Assessing the long-term attractiveness of mining a commodity based on the structure of its industry

by

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Abstract. Throughout this thesis, we sought to determine which forces drive commodity attractiveness, and how a general framework could assess the attractiveness of mining commodities. Attractiveness can be defined from multiple perspectives (investor, company, policy-maker, mine workers, etc.), which lead to varying measures of attractiveness. The scope of this thesis is limited to assessing attractiveness from an investor's perspectives, wherein the key performance indicators (KPIs) for success are risk and return on investments (ROI).

To this end, we have studied the structure of a mining industry with two concurrent approaches. Both approaches aggregate 18 key drivers of ROI and risks, like demand growth, the size of the reserves pool, or the share of state-owned enterprise. The first approach was based on a microeconomics model of cost curve updates and led us to developing the *Cost curve model*. The second one is based on industry expertise and on intuitive, logical and transparent ways to account for the effects of different industry forces like barriers to entry, market power or spikes likelihood on industry attractiveness. It led us to developing the *Decision tree model*.

These two models are complementary: while the first is a rigorous framework that relies on simplifying assumptions, the second relies on intuition and logic. Through this complementarity the two models provide clear and aligned insights about (i) which key combinations of key drivers are preeminent for attractiveness, (ii) how key drivers interact to mitigate or enhance attractiveness, and (iii) how commodities can be screened at a high-level in order to prioritize commodity investigation.

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BACKGROUND AND MOTIVATION

Socio-economic enterprises can be understood as utility maximization problems. The entity that conducts a given enterprise uses its assets in order to obtain results as good as possible, or in other words, in order to maximize its utility function.

The utility function depends on who is enterprising. This entity can be an individual, a company, a non-governmental organization or the government. Basic economic theory assumes companies maximize profit. On the other hand, policy makers may want to increase consumers' welfare by making sure that supply meets demand without causing demand shrinkage due to price increase. They may also want to increase society's welfare by taking into account externalities and labor's welfare, in addition to consumers' welfare.

Once the utility function is defined, the remaining question is to know how it can be maximized. For example, a financial investor can buy several financial products, which all boil down to some expected returns, and some expected level of risk. The investor knows her utility function (it is probably increasing in the returns and decreasing in the level of risk, and it otherwise depends on her personal preferences). Thus, in order to know how she can maximize her utility function; the investor has to assess the expected returns and risk-level.

Another example, perhaps more tangible than that of investment funds, is that of a company's board when it decides on its strategic plan and on its external growth prospects. Suppose that the board of SomeCompany Inc. pursues profit maximization only. How will they pursue this goal? They may plan to grow organically, to innovate, to diversify horizontally or vertically, to invest in operations, marketing or R&D, etc... They have limited assets and virtually unlimited prospects. Thus, they have to take a decision on how to optimize their assets in order to maximize profit. A straightforward way to do so is to rank the main prospects by how attractive they are. Attractiveness is defined here as a combination of profitability, feasibility, and uncertainty. An attractive enterprise is one that has a high utility for the entity conducting it, given the utility function it seeks to maximize.

Large mining companies stand somewhere between regular companies and investment funds. Where investor have a limited number of financial products to pick from, a mining company has an even more limited number of commodities to pick from. And while commodities can be understood as financial products, it is also true that a mining company can decide to vertically integrate and sell modified or manufactured products. Thus conceptualizing the attractiveness of mining commodities lies at the intersection of theoretical investment an business strategy.

While the fields of *Financial Economics*[1] and *Business Strategy*[2] provides various case studies and literature regarding the two examples above – namely, investment strategy and business strategy –, the literature doesn't provide an in-depth, systematic, approach to conceptualizing the attractiveness of mining commodities.

[1] W. Sharpe, *Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk*
[2] M. Porter, *What is Strategy*; H. Hayes & M. Upton, *Operations-based Strategy*

As outlined above, attractiveness of mining commodities can be defined from two main perspectives: (i) a financial investor's perspective and (ii) society's perspective. (i) assumes that the utility is a function of expected returns and risk and (ii) assumes it is a function of how efficiently the market works, and takes into account externalities (through, for instance sustainable supply chain management (SSCM)[3, 4], corporate social responsibility (CSR)[5, 6], and socially responsible investment (SRI).

The scope of this study is limited to identifying and quantifying the drivers of attractiveness when it is defined as in (i): from a financial investor's perspective.

INTRODUCTION

As we outlined in the previous section, from an investor's perspective, the two main key performance indicators (KPI) are the return on investment (ROI), and the risk. Those two drivers are hard to quantify because of imperfect information. The ROI metric takes into account both the funds and effort required to invest. The risk measure has to be combined with the investor's "risk aversion". We will detail later the concept of risk aversion applied to mining. In a broad sense, a highly risk averse investor will favor a secure investment over a more uncertain one, even if the expected returns are lower.

Which driving forces make commodities attractive? What are the benefits of a general framework to assess mining commodities attractiveness?

A general framework has to be scalable across all commodities, without in-depth commodity analysis. Thus, we need to be able to scale our assessment framework to any commodity with a reduced number of data inputs. To that end, we first identify the most important data inputs that are necessary to assess the attractiveness of a commodity, at a high level. Thus, we identify the elementary drivers that are required to assess any commodity's attractiveness level (I.). We then introduce the two economics theories (II.) that underpin two sound approaches to aggregating these drivers in a measure of attractiveness (III.). We then describe a possible implementation of each framework (IV.) and compare the results obtained in each model (V.).

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[3] Helmut Asche, U Mainz, *Industrial Policy Challenges in Resource-Rich Countries*

[4] Christoph Kolotzek, et al, *A company-oriented model for the assessment of raw material supply risks, environmental impact and social implications*

[5] Zambia Institute for Policy Analysis & Research, *In the Eye of a Storm: The impact of the economic slowdown on the labour market in Zambia.*

[6] Moritz, T., & Ejdemo, T., & Söderholm, P., & Wårell, L. *The local employment impacts of mining: an econometric analysis of job multipliers in northern Sweden.*

I. Industry structure drivers of attractiveness

We are interested in assessing the long-term attractiveness of mining commodities. Thus, we need to predict risk and returns. Although it is hard to forecast these two KPI's directly, we notice that several factors drive them up or down. The first step was therefore to identify these drivers. This was done through literature review[7], experts' interview, and iterative thinking when designing the models that we will present later on. The identified drivers and their definitions are summarized in **Table 1**, below.

	Drivers	Definition
ROI	Current Margins (%)	Margins of the 25th percentile asset (P90/P25-1)
	Reserves (Or Production Cover)	Reserves, as defined by USGS[8]. Production cover is the reserves, in years of current production
	Asset concentration (%)	Share of supply produced by the 10 largest mines
	Geopolitical risk of reserves	$\sum_{country} Reserve\ Share \cdot Country\ Risk$
	Intensity of regulations on Supply	Qualitative - Scored between 0 and 1 by experts
	Industry maturity	Qualitative - Scored between 0 and 1 by experts
	Technical complexity	Qualitative - Scored between 0 and 1 by experts
	Capital intensity	CAPEX/P90 (Ratio of the capital expenditure of a typical project to the cost curve's 90% percentile's cost)
	Geopolitical risk of supply	$\sum_{country} Supply\ Share \cdot Country\ Risk$
	SOE Concentration (%)	Share of supply that is state-owned
	Vertical integration (%)	Share of supply that is vertically integrated
	Growth of demand (%)	Base case, long-run forecast of the demand CAGR
	Stocks (kt)	Stocks, as defined by USGS[9]
	Depletion (%)	Share of yearly capacity decline due to ore grade loss
ROI - Applies to oligopolies only	Risk of oligopoly stability disruption	Qualitative - Scored between 0 and 1 by experts
	Historical stability of oligopolist supply	10-year average of capacity utilization of oligopolist, weighted by share of supply
	Historical volatility of non-oligopolist supply	10-year absolute growth of the share of supply produced by non-oligopolist
	Industry concentration (%)	Share of supply produced by the oligopoly
RISK	Substitution risk	Qualitative - Scored between 0 and 1 by experts
	Disruption risk	Qualitative - Scored between 0 and 1 by experts
	Geopolitical risk of supply	Same as in ROI section
	Intensity of regulations on Supply	Same as in ROI section
	SOE Concentration	Same as in ROI section

Table 1 : Elementary drivers of ROI and risk

[7] Kanters, *Supply risk assessment of major agricultural commodities*; Spohn, *Evaluating Market Attractiveness;* Surujhal *et al., Mining Company Strategy Evolution*

[8] *USGS Mineral Commodity Summary 2018 – "Appendix C—Reserves and Resources"*

[9] *USGS Mineral Commodity Summary 2018*

We now succinctly expand on why we considered these drivers. Note that we considered many other possible inputs, that we did not keep as they were not as relevant as these one.

