral m in country c as a percentage of the world's proven reserves of minerals and S is the investment attractiveness index score for country c from the Annual Survey of Mining Companies conducted by the Fraser Institute (2022).[6]

[5] There is no geological data on proven reserves for the other 34 critical minerals classified by the U.S Department of Energy (2023). It is expected that more knowledge on global proven reserves will become available as AI applications improve, making it possible to calculate non-technical risks for other critical minerals in the future.

[6] We provide more information on the construction of the non-technical risk indexes in Appendix A.

In Figure 4, we show the non-technical risk for each of the 16 critical minerals and an equal-weighted average of three front-ended risk minerals (coal, iron ore and gold) for 2022. The index reflects the investment attractiveness for each mineral, in which a higher value is associated with less non-technical risk. The non-critical minerals benchmark has a median investment attractiveness index of 64.5, compared to the median of 54.5 for the 16 critical minerals. Thus, the non-technical risk of investing in the front-ended non-critical minerals benchmark is lower than each critical mineral. There is considerable heterogeneity in the non-technical risk of specific critical minerals. Rare earth elements has the highest non-technical risk/lowest attractiveness index of 44.7, followed by platinum (46.8), chromium (47.4), tungsten (47.7), graphite (47.8), barite (52.2), tin (54.3), manganese (54.6), antimony (55.0), cobalt (55.5), vanadium (57.0), lithium (58.2), bauxite (58.4), cooper (60.5), zinc (61.5) and nickel 62.7.[7]

Using these indexes, we construct a measure of the non-technical risk premium, which is the critical mineral non-technical risk expressed as a percentage of the non-technical risk of the non-critical front-ended mineral benchmark.

Formally,

$$Non-technical\ risk\ premiun = \frac{(IAI_{NC,} - IAI_{C})}{IAI_{NC}} \qquad (2)$$

Where IAI is the investment attractiveness index and NC and C denote non-critical minerals and critical minerals respectively. Figure 5 presents the non-technical risk premium for each of the critical minerals for 2013-2022. Consistent with Figure 4, each of the critical minerals exhibits a non-technical risk premium, relative to the front-ended non-critical mineral benchmark. The non-technical risk premium varies from rare earth elements (30.6%) to nickel (2.9%), with the average being 15.7%. The heterogeneity in non-technical risk between critical minerals largely reflects the geographical distribution of specific critical minerals, with those exhibiting higher non-technical risk concentrated in countries having less attractive investment environments.[8]

2.1.2 Technical risk premium

Sykes et al. (2016) measured the technical risk of minerals for 49 minerals on the basis of six characteristics (crustal abundance, crustal concentration, ease of mining, and ease of processing, criticality of use and diversity of use).[9] Each of the minerals was given a score of either zero, 0.5 or 1 for each characteristic. Thus, technical risk for each mineral takes a value between zero (lowest) and six (highest), with higher values indicating lower technical risk.

[7] In supplementary material 1, we provide the data used to calculate these indexes with all of the calculations in excel format and corresponding indexes for the period 2013 to 2021.

[8] In Appendix A, we show the results for the non-technical risk premium are robust to including the only major front-ended critical mineral (copper) in addition to coal, gold and iron ore in the benchmark of front-ended minerals.

[9] Details of these definitions are given in Appendix A, Section 2.

Figure 6 show the scores of this measure of technical risk for 14 critical minerals and our benchmark of front-ended non-critical minerals, consisting of the average for coal, gold and iron ore.[10] Ten of the 14 critical minerals have higher technical risk than the non-critical mineral benchmark (3.5), with tin, manganese, rare earth elements and zinc exhibiting the highest technical risk (1.5-2). Copper and antimony have a score of 4 which reflect less technical risk, while bauxite and barite have the same technical risk as the non-critical benchmark.

Using the technical risk index in Figure 6, we construct a measure of the technical risk premium, which is expressed as the percentage difference between the critical mineral technical risk and the technical risk of the non-critical mineral benchmark.

Formally,

$$Technical\ risk\ premiun = \frac{(TR_{NC,} - RR_{C})}{TR_{NC}} \qquad (3)$$

Where TR is the technical risk of the non-critical mineral benchmark (NC) and critical minerals (C), from Sykes et al (2016). Figure 7 presents the technical risk premium for each of the 14 critical minerals. Consistent with Figure 6, tin has the highest technical risk premium, while copper and antimony have a technical risk discount, relative to the non-critical mineral benchmark. The average technical risk premium across the 14 critical minerals is 18.4%.

2.1.3 Total risk premium for critical minerals

In Figure 8, we plot technical risk scores on the horizontal axis and non-technical risk scores on the vertical axis for 14 critical minerals (green dots) and the non-critical minerals benchmark (black dots). The values are normalised from 0 to 1 and inversed, such that values closer to the intercept of each axes denote lower technical and non-technical risks. Rare earth elements has the highest non-technical risk of 1 and also has a very high technical risk of 0.6. Tin exhibits the highest technical risk of 1 and the third largest non-technical risk of 0.25.

In Figure 9 we present estimates of the total risk premium for the 14 critical minerals for which we have data on technical and non-technical risk. The total risk premium is the sum of the standardized technical and non-technical risk premium/discount with possible values in absolute values between zero and 1. Rare earth elements, tin, manganese, tungsten and zinc have the highest total risk premium. The only mineral showing a total risk discount is copper, reflecting its lower technical score, relative to the benchmark.

[10] Of the 16 critical minerals for which we calculate the non-technical risk scores, Sykes et al (2016) do not include graphite or platinum in their study.

2.2. Estimates of the back-ended risk premium

Next, we provide conservative estimates of the cumulative back-ended risk premium depicted in Figure 3 until 2035 under the Sustainable Development Scenario (SDS) and Stated Policy Scenario (STEPS).[11] For each scenario we calculate the total risk premium based on the weighted average of the market value of each critical mineral. Using the weighted average of the market value has the advantage that it takes into account differences in the relative importance of critical minerals to the clean energy transition. For the SDS, we calculate the total risk premium to be 32.5%, while for the STEPS the total risk premium is 31.6%.

The BRP is estimated as follows:

$$Back - ended\ Risk\ premiun = Total\ Risk\ Premium * WACC \quad (4)$$

WACC is the weighted average cost of capital for the average of front-ended mining company. To estimate the WACC, we employ a random sample of 368 mining companies, spanning the period 2007 to 2023, giving a total of 2609 observations. [12] For these firms, the WACC was 13.49%, which is consistent with the finding reported in Rasnosz (2017) that the WACC of mining companies typically ranges from 8% to 20%, with an average of approximately 14%. In our main analysis, we use 13.49% as the WACC. In sensitivity analysis, we use a lower bound value of the WACC of 12% and an upper bound value of 16%. Our benchmark estimation from Equation 4 for the BRP is 4.44% for the SDS and 4.26% for the STEPS.

Our estimates of the cumulative BRP until 2035 are given in Figure 10. The cumulative BRP by 2035 ranges between USD 660 billion and USD 678 billion in the STEPS and SDS scenarios respectively. In Appendix A in Figure A2, we assume that the WACC to calculate the BRP is 12%, while in Figure A3 we assume the WACC is 16%. When the BRP benchmark for front-ended minerals is estimated using a WACC of 12%, the cumulative BRP decreases from USD 660-678 to USD 587-604, which can be considered a lower-bound estimate on the cumulative BRP. In the upper bound case, when the BRP benchmark for front-ended minerals is estimated based on 16%, the cumulative BRP increases to the USD 775-804 billion range. This figure represents the additional cost of capital for back-ended projects and helps explain why investment in critical minerals is low even when long-term demand (and prices) are increasing.