- The long-run ROI of a commodity is defined as the long-run predicted margins for a good asset (25th percentile on the cost curve). 14 drivers affect the ROI.
  - *Current margins* are a zero-degree approximation of long-run margin, they have some indicating power. They also give the cost curve flatness (P25/P90 :Ratio of the cost curve's 25% percentile's cost to the 90% percentile's cost). *Cost curve flatness* disincentivize non-economic firms to retire as the incurred loss is smaller as the curve gets flatter.
  - The amount of *Reserves* is also a driver of long-term profitability. This is easily seen as a shortage in reserves will induce a shortage in supply, or a higher cost of supply.
  - *Asset concentration* is a proxy for the granularity of the industry, which translates into high or low barriers to entry, and thereby into high or low margins.
  - *Geopolitical risk of reserves* restricts the availability of deposits that could be incentivized.
  - *Intensity of regulations on supply* limits the ease with which new entrants can start mining a commodity
  - *Technical complexity* and *Industry maturity* limits the number of potential new entrants. Only a few firms can manage to mine particularly complex ore bodies. On the other hand, when the industry is fairly new, like that of lithium, technological improvements are to be expected. In turn, these improvements might decrease the long-term technical complexity.
  - *Capital intensity* also limits the number of potential new entrants.
  - *Geopolitical risk of supply* generates price increase due to unforecastable capacity shutdowns.
  - *SOE concentration* disincentivize non-economic firms to retire, as the main goal of SOE might go beyond mere profitability.
  - *Vertical integration* disincentivize non-economic firms to retire, as the main goal of vertically integrated firms might not be limited to the profitability of the mining segment of the value chain.
  - *Growth of demand* increases consumption, and therefore the selling price (by sliding towards the right-side of the cost curve)
  - *Stocks* counterweight the growth of demand
  - *Depletion* increases the need for new supply

- In the situation where the market is oligopolistic, 4 additional drivers affect the ROI:
  - *Industry concentration* is a proxy for how much market power the oligopoly firms can exert
  - *Risk of oligopoly disruption*, *Historical volatility of non-oligopolist supply*, and *Historical stability of oligopolist supply* is a proxy for how much of this market power is actually exerted.

- Risk is a measure of how uncertain our forecast of ROI is. We will use the 16 drivers listed above (20 in the case of an oligopoly) to predict an expected value of ROI. Risk can be understood as a measure of the variance associated with that prediction. It depends on the supply and demand sides and results from the 5 following drivers:
    - On the supply side, *Geopolitical risk of supply, SOE concentration* and the *Intensity of regulation on supply* add uncertainty to the ROI forecast.
    - On the demand side, Substitution and *Disruption risk* add uncertainty to the demand growth forecast, and in turn, to the ROI forecast.

These drivers are numerous, so they need to be aggregated to be readable. Margins and Risk are two complex functions of these drivers. Moreover, these drivers have a lot of interdependencies. For instance, high *Growth of demand* is of little use when barriers to entry, like the low level of *Reserves* or high *Technical Complexity* are very low (we will expand further on these considerations in section III., by providing real world case studies). Therefore, simple aggregations like a weighted average do not make sense and cannot inform decision-making.

We develop two sound approaches to aggregating these drivers in the following sections.

II. Microeconomics and business economics theories

In this section, we develop two approaches to aggregating the drivers identified in section I.. One based on microeconomics theory, and the other based on business-economics theory.

II.1. Microeconomics Theory

Fundamental principles:
Firms and consumers behave mostly in a rational way, based on imperfect information. They have given assets, which they allocate in order to optimize their utility functions. Their utility function can include several elements, like profit, market share or consumption.

The behaviors of individual economic entity are then aggregated to obtain supply and demand. Supply and demand are interdependent: a lack of supply will result in an increase in price (mostly because customers are more willing to pay, to obtain the scarcified good). An excess supply will result in a decrease in price (mostly because suppliers want to sell all their stocks, so they lower their prices to attract more customers). In turn, this change in price adjusts supply and demand, and the market converges to a steady state, which defines the long-run market price.

Takeaway – Firms' objective:
The most basic theory assumes that firms are maximizing profit. Thus, their aim is to produce as much as possible, as long as the cost of production is below the market price. This implies that the market price is the marginal cost of production.

II.2. Business Economics Theory

Definition:
Industries are shaped by forces that interact and push the industry towards a stable state. Depending on these forces, the industry is considered attractive or not. The most prominent model in Business economics is the model of Porter's five forces[10]. According to this simple and high-level model, five forces shape strategy: barriers to entry, the threat of substitutes and the potential of complements, the bargaining power of suppliers, the bargaining power of consumers, and the intensity of competition (see **Figure 1**).

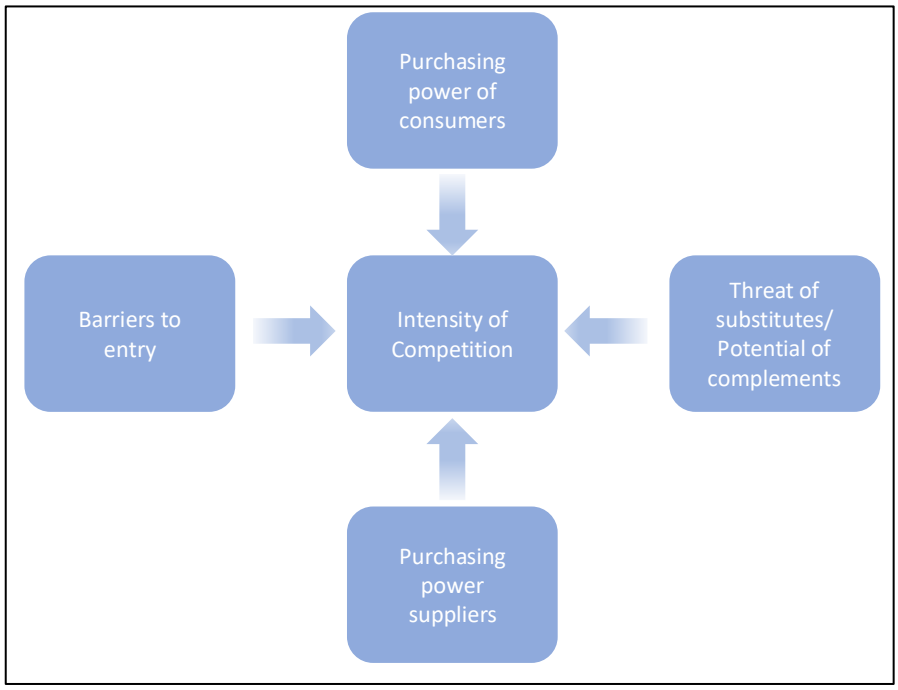

Figure 1: Illustration - The five forces of Porter

For instance, high barriers to entry contribute to an industry's attractiveness, because if margins are high, the incumbents have more chances (i) to secure a large share of them on the long-term, and (ii) to maintain them on the long-term.
Similarly, high intensity of competition hurts the industry's attractiveness, because high competition usually drives the prices (and therefore, the margins) down.

Note: The literature bursts with such models[11], which all have interesting takeaways that we tried to incorporate in this study. We won't detail all such models as we did with Porter's five forces.
Takeaway – Firms' objective:
For a given industry, the force outlined above shape long-term attractiveness of this industry. Thus, depending on the current state, and on the investor's strengths and weaknesses, the investor will decide to enter or leave the market.

[10] Porter, The five competitive forces that shape strategy
[11] SWOT analysis, PESTEL analysis, BCG matrix, https://www.mckinsey.com/business-functions/strategy-and-corporate-finance/our-insights/enduring-ideas-classic-mckinsey-frameworks-that-continue-to-inform-management-thinking

III. The microeconomics and business economics of mining

In the previous section, we briefly summarized the two economics theories on which we will base our approaches to aggregating the drivers identified in Section I.. In this section, we come back to the more specific case of mining industry. We explain the ins and outs of both theories in the specific case of the mining industry.

III.1. The Microeconomics of mining

In subsection II.1. we derived from fundamental principles that the market price is the marginal cost of production. **Figure 2** shows how this mechanism sets the price in practice. All available mines are sorted by increasing cost. They each have a given capacity. The market price is the operating cost of the last mine that has to operate in order to satisfy demand: Mine E. If it were higher, Mine F could operate, and the market would be overflowed, so the price would go down. If it were smaller, then Mine E would not operate, so there would be a supply shortage, so the price would go up.

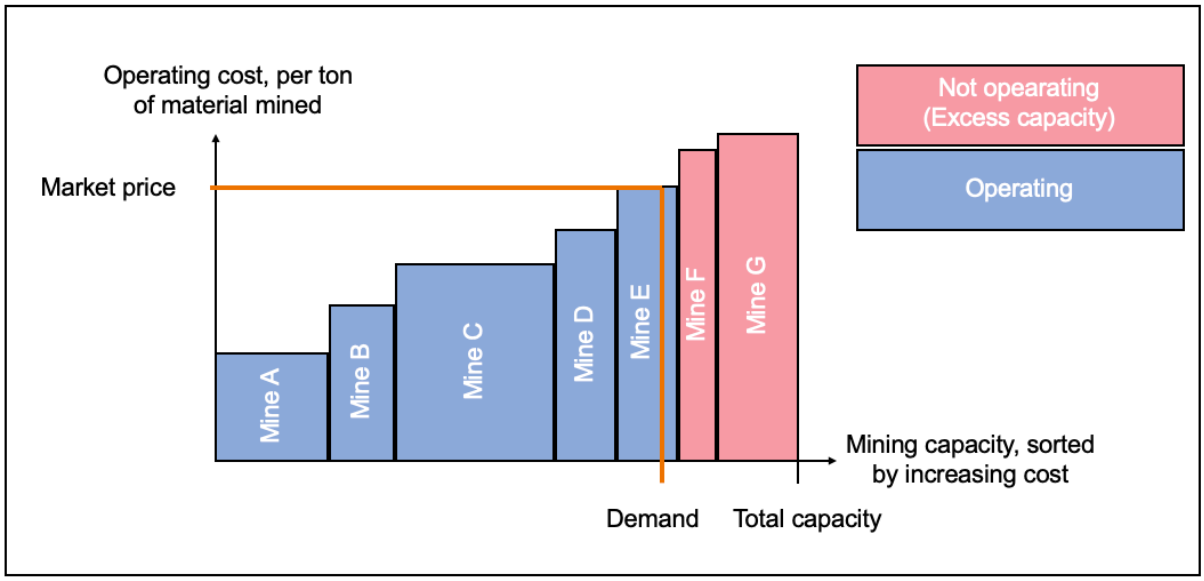

Figure 2 : Illustration – Cost curve, for a given commodity

As explained in Section I., we want to predict the operating margins of a first-tier mine (i.e. typically the mine that produces the 25th percentile of the supply: Mine B in **Figure 2**). The operating margins of this mine are defined as:

$$Margins = \frac{Revenue}{Cost} - 1 = \frac{Price * volume}{Unit\ cost * volume} - 1 = \frac{P90}{P25} - 1 \qquad \textbf{(1)}$$

where *P90* denotes the price of the 90th percentile asset and corresponds to the market price (in theory, the market price should correspond to the 100th percentile assets, but in practice, there is a lot of volatility for players at right the extremity of the cost curve).

Thus, in order to rank commodities by expected ROI, we will leverage the drivers identified in section I. to forecast the long-term *P90* and *P25.* We will then be able to infer the next margins.

So far, we described mining cost curves as static. Forecasting the long-term margins entails of the 25th percentile asset requires to adopt a dynamic view of cost curves, wherein we predict the evolution of the operating cash cost curve, by taking into account the changes to the existing supply (supply loss due to depletion and mines closure), and the new supply coming from the incentive curve (i.e. the supply that is available but not operating). We do this with a discrete model that is illustrated in **Figure 3**.

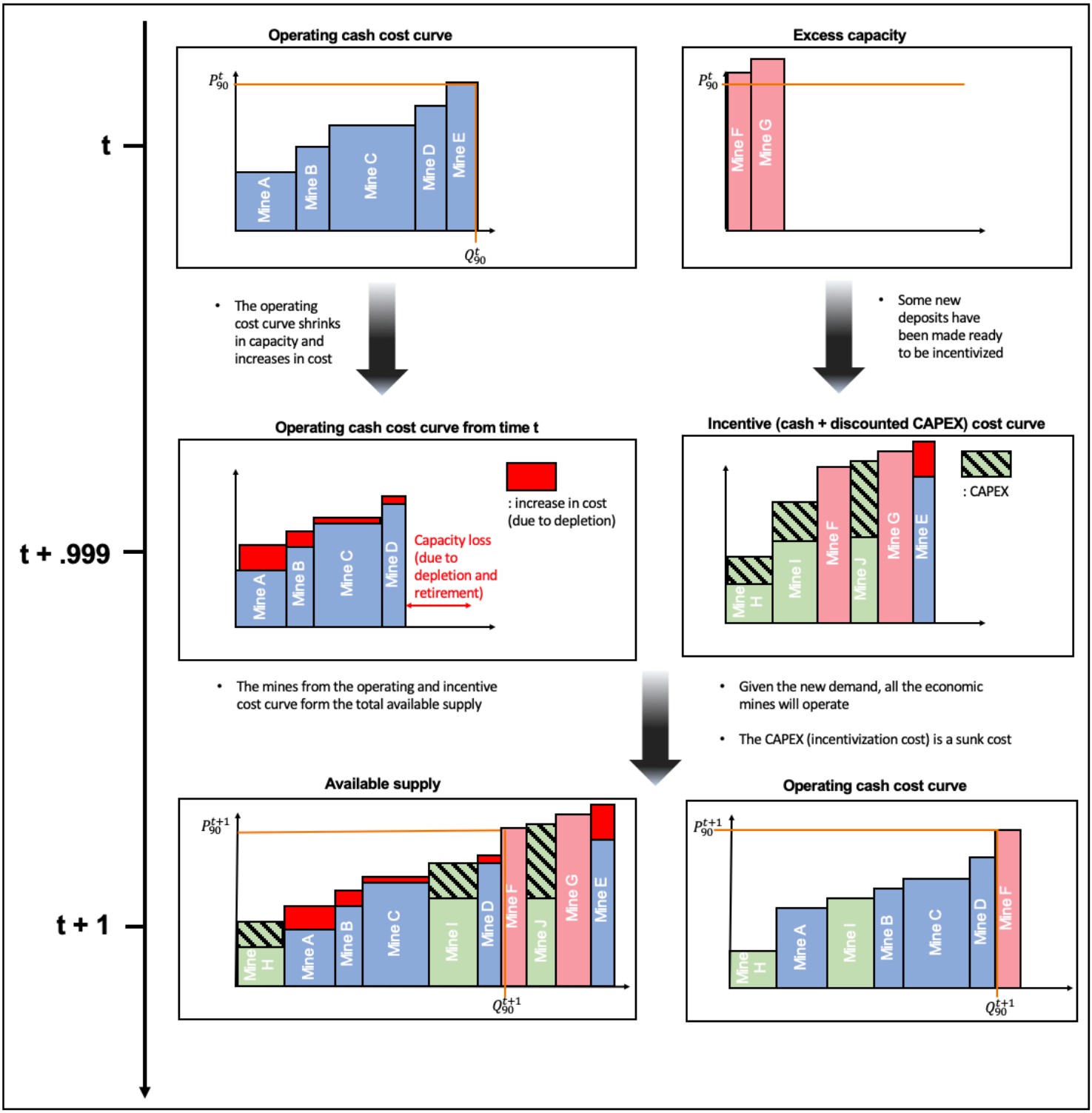

Figure 3 : Illustration -Discrete Model for the operating cost curve updates

At time t, part of the supply is operating (**top left quadrant**), and part of it is excess capacity (**top right quadrant**).

With time, the operating parts shrinks in capacity due to retirement and depletion, and it increases in price due to depletion (**middle left quadrant**). Indeed, depletion consists in an ore grade loss, so with the same amount of effort and cost, a given mine will obtain less and less of the mineral as time passes by. Meanwhile, new deposits are prepared and can become operating if they are economical. These deposits add up to the excess capacity of time t, to form the incentive cost curve (**middle right quadrant**)

By merging the supply from the incentive curve and from the remainder of time t's operating curve, we obtain the total available supply at time t+1 (**bottom left quadrant**). Lastly, by using the demand in t+1, Q_{90}^{t+1}, we find out which mines will be operating at time t+1 (**bottom right quadrant**).

From there, we can easily find out P_{90}^{t+1} and P_{25}^{t+1}, which in turn will provide us the margins, using **Equation (1)**.

To get there, we start from the information available at time t (**top left and right quadrants**), and we need to answer the following questions:

- What is the supply loss between *t* and *t+1*? Or in other words, how do we get from the top left to the middle-left quadrant?
- What are the shape and capacity of the incentive cost curve Or in other words, what is the middle right quadrant?
- What is Q_{90}^{t+1}? Or in other words, what is the real demand change: $Q_{90}^{t+1} - Q_{90}^{t}$?

Thus using microeconomics theory and this cost curve model, the next *P90* and *P25* can be inferred from **Table 1 : Elementary drivers of ROI and risk** by following three steps:

- Computing the supply loss
- Computing the incentive curve capacity and cost distribution
- Computing the real demand change

In the following development, we map **Table 1**'s drivers to these three objectives.

III.1.a. Computing the supply loss

Given our development so far, it is fair to assume that supply loss can come from one of two sources: ore grade loss, which decreases the capacity of a mine with time, and retirement (mine closure). We then break these two types of supply loss in elementary drivers from **Table 1 : Elementary drivers of ROI and risk** (in blue), and other cost curves metrics (in yellow) (see **Figure 4**).