3. Implications of the Back-ended Risk Premium for Meeting the Shortfall in Critical Mineral Production from AI Developments in Mining Production

West and Allen (2023) explain that a key feature of the AI revolution is that many roles will be automated and machine learning procedures that heavily depend on capital will replace mundane labour tasks. Grace et al.

[11] According to the IEA, the Stated Policies Scenario (STEPS) is designed to provide a sense of the prevailing direction of energy system progression based on a detailed review of the current policy landscape. The Sustainable Development Scenario (SDS) presents the most desirable scenario for the clean energy transition, in which nations work together to successfully limit climate change, by transforming the energy market and addressing air pollution.

[12] The dataset consists of 368 mining companies engaged in mineral production worldwide, including but not limited to gold, copper, iron ore, and coal and is compiled from Bloomberg. In Supplementary Material 1, we provide the dataset and our calculations.

(2018) report the results from a large survey of machine learning researchers. The consensus among respondents was that AI will outperform humans in many activities over the next decade. The expected gains in productivity in critical minerals production that is hoped will meet the shortfall in supply will be in automation of the labour force and high-level machine intelligence in which capital is the key component at all stages of the mining industry production process from exploration to extraction (see e.g., Hyder et al, 2019). The back-ended risk premium theory, presented in the previous section, implies that the cost of capital for back-ended minerals is higher than that for front-ended minerals. Our findings suggest that, on average, the WACC for front-ended minerals is 13.49%, whereas for back-ended minerals is 4.26% and 4.44% higher depending on the scenario (17.75% and 17.93%, respectively). Thus, in a capital-intensive industry in which productivity gains are expected to be made in AI developments, the increase in capital cost because of the back-ended risk premium is expected to be economically large, lowering productivity growth in the critical mineral sector.

In Figure 11, we employ a production possibility frontier (PPF) to show how the back-ended risk premium affects the potential to increase productivity in back-ended critical minerals via AI. The initial curve shows the combination between capital *(K)* and labour *(L)* that is required to produce the maximum amount of minerals for a firm or economy, in which the factors of production are any combination along the PPF of L_1 and K_1. The green line represents a potential increase in productivity due to AI-technologies which requires more investment in capital (technology). Here capital increases from K_1 to K_2 and the initial PPF rotates outwards and to the right to L_1 and K_2. The broken blue line represents the new PPF when the back-ended risk premium is taken into account. The blue line shows that some of the gains in production made by development in AI-technologies is lost due to the higher cost of capital, reflecting the back-ended risk premium. The loss in production is represented by the move from K_2 to K_3.

The analysis in Figure 11 may be overly pessimistic. It overlooks the potential for AI to potentially reduce the back-ended risk premium through reducing the cost of capital of critical minerals mining projects. AI could reduce the back-ended risk premium via reducing the duration of mining projects and reducing the required rate of return on investment.

There are multiple ways through which AI could reduce the time from exploration to extraction in mining projects. One way is through improved mineral mapping. AI techniques, such as drone-based photogrammetry and remote sensing, can be used to automate the process of mineral mapping, making it possible to predict with greater accuracy regions with higher potential for new deposits (Ali & Frimpong, 2020; Honarmand & Shahriari, 2021; Jooshaki et al., 2021; Kohler et al., 2021). Deep learning algorithms have been shown to provide a very high level of accuracy in image recognition, which can be used for mineral resource mapping with surface and sub-surface image data (Ali & Frimpong, 2020).

Supply-side risk stemming from geographical concentration of critical minerals in a few countries has led to increased focus on the role of AI in detecting unconventional deposits of critical minerals in situ geological deposits of oil, gas or coal mineral deposits from secondary byproducts of anthropogenic processes (Chaterjee et al., 2022; Creason et al., 2023; Presley, 2024; Roth et al 2017). An advantage AI has in such contexts is that a large amount of data has been collected through fossil fuel exploration on such geological deposits, which is well suited to machine learning (Bishop & Robbins, 2024)

A second way in which AI could reduce the risk associated with duration from exploration to extraction is through by making it possible to more accurately calculate the duration of the extraction period of the mine (Jooshaki et al., 2021). One of the most important risks for all mining projects relates to the orebody itself - ie. there is significant uncertainty about mineral resources (Al-Bakri et al., 2023; Dominy et al., 2002). One specific contributor to uncertainty being higher for critical minerals than conventional minerals in this early stage is that there are relatively few sources of data on critical mineral reserves. A second point of difference is that critical minerals are recovered as by-products from refining other metals. This means that the metal supply responds not only to the price of the by-product metal, but also to the price of the host metal, which affects reserve estimates (Spiers et al., 2015). Uncertainty about the potential to recover critical minerals from mine waste, such as tailings, is particularly acute (Suppes & Heuss-Aßbichler, 2021). A third important way in which critical minerals differ from fossil fuels is that the former can be recycled, although the implications of recycling on future reserves is difficult to quantify, adding to uncertainty about available reserves (Spiers et al., 2015). Mining and extraction methods are dictated by the geology of the orebody or oreobodies. AI can be used to provide a more accurate depiction of the geology of the oreobody and its associated uncertainties (Nwaila et al., 2022). Several AI methods have been developed to predict the grade and recovery of mineral deposits, reducing the associated technical risk (Gomez-Flores et al. 2022.

A third avenue for reducing the time period from exploration to extraction is through employing AI to improve mining productivity. Risks associated with drilling and blasting performance depends on proper rock fragmentation. AI can be used to predict rock fragmentation and provide real time evaluation of drilling performance that improves efficiency (Ali & Frimpong, 2020). Automated drilling can be fitted with sensors that target specific ores; hence, reducing exploration time (Onifade et al 2023).

AI can also be used to reduce the required rate of return on investment in two main ways. One way is through reducing uncertainty with the risk of a blow out in the cost, which is particularly important for back-ended minerals given that the initial cost of capital is higher than for front-ended minerals. For example, AI can be used to forecast the capital cost of open pit mining projects (Zhang et al., 2020). Equipment selection is the most important phase during mine planning. The capital investment in selecting the right equipment represents a major risk. AI algorithms can be used to reduce the risk with equipment selection (Ali & Frimpong, 2020). Once the mine is in operation, AI can be used for predictive maintenance and management of equipment, minimizing repairs (Onifade et al. 2023).

AI could also reduce the required rate of return on back-ended projects through reducing the risk, particularly environmental risks, associated with such projects. You et al (2021), for example, review evidence which shows that AI algorithms can be effective in reducing disasters and environmental hazards associated with energy mining. This is particularly important in the case of some key back-ended critical minerals, such as cobalt and lithium.

According to the US Geological Survey (2023), more than 50% of the global proven lithium reserves are concentrated in the lithium triangle between Chile, Bolivia, and Argentina. Lithium in this region is mined from salt deserts or so-called salars. Extracting lithium from salars has generated long-term environmental damage, with locals complaining that lithium mining has increased the prevalence of droughts, threatening livestock farming and drying out vegetation (Oritz, 2021). About half of the proven reserves of cobalt are located in Congo Kinshasa. Weak institutions, corruption, and conflict in the region exacerbate environmental risks associated with mining Cobalt. The technical risks associated with artisanal mining practices in Congo Kinshaha have caused environmental degradation, including deforestation, soil erosion, water pollution, and biodiversity loss. Unregulated mining activities, using mercury and other chemicals, and inadequate waste management practices can negatively affect ecosystems and local communities in the long term (Nkulu et al, 2018).