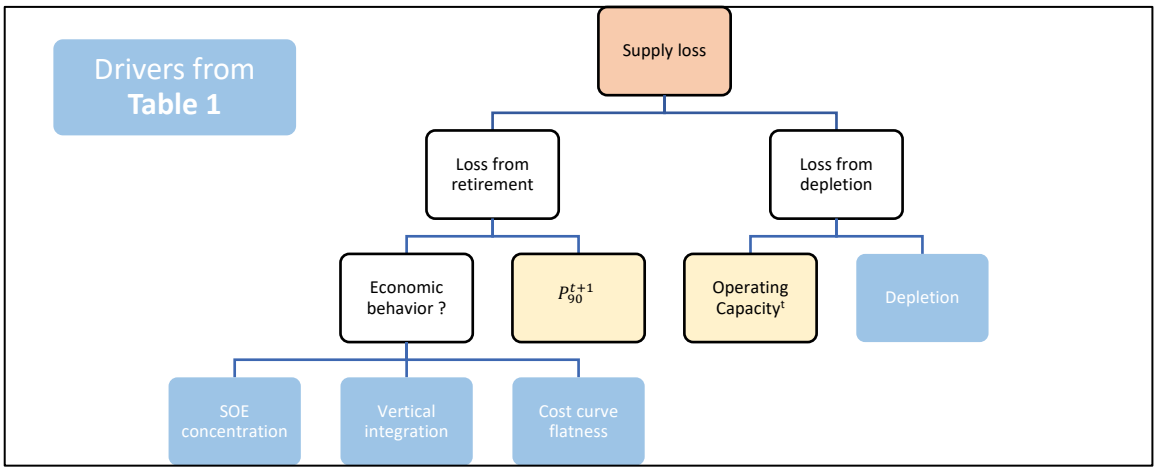

Figure 4 : Computing the supply loss

The loss from depletion is easily computed with the operating capacity and the depletion level. On the other hand, the loss from retirement comes from the next price and the barriers to exit (SOE concentration, vertical integration and cost curve flatness). As explained in section II.1., it is a fundamental principle of microeconomics theory that a mine which produces at a cost higher than the market price should close. However, to take into account real-world factors, we consider three barriers to exit that might curb this behavior: SOE concentration, Vertical integration and Cost curve flatness (as this consideration was mostly motivated by the business economics approach, we will explain it in further details in section III.2.b).

III.1.b. Computing the incentive curve capacity and costs

This step is one of the most perilous in our approach: there is no obvious way to infer precisely what the incentive curve is composed of.

We reverse-engineer where the incentive mines come from. There is a given amount of reserves. Various reasons explain why all the reserves don't make it to the incentive curve. It might be that no company has decided to develop the required mining facilities because the enterprise is too uncertain, too hard, or unlikely to be profitable.

Quantifying the uncertainty related to deposits is outside the scope of this study. Therefore, we use barriers to entry and the current margins as a proxy to explain the share of deposits that become incentive mines between t and t+1 (see **Figure 2**).

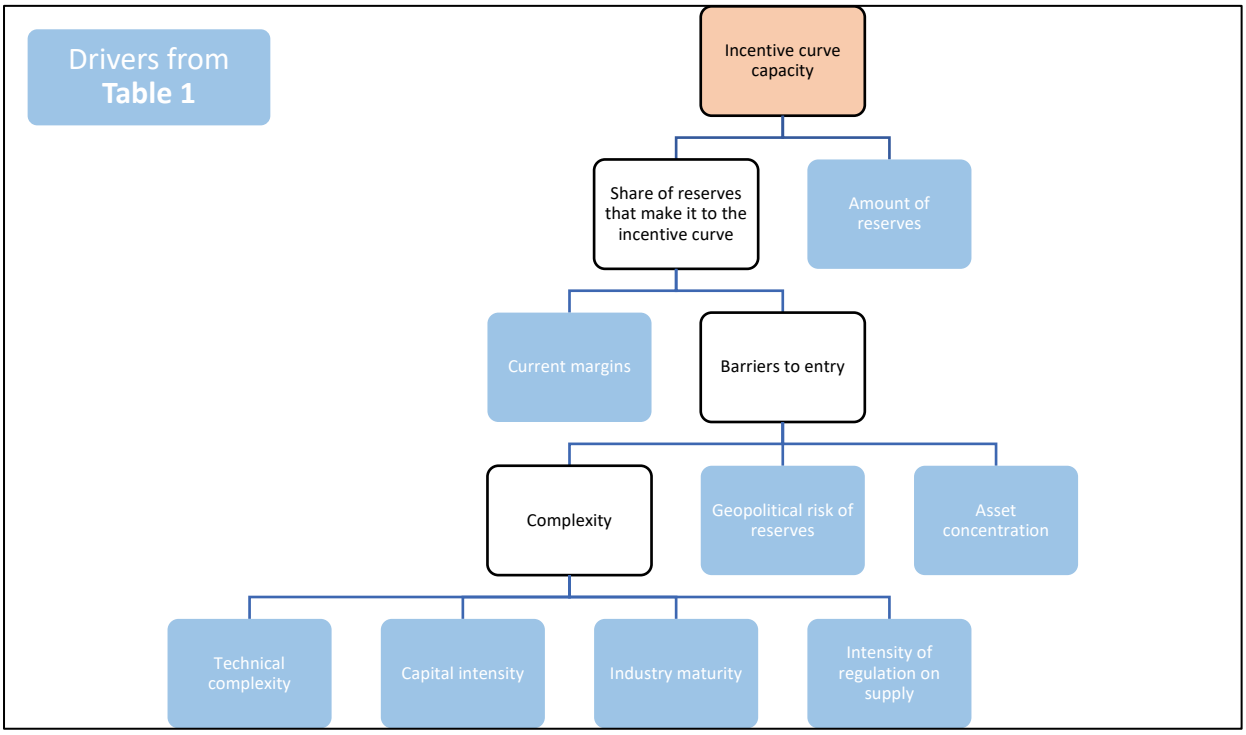

Figure 5: Computing the incentive cost curve capacity

There are three barriers to entry, responsible for some deposits not making it to the incentive capacity:

- Complexity is an aggregate measure of *Technical complexity*, the *Likelihood of a new technology* (for which we use *Industry Maturity* as a proxy), *Capital intensity* and *Intensity of regulation on supply.* It accounts for the time it takes to set up operating facilities, once the investment decision is made
- *Geopolitical risk of reserves* is a weighted average of country risk and reserve shares by country. It accounts for the inability to mine in certain areas due to corruption, policies, political instability, and safety.
- *Asset concentration* is measured by share of production corresponding to the 10 largest assets. It accounts for the difficulty for small players to penetrate the market.

Now that we mapped Section I.'s drivers to the incentive capacity, we still have to infer the cost distribution of the incentive curve. The discrete model for cost curve update explained at the begin implies that the incentive cost curve is composed of the incentivization cost (or CAPEX), which can be inferred from capital intensity and price, and of the cash cost. Inferring the cash cost distribution is yet another perilous step.

Data analysis for copper indicates that it is fair to assume that the mine distribution of operating cash cost (OCC) is approximately linear between Q25 and Q90 (see **Figure 6**). Moreover, the incentive cash cost curve (ICCC) has approximately the same distribution as the OCC between Q25 and Q90. In other words, for any percentile p between 25 and 90, $P^p_{ICCC} = P^p_{OCC}$. This can be seen on the top graph of **Figure 6**.