The potential impact of AI on the rate of return and duration of the project are illustrated in Figures 12 and 13 respectively. In Figure 12, the potential impact of progress in AI on reducing the risk/rate on the back-ended risk premium is represented by the shift from R_B to R_{AI} while the volume of this reduction is represented by the grey area. Formally:

$$\int_{R_F}^{R_B} F(R_B) - \int_{R_{AI}}^{R_B} F(R_{AI}) \ = BRP\ reduction\ by\ AI \ \ (risk/rate) \tag{5}$$

In Figure 13, the impact of AI progress on reducing the mining project time is represented by the shift from T_B to T_{AI} (the volume is represented by the grey area). Formally:

$$\int_{T_0}^{T_B} F(T_B) - \int_{T_{AI}}^{T_B} F(T_{AI}) \ = BRP\ reduction\ by\ AI\ (time) \tag{6}$$

In Figure 14, we consider the impact of lowering the rate of the back-ended risk premium as a result of advancements in AI technology. For simplicity, we assume a 50% reduction in risk. Since our estimates are proportional, readers can infer proportional reductions at different percentages. A 50% reduction in risk resulting from AI improvements leads to a corresponding decrease in the back-ended risk premium, falling within the range USD 330 (STEPS) to USD 341 billion. In Figure 15, we demonstrate a reduction in the duration of mining projects due to AI technological advancements. For instance, a 50% shortening of project duration resulting from AI improvements leads to a corresponding decrease in the back-ended risk premium, falling within the range USD 330 billion (STEPS) to USD 334 billion (SDS).

Investment in AI can eliminate the negative impact on the back-ended risk premium on investment in, and production of, critical minerals which is key to achieve net zero. For example, when Equation (5) equals zero, it means that back-end risk equals front-end risk, so that the back-ended risk premium equals zero. Similarly, if Equation (6) equals zero, the time needed from exploration to feasibility is reduced to zero, such that the back-ended risk premium equals zero. Various combinations of reductions in the risk/return associated with back-ended projects as well as the duration of mining project time may achieve a zero back-ended risk premium.

The implication of this result for the energy transition is that an immediate large-scale direct investment in critical minerals' projects by governments between USD 660 and USD 678 billion is needed over the next decade. This amount is consistent with the shortage in investment estimated by the IEA (2021). The back-ended risk premium is an additional cost to achieve net zero 2050 that policymakers, thus far, have not considered when estimating the shortfall in investment.

3.1. What if meeting carbon net zero by 2050 is not possible?

Some studies have posited that, given existing mining constraints and known reserves of critical minerals needed for clean energy transition, replacing existing fossil fuel sources for energy requirements with renewable alternatives will not be possible by 2050. For example, Moreau et al (2019) find that of 29 necessary metals in the lifecycle of renewable energy technologies, known reserves of eight metals might be depleted by 2050. Micheaux (2021) presents several scenarios for transition to carbon net zero concluding that ultimately global reserves of cobalt, nickel and lithium may not be enough to resource the quantity of batteries needed to power the electric vehicles needed for clean energy transition.

What does this mean for the back-ended risk premium and AI's potential mitigation of this risk premium? Our interpretation is that the conclusion from such studies reinforces the importance of attracting investment in back-ended critical minerals to reduce the expected shortfall to realize the clean energy transition. It also highlights the importance of investment in AI applications in development and exploration to reduce the duration of mining projects and reduce required rate of return on investment. Micheaux (2021) suggests that if existing critical minerals reserves are not sufficient to resource clean energy transition that a new social contract may be required that limits energy demand. A pessimistic conclusion from this might be that if commitment to energy transition by 2050 is ignored this might erode the motivation for global support for net zero emissions from governments and lending agencies. In such circumstances, other solutions would need to be found and financing investment in back-ended critical minerals would be less important, making the back-ended risk premium less important. However, this is unlikely. Given the global recognition of the threat posed by climate change, it is very unlikely that commitment to clean energy transition will be eroded even if meeting 2050 targets prove not to be feasible. If commitment to clean energy transition did look like faltering, reducing expected demand for critical minerals, the added uncertainty would increase the back-ended risk premium by increasing the required rate of return on investment (Carruth et al., 2000). In this sense, the potential that political commitment to clean energy transition, broadly defined, could wane is a nontechnical risk, which increases the uncertainty associated with investing in critical minerals, meaning investors require a higher rate of return. Most likely, as Micheaux (2021) acknowledges, even if critical minerals do not provide the full solution to resourcing the clean energy transition, they will at least still provide some of the solution, in conjunction with other initiatives, and further investment in critical minerals will be needed to facilitate this.

3.2 Limitations on AI as a solution to the back-ended risk premium

We show that improvements in AI have the potential to reduce the back-ended risk premium. However, AI is going to require further investment to ensure the required gains and there is uncertainty about whether and when the benefits of AI will be realized. While it is often touted that AI will lead to improvements in productivity in mining and a reduction in mining project risks, there is a distribution of AI applications in mining and mineral processing in terms of maturity on the Gartner hype cycle for developing new technologies (Linden & Fen, 2003), with many technologies still early on the curve (especially at 'peak of inflated expectations'). AI has experienced a number of 'hype cycles' in which unrealistic expectations have preceded periods of under-delivery, funding cuts and slowdowns in investment in R&D (McCoy & Auret, 2019).

Recent meta-studies have also revealed a worrying tendency for overly optimistic AI performance reporting, due to data leakage and lack of reproducibility (Kapoor & Narayanan, 2023; Rosenblatt et al, 2024). Messeri and Crokett (2024, p. 49) argue that "AI solutions can exploit our cognitive limitations, making us vulnerable to illusions of understanding in which we believe we understand more about the world than we actually do". AI faces specific challenges in mining and mineral processing projects. One of the main challenges facing the mining sector in exploiting the potential of AI is addressing the skills gap with many workers requiring reskilling or upskilling to take advantage of AI (Noriega & Porrahimian, 2002; Onifade et al 2023; Young & Rogers, 2022).

A second set of challenges facing AI in mining studies is the lack of high-quality training data (Jooshaki et al, 2021; Maleki et al., 2022; McCoy & Auret 2019). The application of AI has been limited by the use of small datasets (Gomez-Flores et al. (2022; Maleki et al., 2022). Cost forecasting applications are typically based on relatively few data points (Noreiga & Pourrahimian, 2022). Given that exploration of critical minerals is relatively new and that there are relatively few critical minerals (and particularly back ended critical minerals) the lack of databases and experimental data to train and test AI models is particularly acute.

A third, related problem, is that mining operations often take place in remote locations making access difficult. Abrasive materials, dust and humidity that are commonplace in mines do not create a congenial environment for the deployment of digital technologies. In underground mining, installed sensors need to be resistant not only to dust and humidity, but also blasting that can damage the senses. Transmitting the data can be problematic due to the limited bandwidth of communication networks employed in underground and open pit mining. Connectivity can be particularly weak and unstable in deep mine sites (Onifade et al 2023). This makes the storage and transmission of useful data challenging (Etsay et al. 2023).

3.3 Policy recommendations

The main problem that back-ended critical minerals has is that they provide lower value to investors during the initial stages of project development and exploration, due to technical and non-technical risks. Our analysis suggests that the most important stages to invest in AI to reduce the back-end premium is in applications between exploration and development.

It is important to highlight that investing in mining in these stages is distinct from investment in AI made by governments, the private sector and global funding agencies more generally. In 2021-2022, the United States Federal Government, as the global leader in AI investment, spent USD 3.3 billion on AI, while worldwide private sector investment in AI was USD 91.9 billion (Stanford, 2023). In comparison, mining companies were expected to spend just USD 218 million on AI globally in 2024 (Mining Technology, 2024) with only a fraction of this invested in AI in supporting development and exploration in back-ended critical minerals.