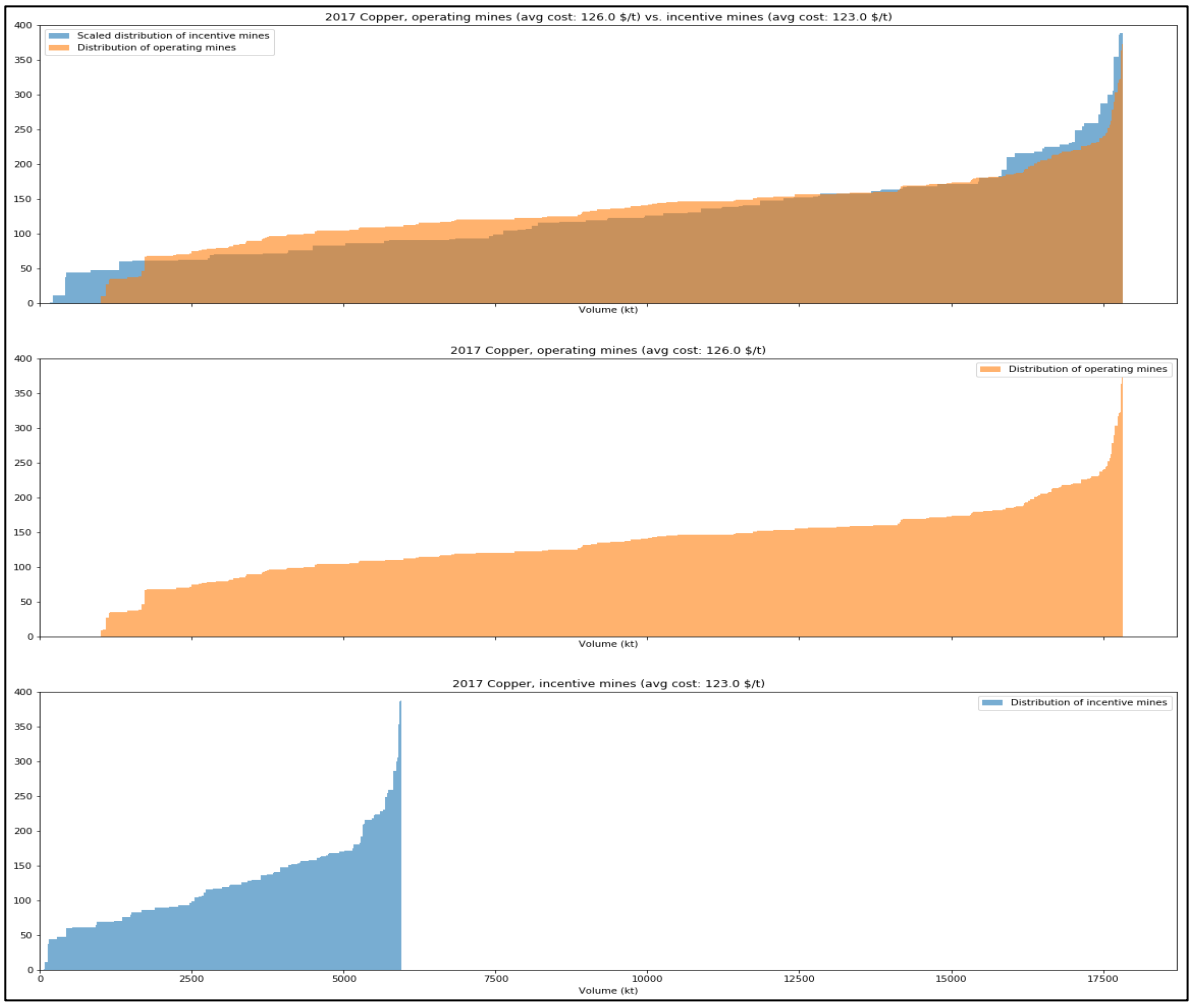

Figure 6: Comparison of ICC and OCC, for copper

Relying on these assumptions, we can assume two things:

- In first approximation, cost curves are linear
- Since the ICC and OCC have the same distribution of costs (i.e. same extrema, median, percentiles…) it follows that the slope of the incentive curve is derived from the slope of the incentive curve by:

$$Slope_{ICC} = Slope_{OCC} \cdot \frac{Capacity_{OCC}}{Capacity_{ICC}} \quad \textbf{(2)}$$

Hence, we have fully described how we can obtain the incentive curve cost distribution from Section I.'s drivers and some exogenous assumptions. The results are summarized in

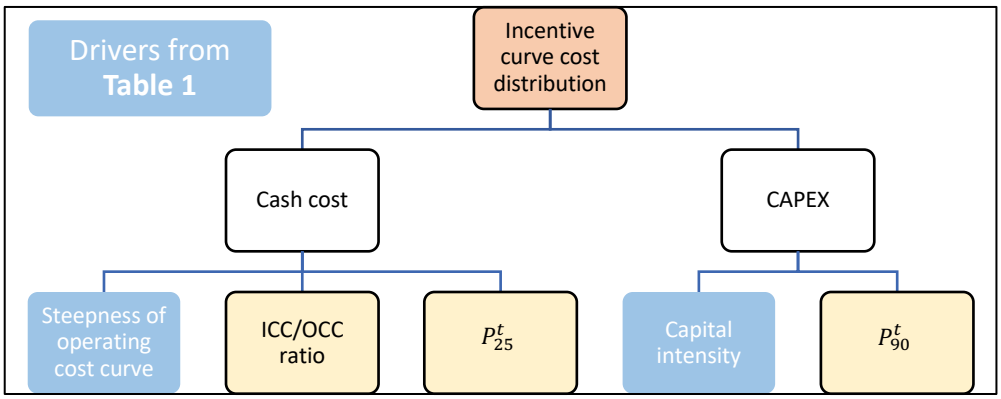

Figure 7: Computing of the ICC distribution

Note: the assumption leading to **Equations 2** has been obtained based on copper data alone. Studying further the relationship between ICC and OCC could improve this framework, but it is out of the scope of this work.

III.1.c. Computing the real demand change

The last step to inferring the next *P90* from **Table 1 : Elementary drivers of ROI and risk** is to obtain the new demand Q_{90}^{t+1}.

This step is more straightforward, as we use *Demand Growth* as an input. We simply have to adjust have to be careful about *Stocks*. The intuition is that when the price gets high, stocks decrease because they are sold, so some of the demand is artificially filled by stocks, and doesn't require new supply. **Figure 8** sums up how we can compute the real demand change, from elementary drivers.

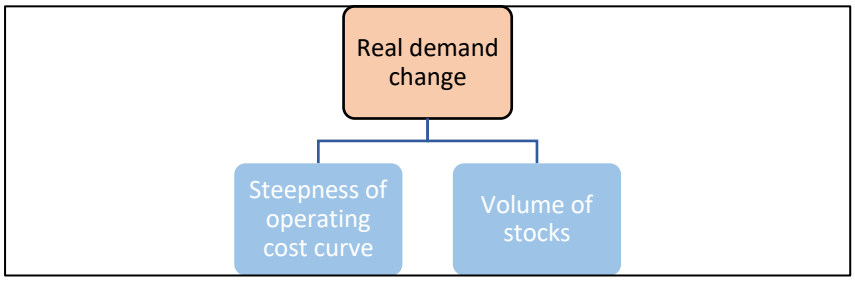

Figure 8 : Computing real demand change

III.2. The Business Economics of mining

In the section III.2, we have introduced Business Economics theory. In this part, we first introduce the mechanisms by which elementary drivers shape the attractiveness of commodities, based on Business Economics theory. Then, we outline the complete framework through which individual drivers impact the attractiveness of commodities, and we argue why this framework is sensible.

III.2.a. Examples: Drivers interact in complex ways that shape commodity attractiveness

We first introduce how the elementary drivers defined in section I. affect industry attractiveness, from a business theory perspective. For that, we try to find out what happened in the past, that made commodities (un)attractive today.
We will detail two interesting case studies here: Aluminium, and Lithium.

III.2.a.(i). Case study 1: Aluminium

Aluminium demand grew steadily over the last 20 years, as illustrated on **Figure** 9 below. This growth was mainly driven by transport and construction.

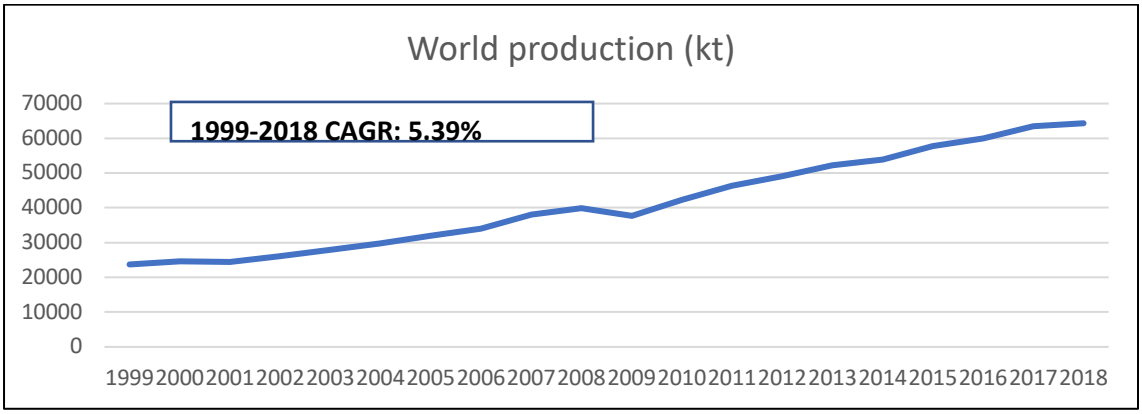

Figure 9 : worldwide production of aluminum: 1999-2018[12]

However, the aluminium industry is not attractive currently, as it is very competitive and has a very flat cost curve ($\frac{P90}{P25} = 1.31$, see **Figure** 10 below).