Our suggestions below for areas of investment in AI apply to governments, the private sector and lending agencies such as the World Bank and IMF. The argument for government investment in AI applications is that it is broad based and the benefits of technical breakthroughs can extend beyond a single firm or sector. However, there is also a strong argument for the critical minerals sector investing in AI to reduce the back-ended risk premium, given it is in their interests to attract investment. Improvements in AI in the development and exploration phase can reduce the back-ended risk premium through both reducing the duration of the project and reducing the required rate of return on investment.

Most AI applications in mining have focused on the development and exploration phase, which is where AI is particularly useful in mitigating the technical risks (Kohler et al. 2021; Noreiga & Pourrahimian, 2022). One specific AI application in which governments and mining companies could invest is in data-driven prospectivity modelling where random forest (Flores et al 2020) and extreme learning machine models (Chen & Wu, 2017) have been used to more accurately predict recovery rates and reduce the time from exploration to extraction. A second related AI application is in mineral mapping in which drilling sensors, geophysical-geochemical-remote sensing surveys and 3D geological modelling can be used to more accurately predict locations with the most potential for mineral deposits (Acosta et al., 2019; Jindai et al., 2012; Tusa et al., 2019; Wang & Huang, 2012).

A third area for potential investment would be in AI methods, such as artificial neural networks (Chatterjee et al, 2010) and extreme learning models (Jain et al, 2021), to predict the grade and recovery of mineral deposits. A fourth promising area for investment in AI is in the recovery of critical minerals from mining waste. AI has proved particularly useful in improving secondary recovery approaches, such as adsorption (Briao et al 2023; Sadi & Solemani, 2023), reducing time from exploration to extraction.

Lithium extraction in Chile, Bolivia, and Argentina is plagued by water scarcity. Scarcity of water and water management is one of the main challenges of mineral processing plants that lead to delays (Nwaila et al. 2022). Automated 'dry' or water-savvy sensing AI techniques can be employed to minimise these risks (Nwaila et al. 2022). The benefits of using critical minerals, such as lithium, to facilitate the clean energy transition will be muted if they are extracted in an environmentally unfriendly way. More generally, investment in AI powered environmental monitoring systems, such as smart earth technologies, could help mitigate the impact of minerals such as cobalt and lithium on the environment by detecting and addressing pollution in real time (Dhanwani et al., 2021). One of the biggest obstacles to the successful adoption of AI in addressing back-ended risk is the lack of data. Creating publicly available material datasets that can be used as a source of model training and testing is a common recommendation to further AI applications in mining (Maleki et al, 2022). Given the public goods nature of having open access material datasets, this is one area in which governments and international lending agencies in particular could invest.

4. Conclusions and Further Directions

One of the biggest impediments to achieving global decarbonization targets is the shortage of critical minerals supply for both clean energy production and storage. According to the IEA (2021), current investment in critical mineral projects is around half of what is needed to achieve net zero. Electric vehicles will require six times the number of minerals and clean energy six to nine times the number of minerals than traditional energy sources. The theory that we have developed in this paper - the back-ended risk premium - explains why investment in some critical minerals is still scarce despite their expected high demand over the next two decades. We show that the back-ended risk premium increases the cost of capital, which weakens the possible gains in productivity expected from AI technologies in mining as a capital-intensive sector.

We have provided some back-of-the envelope calculations of the back-ended risk premium as well as the potential for AI to reduce the back-ended risk premium until 2035, based on fairly conservative assumptions about the total investment needed in critical minerals over the next decade. We suggest that the best way to reduce the enormous cost associated with energy transition is for governments to invest heavily in AI mining technologies and research.

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Figure 1: Medium Term (2025-2030) Critical Minerals Supply Risk Matrix