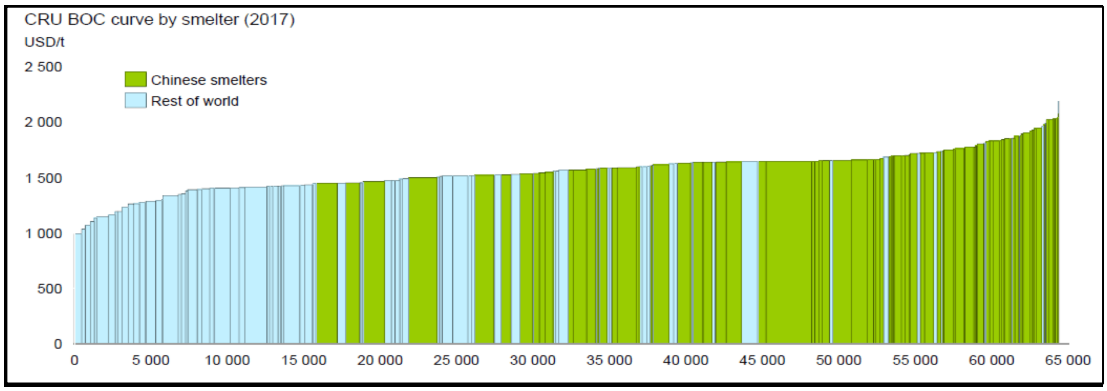

Figure 10 : 2017 Aluminium cost-curve[13]

[12] Source : www.world-aluminium.org
[13] Source : https://aluminiuminsider.com

Aluminium's growth has been almost entirely captured by Chinese new entrants, as showcased on **Figure 11**, below:

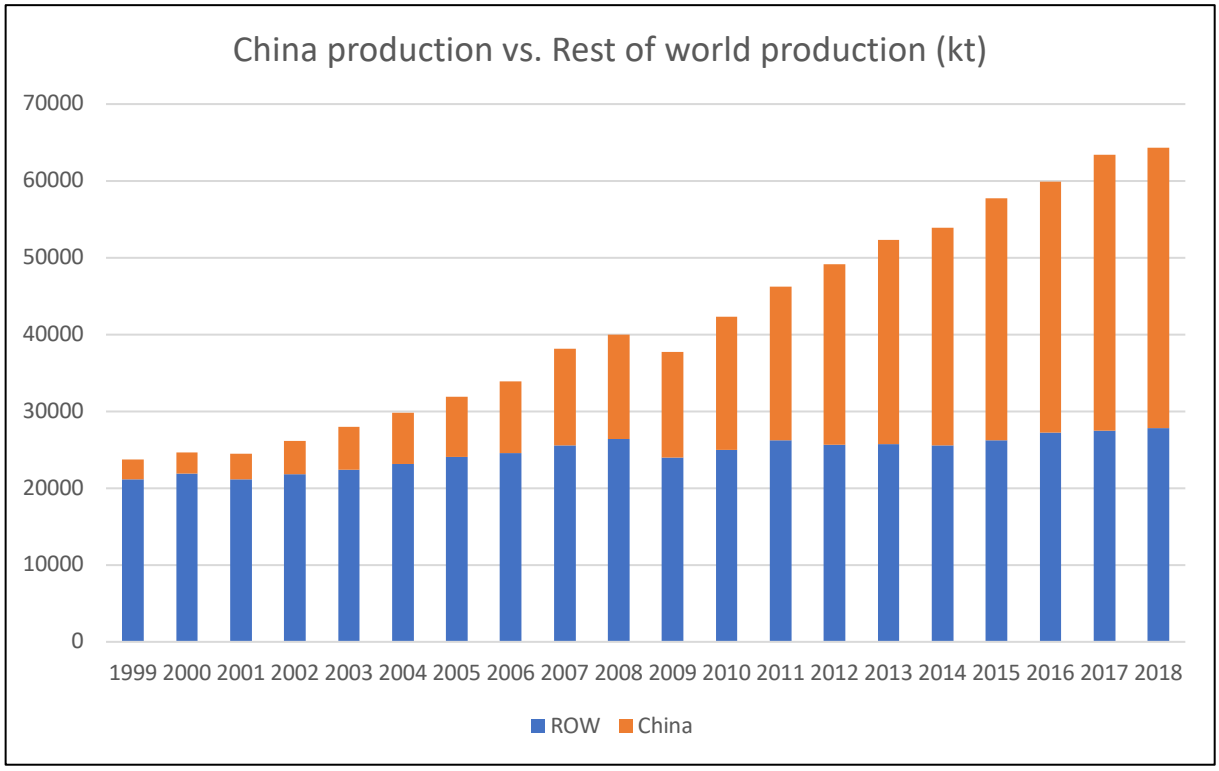

Figure 11 : China and Rest of World Production of Aluminium – 1999-2018[14]

So it is China's ability to build smelters at low cost and fast pace that absorbed all the demand growth and prevented incumbents from extracting margins. What made it easy for China to ramp up production in such a dramatic manner?

We can identify a few factors:

- With over a 100 years of production cover there is no shortage of aluminium.
- The country concentration of reserves being very low, aluminium is spread across the world, and easy to access for Chinese smelters (The country with most reserves is Chile, with 20%. And 1% of reserves represents 1 year of production).
- As showcased by the very low asset concentration, small operations can be competitive. In 2017, only 21% of the production was produced by the 10 biggest assets. (this comes partly from the nature of the aluminium industry, which is not directly a mining industry)
- Capital intensity is very low for aluminium smelters, the CAPEX/P90 ratio being at 1.12 in 2017.

What these factors boil down to is that there are virtually no barriers to entry to the aluminium industry. China's ability to build smelters at low cost and fast pace absorbs all the demand growth, keeping the cost curve flat. **Thus, high demand growth alone doesn't make a commodity attractive unless barriers to entry are high.**

[14] Source : www.world-aluminium.org/

III.2.a.(ii). Case study 2: Lithium

Between 2002 and 2018, the price of Lithium continuously increased, with a CAGR of 13.3%, while the price of cobalt peaked and dropped after the 2008 financial crisis, started recovering slowly in 2017 and dramatically in 2018 (see **Figure 12**).

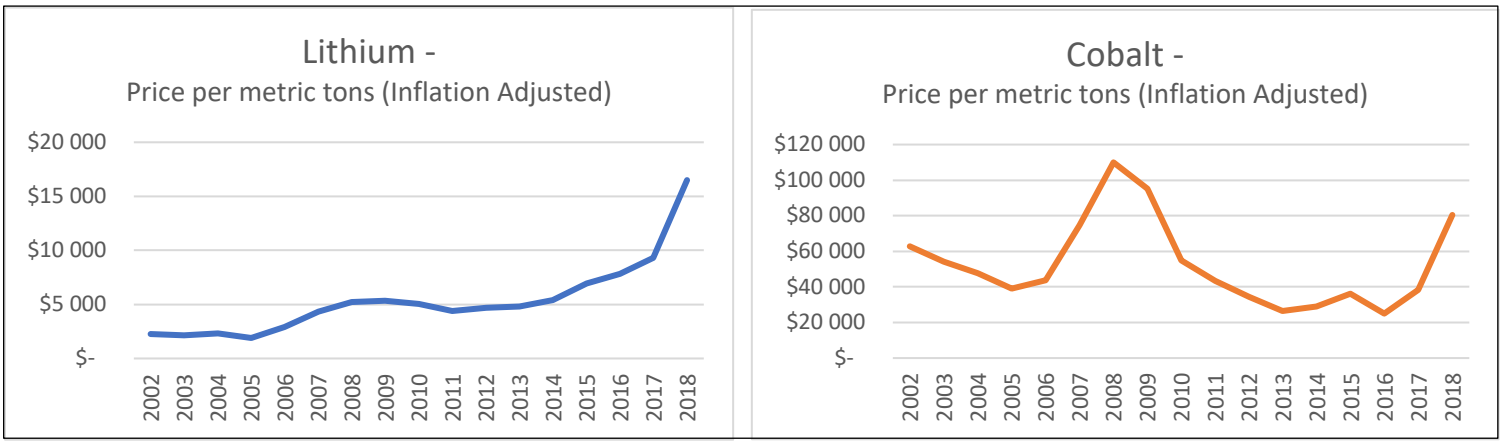

Figure 12: Lithium and Cobalt price, 2002-2018 [15]

This results from the electric vehicles (EV) revolution and from the advent of other battery-intensive technologies like battery energy storage. This increase in demand should continue. According to McKinsey & Company's *Lithium and Cobalt, a tale of two commodities*, the demand will continue to increase at a very high pace for both commodities: +60% for cobalt and +300% for Lithium between 2017 and 2025.

The structure of the mining industries of these two commodities are very different, as Lithium is mainly a primary product, while cobalt is mainly mined as a by-product. Moreover, while both commodities are very geographically concentrated (with over 70% of production in the three top countries) Cobalt production is mainly based in areas of geopolitical instability, such as DRC.

Both commodities possibly face a very attractive future, with a considerable amount of uncertainty.

Uncertainty on the demand side:

- What will be the adoption rate of EVs?
- Will new battery technologies emerge?

And on the supply side:

- how will the barriers to entry evolve in the Lithium industry? (for now supply is very concentrated, but the resource base is enormous, so this could change in the future ; for now, mining Lithium is relatively complex, but the increased demand might lead to technological improvements…

Thus, the case of Lithium allows us to think of uncertainty. Uncertainty can come from the demand and supply sides, and the way to treat it will essentially depend on the investor's risk aversion (see next paragraph: subsection III.2.b). It also makes us think of barriers to entry dynamically: Lithium seems to have high barriers to entry in 2017, with a high concentration of production and reserves, and with a high technical complexity. However, the resource base being very large, and the R&D for new mining technologies being thriving, one might expect a decrease of these barriers to entry in the near future.