Source: U.S. Department of Energy, Critical Materials Assessment 2023

Figure 2: Project Development with Back-ended and Front-ended Risk

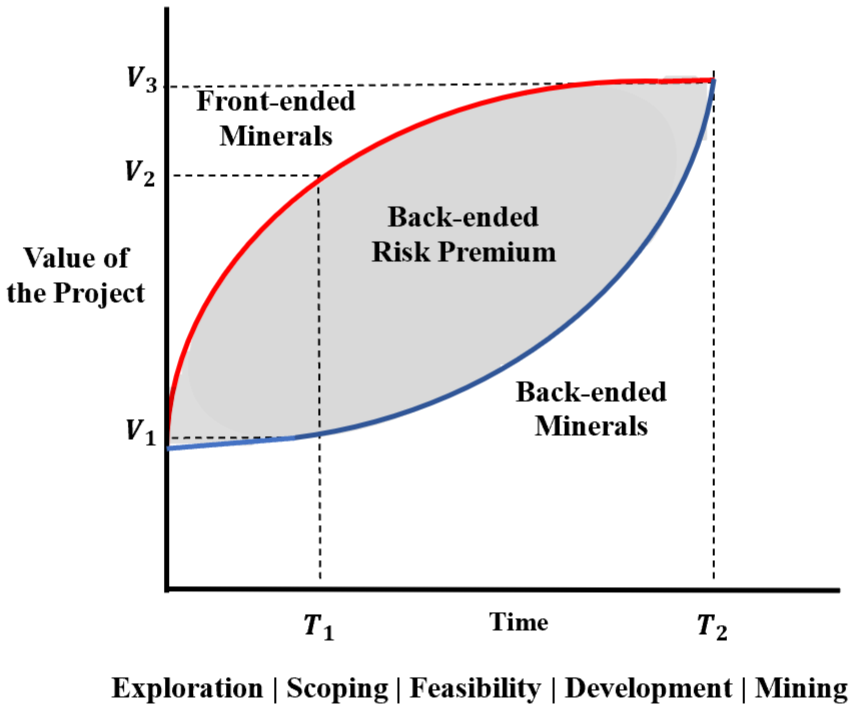


Figure 3: The Required Rate of Return for the Back-ended Risk Premium

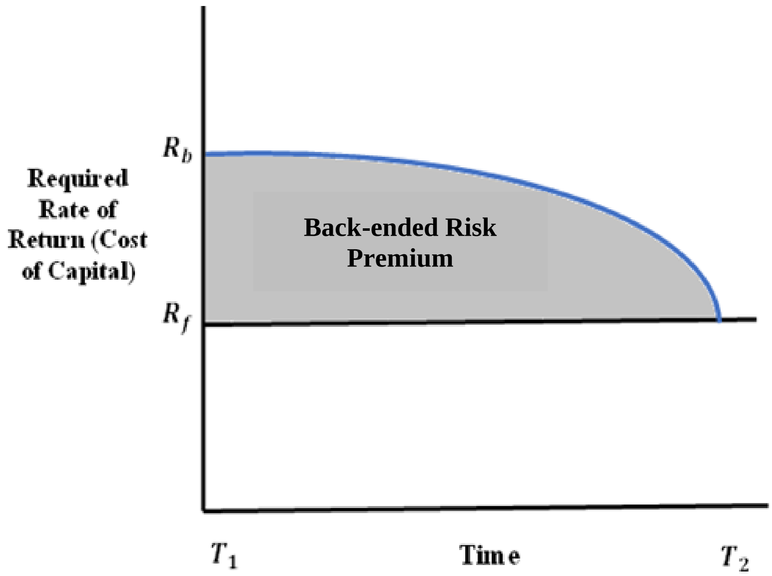


Figure 4: Non-technical Risk Index of Minerals

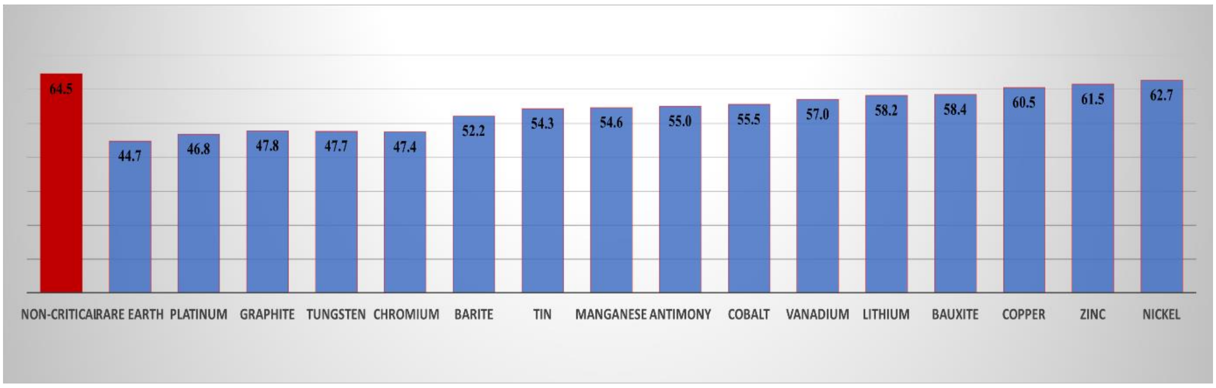
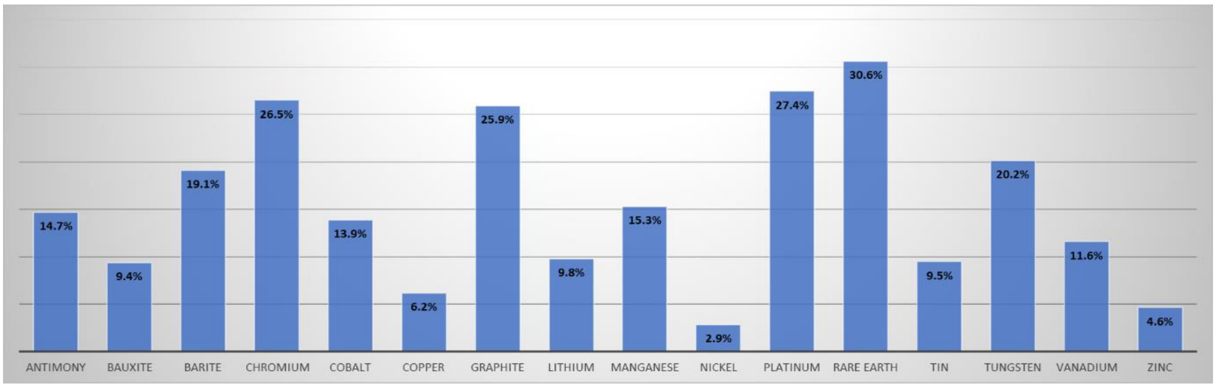


Figure 5: Non-technical Risk Premium for Major Critical Minerals



Source: This index is constructed using data from USGS (2022), Fraser Institute (2022) and BP Statistical Review of World Energy (2022) for the period 2013-2022. Details of the construction of this measure of non-technical risk premium, data and calculations are available in Appendix A and Supplementary Material 1.

Figure 6: Technical Risk Index of Minerals

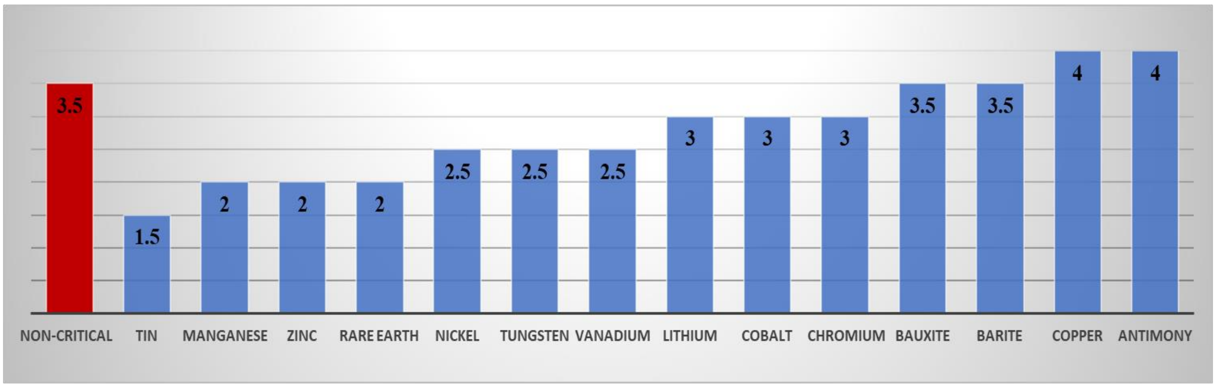


Figure 7: Technical Risk Premium for Major Critical Minerals

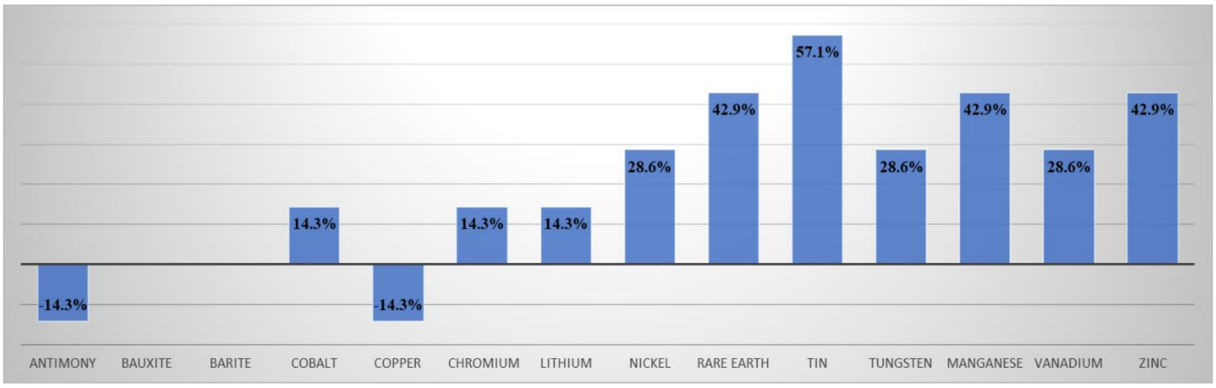


Figure 8: Technical and Non-technical Risk Scores

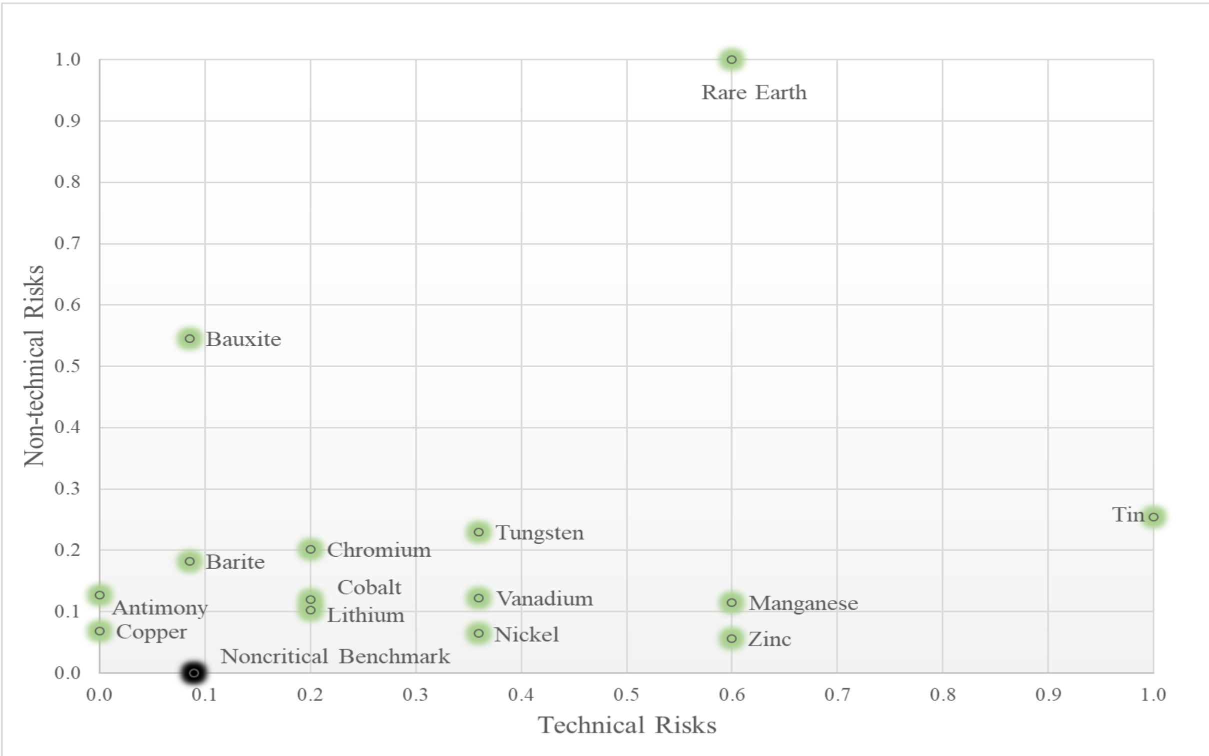


Figure 9: Total Risk Premium of Major Critical Minerals

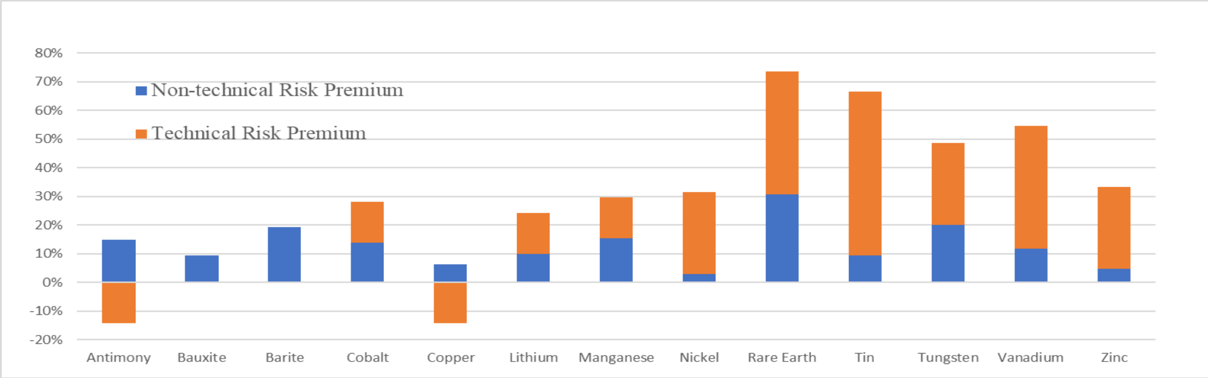


Figure 10: The Cumulative Back-ended Risk Premium in Billions of USD (2023-2035)

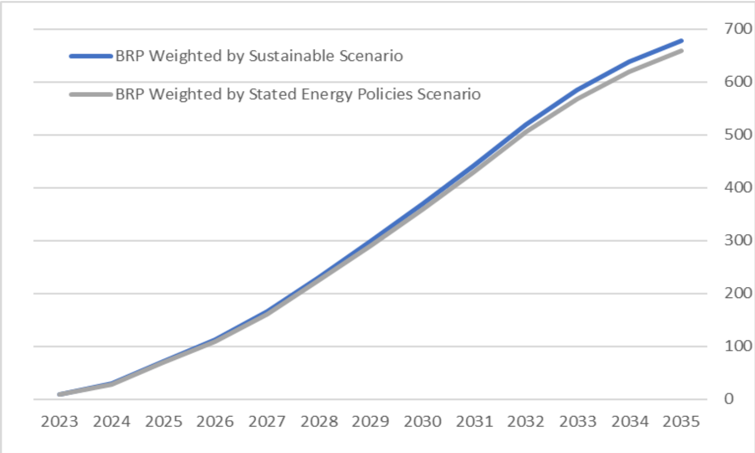


Figure 11: The Effect of the Back-ended Risk Premium on Productivity Gains Due to AI

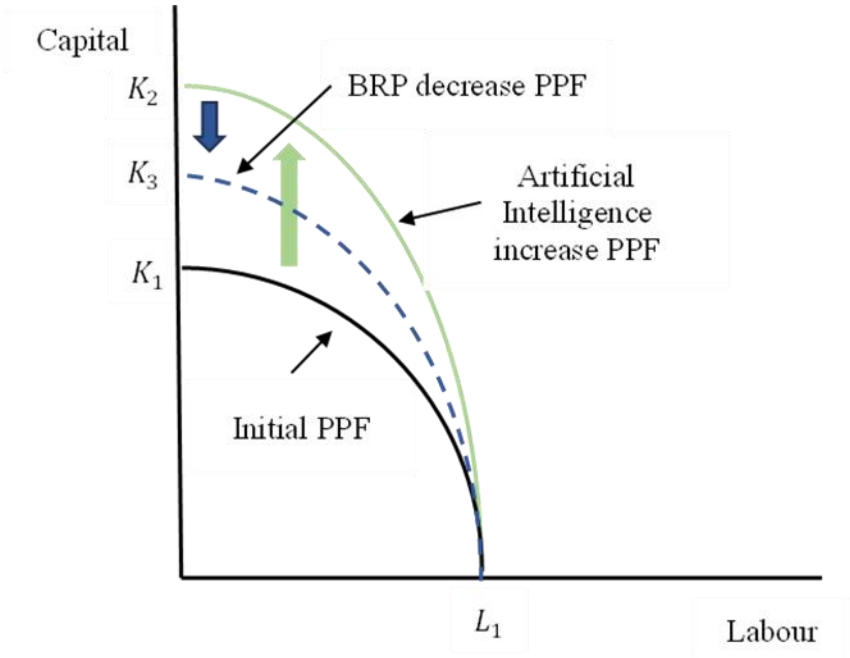


Figure 12: The Impact of Changes in the Required Rate of Return Caused by Artificial Intelligence Technological Progress on the Back-ended Risk Premium

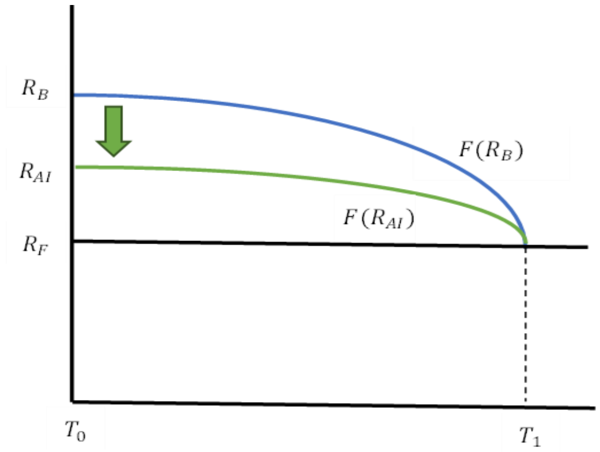


Figure 13: The Impact of Reductions in the Duration of Mining Projects Caused by Artificial Intelligence Technological Progress on the Back-ended Risk Premium