[15] Source : https://www.metalary.com

III.2.b. Framework: a logic tree approach to aggregating root drivers

So far, we have established that:

(i) from a financial investor's perspective, two KPIs matter for attractiveness: returns on investment (margins) and risk.

(ii) These KPIs are driven by the features defined above (see section I.)

(iii) These features interact in various ways that creates the conditions for attractiveness or unattractiveness (see previous paragraph: III.2.a.)

In this subsection, we explain at a high level the mechanisms by which these features cause a positive or negative attractiveness. Later on, we will rigorously quantify these mechanisms with mathematical functions.

The current margins of a given industry can evolve in two directions: they can shrink or increase. As established in section I., several factors drive this change. These factors aggregate in forces that shape the evolution of supply on the one hand and demand on the other hand (see **Figure 13** below).

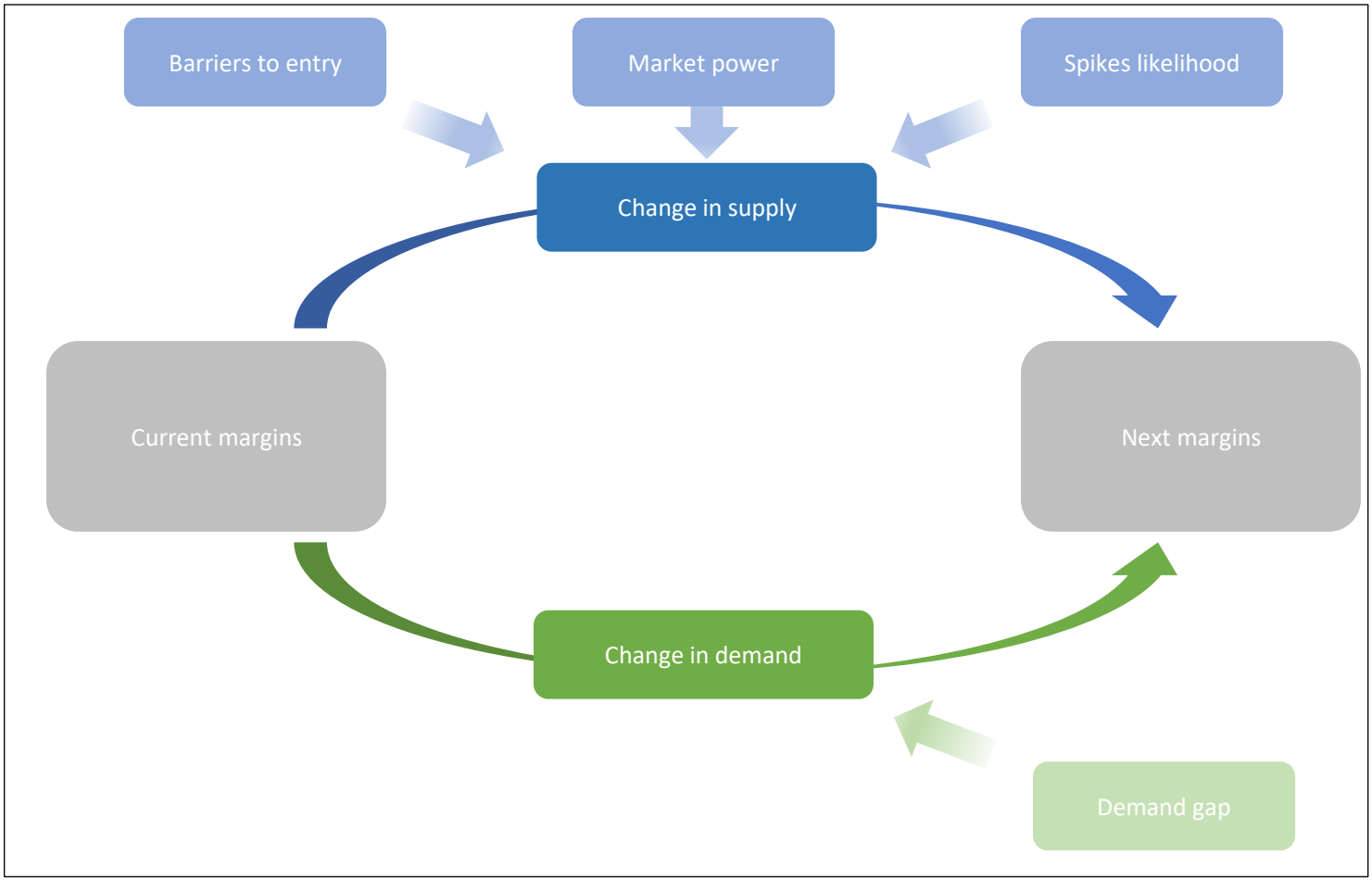

Figure 13 : Forces that affect long-term ROI

The forces that shape the change in supply are barriers to entry, market power and spikes likelihood. The force that shape the change in demand is the demand gap.

We quantify each force through a semi-quantitative, bottom-up approaches, from elementary drivers (see **Figure 14** below). Each force is a function of given elementary drivers. In other words, elementary drivers interact in logical ways (that we formulate mathematically later on), that cause the forces outlined above to be strong or weak.

In the following development, we explain which elementary drivers determines which force, and how. The elementary drivers coming from supply data are colored in blue, those from demand data are colored in green, intermediary aggregation steps are colored in white.

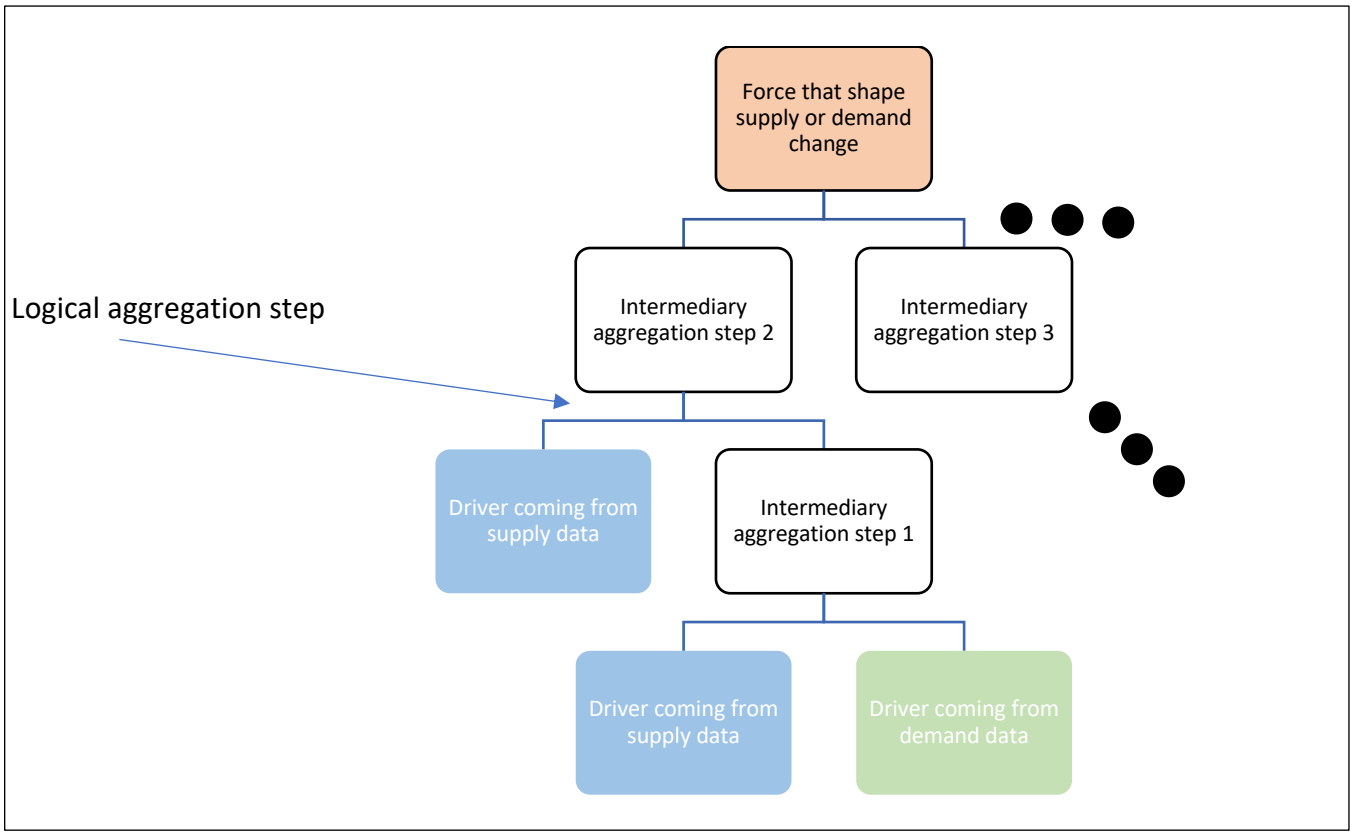

Figure 14 : Principle of our semi-quantitative, bottom-up approach to aggregating elementary drivers

III.2.b.(i). Forces that shape the change in supply

Three forces shape the change in supply and the sustainability of margins, from a supply perspective: barriers to entry, spikes likelihood and market power.