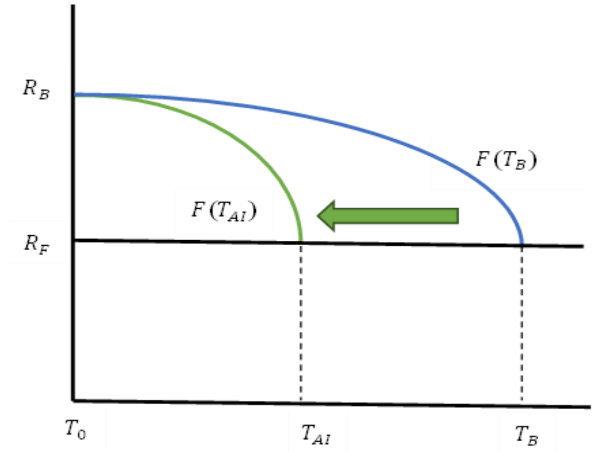


Figure 14: The Cumulative Effect of a 50 Per Cent Reduction in the Risk/Rate on the Back-ended Risk Premium in billions of USD (2023-2035)

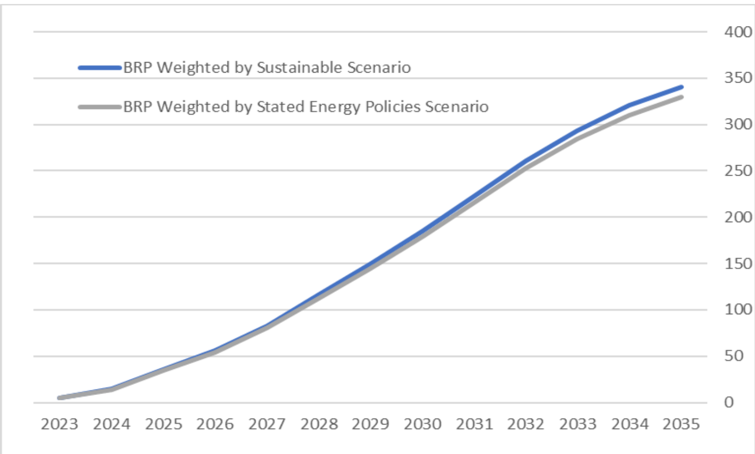
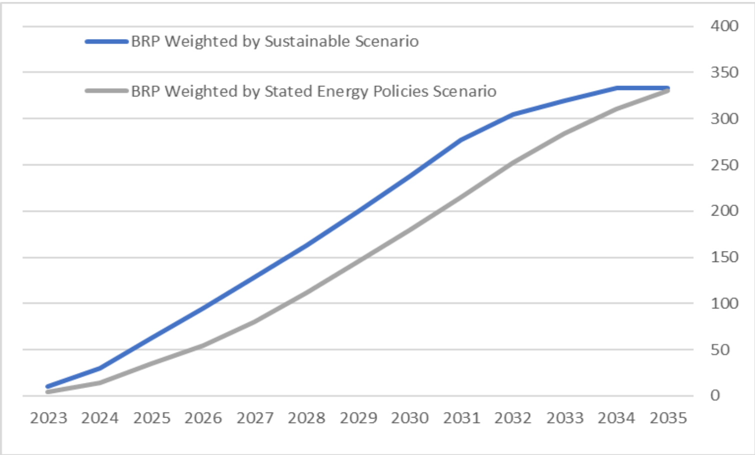


Figure 15: The Cumulative Effect of a 50% Shortening in the Project Duration on the Back-ended Risk Premium in billions of USD (2023-2035)



Appendix A: Non-technical and Technical Risks of Critical Minerals

In section A1.1 we describe how we calculate the investment attractiveness index by country, based on the Fraser Institute's (2022) Annual Survey of mining companies. In section A1.2 we present details on the calculation of the percentage of proven reserves for the benchmark non-critical minerals and each of the 16 top critical minerals. In section A.2 we describe the components of technical risk for 14 critical minerals, coal, gold and iron ore that were employed by Sykes et al. (2016). In Section A.3 we examine the sensitivity of our front-ended minerals index to the inclusion of copper, while in Section A4, we examine the sensitivity of the cumulative BRP to alternative values for the cost of capital.

A1. Non-technical Risks

Non-technical risk refers to country-specific or geographical risk and consists of the risk of resource nationalization, land access, land claims, red tape, green tape, corruption, social unrest, infrastructure, civil unrest, natural disaster, and labour relations (Trench, Packey and Sykes, 2014). We develop an index of non-technical risk for the 16 major critical minerals using the investment attractiveness index (Fraser Institute, 2022), weighted by country proven reserves of each individual mineral from United States Geological Survey (USGS) (2022) and BP Statistical Review of World Energy (2022).

A.1.1 Investment Attractiveness Index

The Fraser Institute's Investment Attractiveness Index is constructed from an annual survey administered by the Institute. This index provides an overall ranking of jurisdictions based on their attractiveness for mining investment. The investment attractiveness index is composed of the policy perception index (reflecting country specific mining policies) and best practice mineral potential (environmental risks).[13] We posit that this index is a good proxy for non-technical risks since it reflects the mining companies' perception of the political and environmental risks associated with investing in mining exploration and production.

A.1.2 Proven reserves by country from the U.S Geological Survey

Table A1.2, shows the geographical distribution of the 16 critical minerals proven reserves as a percentage of total world proven reserves.[14] According to the U.S Geological Survey, proven reserves refer to the estimated quantities of natural resources, such as minerals, fossil fuels, or groundwater, that can be extracted economically with existing technology and under current market conditions. These reserves have been confirmed through exploration and production activities, and their extraction is technically feasible and

[13]The *Investment attractiveness index* measures the attractiveness of investment opportunities associated with each mineral. Higher values indicate higher investment attractiveness. *Policy Perception Index:* reflects the perception of policies related to each mineral. Higher values suggest more favourable policy perceptions. The *Best Practices Mineral Potential Index* assesses the mineral potential of each mineral based on best practices. Higher values indicate higher mineral potential.

[14] Although the refined production of minerals may be in a different location due to refining costs and scales, we focus on proven reserves rather than on the production side as a measure of long-term supply. Country's proven reserves of coal are taken from the 2022 BP World Energy Report as the US. Geological Survey do not provide this data.

profitable. Although the U.S. Department of Energy identified 50 critical minerals by 2022, the U.S. geological survey only reports complete data for countries' proven reserves for 16 critical minerals.

Table A1.1: The Investment Attractiveness Index by Country for 2022

Country	Investment Attractiveness Index
Argentina	61.53
Australia	73.74
Bolivia	53.97
Brazil	68.98
Canada	73.62
Chile	60.34
China	44.86
Congo	48.52
Guinea	55.59
India	49.63
Indonesia	49.63
Kazakhstan	49.63
Kyrgyzstan	49.63
Mexico	60.16
Papua	51.03
Peru	60.68
Europe	67.82
Philippines	49.63
Russia	49.63
South Africa	44.76
Turkey	49.63
US	74.80
Vietnam	49.63
Zambia	42.18
Median	54.96
Europe Median	67.82
Asia Median	49.63
Africa Median	54.25
Latin America and Caribbean Median	60.44

Source: Fraser Institute (2022), Annual Survey of Mining companies, 2022. When data is missing for a specific country, we replace the observation with the regional mean.

Table A1.2: Country Proven Reserves of 16 Critical Minerals as Percentage of World Reserves (2022)

Country/CM	**Antimony**	**Bauxite**	**Barite**	**Chromium**	**Cobalt**	**Copper**	**Graphite**	**Lithium**	**Manganese**	**Tin**	**Nickel**	**Platinum**	**Rare Earth**	**Tungsten**	**Vanadium**	**Zinc**
Argentina								20.4%								
Australia	6.7%	24.2%			18.1%	10.9%		8.1%	15.9%	12.4%	21.0%				28.5%	31.4%
Bolivia	17.2%							21.4%		8.7%			8.0%			
Brazil		12.8%					22.4%		15.9%	9.1%	16.0%				0.5%	
Canada	4.3%				2.7%	0.9%		3.0%			2.2%	0.4%	16.2%			0.9%
Chile						21.3%		11.2%					0.6%			
China	19.4%	3.4%	12.8%		1.7%	3.0%	15.8%	6.9%	16.5%	15.7%	2.1%			47.4%	36.5%	14.8%
Congo					48.2%	3.5%				2.8%			33.8%			
India		3.1%	17.6%	17.9%			2.4%		2.0%							4.6%
Indonesia		4.7%			7.2%	2.7%				17.4%	21.0%		5.3%			
Kazakhstan			29.3%	41.1%		2.2%			0.3%							3.5%
Kyrgyzstan	14.4%															
Mexico	1.0%					6.0%	0.9%	1.7%	0.3%							5.7%
Pakistan	1.4%															
Peru						9.1%				2.8%						8.1%
Europe						3.4%										
Philippines					3.1%						4.8%					
Russia	19.4%		4.1%		3.0%	7.0%	4.2%			9.3%	7.5%	7.9%		10.5%	19.2%	10.5%
South Africa				35.7%					37.6%			90.0%	16.2%		13.5%	
Turkey			12.1%	4.6%	0.4%		27.3%									
US	3.3%					4.9%		0.0%			0.4%	1.3%			0.2%	3.5%
Vietnam		27.5%								0.2%				2.6%		
Zambia						2.1%							1.8%			
Others	12.7%	24.2%	24.1%	0.7%	14.8%	23.0%	26.9%	27.2%	11.5%	21.5%	25.0%	0.4%	1.2%	36.8%	1.7%	17.1%

Source: US Geological Survey, Annual Publications, Mineral Commodity Summaries 2022

This table provides a clear picture of the degree of geographical concentration of critical minerals. Cobalt is the most extreme case of concertation among the most used critical minerals, with the Republic of Congo having almost half (48.2%) of the world reserves, followed by Australia (18.1%); Rare Earth Elements are also highly concentrated with more than one third of the proven reserves concentrated in China. Other critical minerals are heavily concentrated in a few countries. For Bauxite (aluminium), about two-thirds is concentrated in Vietnam (27.5%), Australia (24.2%) and Brazil (12.8). For Lithium, Argentina, Bolivia, Chile, and Australia have over 60% of the world's proven reserves. For Nickel, around 60% of the proven reserves are in Australia (21.0%), Indonesia (21.0%) and Brazil (16.0%).

A.1.3. Measuring non-technical risk of critical and non-critical minerals

To calculate the investment attractiveness index or non-technical risk for each of the 16 critical minerals, plus coal, gold and iron ore, we use the following formula:

$$Non - technical\ risk = \sum_i^n w_{c,m} * s_c$$

Where $w_{c,cm}$ is the percentage of proven reserves of country c of critical mineral m from the U.S Geological Survey (or BP World Energy Report in the case of coal), and S is the investment attractiveness index score for country c from the Fraser Institute's Annual Survey of Mining Companies.

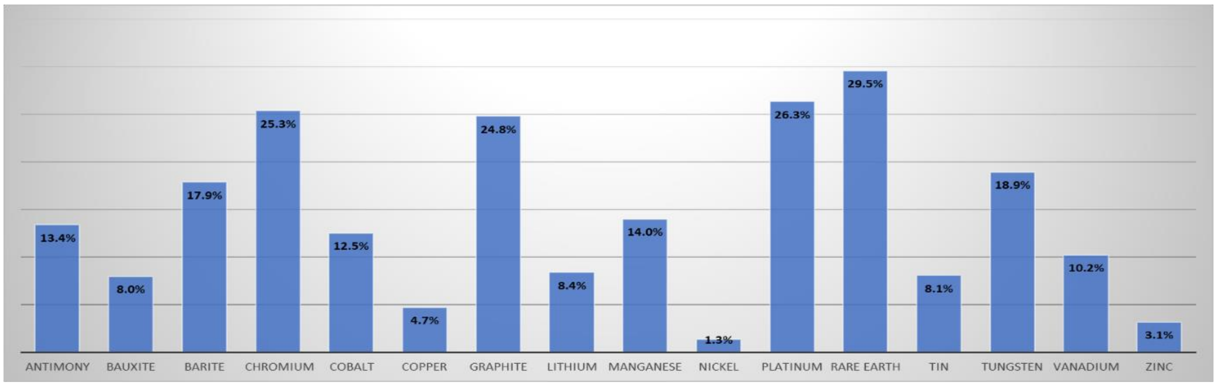
A.2 Technical risks

Sykes et al. (2016) developed a score system to measure technical risks of minerals based on six criteria. *Crustal abundance:* This criterion refers to the abundance of the mineral in the Earth's crust. A higher score indicates a higher abundance, reducing the associated technical risk. *Crustal concentration*: This criterion measures the concentration of the mineral within the crust. A higher score indicates a higher concentration, making it easier to extract, reducing the technical risk. *Ease of mining*: This criterion assesses how easily the mineral can be mined from the earth. Relevant factors are accessibility, depth and extraction techniques. A higher score suggests that the mineral is easier to mine, reducing the technical risk. *Ease of processing*: This criterion evaluates the ease of processing the mineral once it is been extracted. Relevant factors include the complexity of refining processes and the energy required. A higher score indicates easier processing, reducing the technical risk. *Criticality of use*: This criterion assesses how critical the mineral is for various applications. Minerals deemed critical may be essential for specific industries or technologies. A higher score suggests the mineral is more critical, making demand more inelastic reducing risk. *Diversity of use*: This criterion considers the diversity of applications for the mineral. Minerals with a wide range of uses may have greater economic value and stability. A higher score indicates a greater diversity of use. Greater diversity of use reduces the overall risk associated with mining the mineral.

A3. Sensitivity of the front-ended benchmark to the inclusion of copper

In our main estimates for non-technical risk, we use, as our front-ended benchmark, the average of coal, iron ore and gold, which are the largest front-ended non-critical minerals. In Figure A1, in addition to these minerals, we include the only largely produced front-ended critical mineral, which is copper, in this benchmark. This reduces the benchmark score from 64.5 to 63.5, leading to a minor decrease in critical mineral's premium of around 1.6%.

Figure A1: Non-technical Risk Premium for Major Critical Minerals (Robustness Analysis)



A4. Sensitivity of back-ended risk premium to alternative estimates of benchmark cost of capital

Figure A2: Back-ended Risk Premium (cost of capital based=12%)

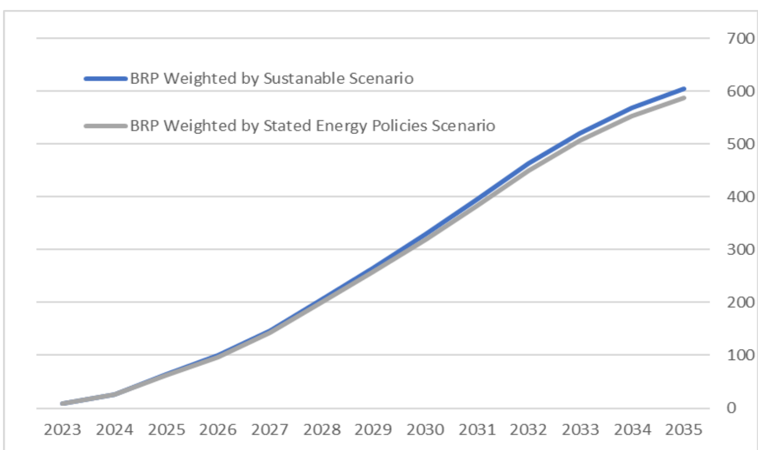


Figure A3: Back-ended Risk Premium (cost of capital based=16%)