(i) Barriers to entry

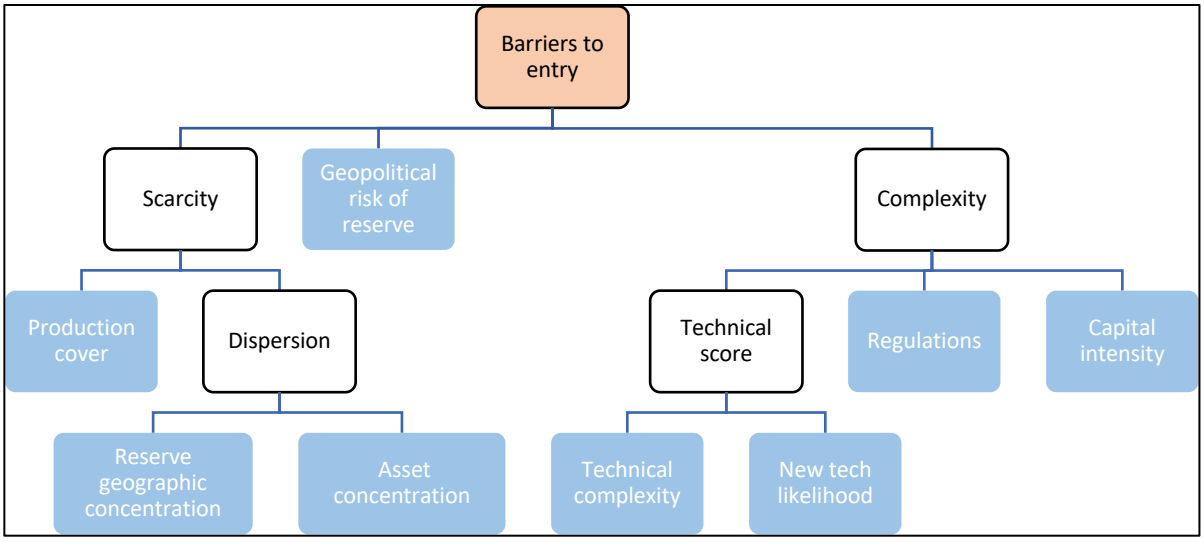

Figure 15 : Bottom-up aggregation of drivers' flow-chart – Barriers to entry

There are three types of barriers to entry in the mining industry (see **Figure 15** above):

- <u>Scarcity:</u> how hard is it for a firm to find available and economic deposits?
  This barrier to entry depends purely on material's availability.
- <u>Geopolitical risk of reserve:</u> how safe are the deposits location? How easily may firms obtain mining permits?
  This barrier complements scarcity, it depends on the geopolitical climate of deposit locations
- <u>Complexity:</u> how hard is the material to mine? Can new entrants with little expertise and technology enter in the industry?
  This barrier complements the two formers, it depends mainly on the geology of deposits and on the ore extraction processes used for a given commodity. It also accounts for international regulations prompted complexity.

Scarcity and complexity barriers are further broken in elementary drivers:

- <u>Scarcity:</u>

Scarcity depends on the amount of material available (that we quantify by the production cover), and the degree of dispersion of this material. Huge deposits that are very concentrated in a given area results in a form of scarcity as fewer players will be able to operate them. On the other hand, even if a commodity is very evenly distributed across the world, if it is present in small quantity it is also scarce. In order to quantify dispersion, we use two measures of concentration: the *geographic concentration of reserve*, which accounts for the country dispersion of deposits, and *asset concentration*.

- <u>Complexity:</u>

Mining complexity essentially comes from the geological aspect of mining. There is a technology barrier and a capital barrier. To measure the capital barrier, we use the *Capital intensity* of a commodity. To measure the technical barrier, we take into account the current T*echnical complexity*, and an adjustment variable for technical improvement (*New tech likelihood*), which helps better describing the long-term technical complexity of fast-growing commodities, like lithium. On the other hand, for some commodities like uranium, *Regulations* add another complexity layer which we consider as a barrier.

(ii) Spikes likelihood

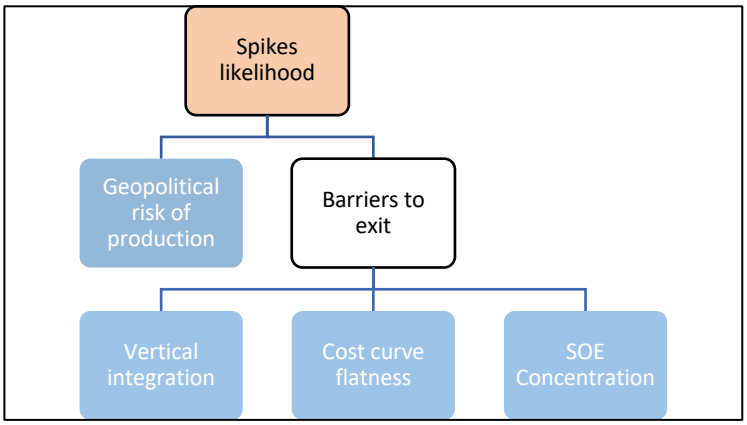

Figure 16: Bottom-up aggregation of driver's flow-chart – Spikes likelihood

Price spikes materialize in higher margins for top-tier players, and they have a particularly strong effect for some commodities, like copper.

They come from two effects (see **Figure 16** above):

- <u>Geopolitical risk of production:</u> prices increase due to supply's inability to meet demand, because of sudden geopolitical crisis that entail capacity to close unpredictably.
- <u>Barriers to exit:</u> prices decrease due to suppliers not exiting the market despite being uneconomic, because of barriers to exit.

Barriers to exit are further broken into three elementary drivers:
The three reasons that may incentivize a mine to continue operating despite being unprofitable are:

- *Vertical integration*: a given mine can be part of a larger business unit, which is profitable other all. In our model, we focus on the margins extracted by the commodity suppliers. By being integrated downstream, company may capture a larger share of the margins across the value chain, and therefore still operate a mine which wouldn't be profitable if it were a stand-alone business unit.
- *SOE concentration* is another barrier to exit. State-owned firm might have uneconomical goals. Actually, *SOE concentration* can be considered as a particular case of vertical integration: the mine is then seen as a micro element in the country's publicly owned economy. It's stand-alone profitability is not a main concern.
- *Cost curve flatness* is the last barrier to exit that we consider: the cost and hustle of shutting down are more likely to outweigh profitability when the cost curve is flatter,

because a flat cost curve entails a smaller loss, and thus a smaller incentive to close. This point is illustrated on **Figure 17** below:

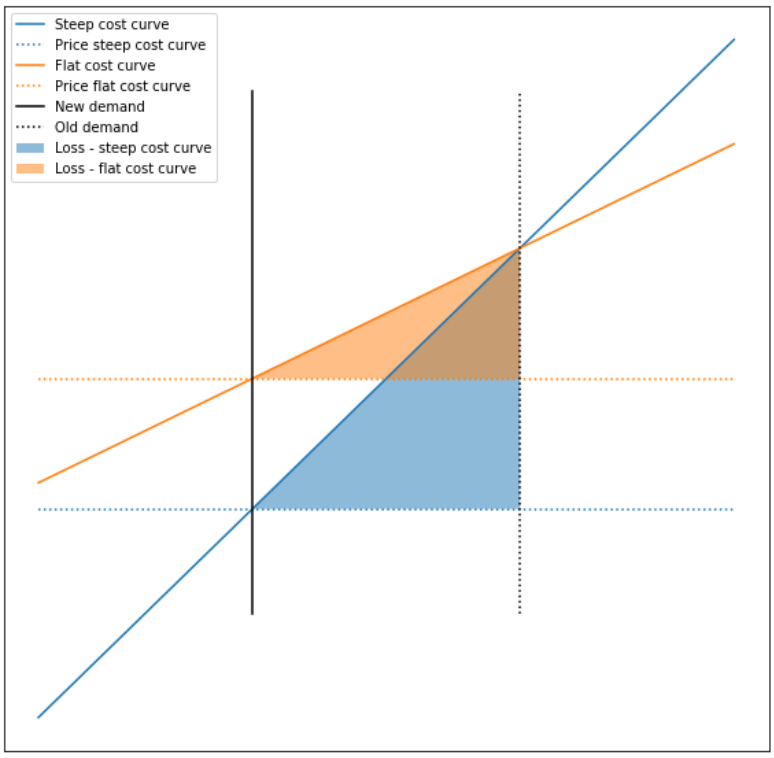

Figure 17: Illustration - Cost curve flatness is a barrier to exit

(iii) Market power

So far, we discussed barrier to entry and spikes likelihood. The last item that contributes to the change in supply and to building long-term margins, is the market power firms exert.

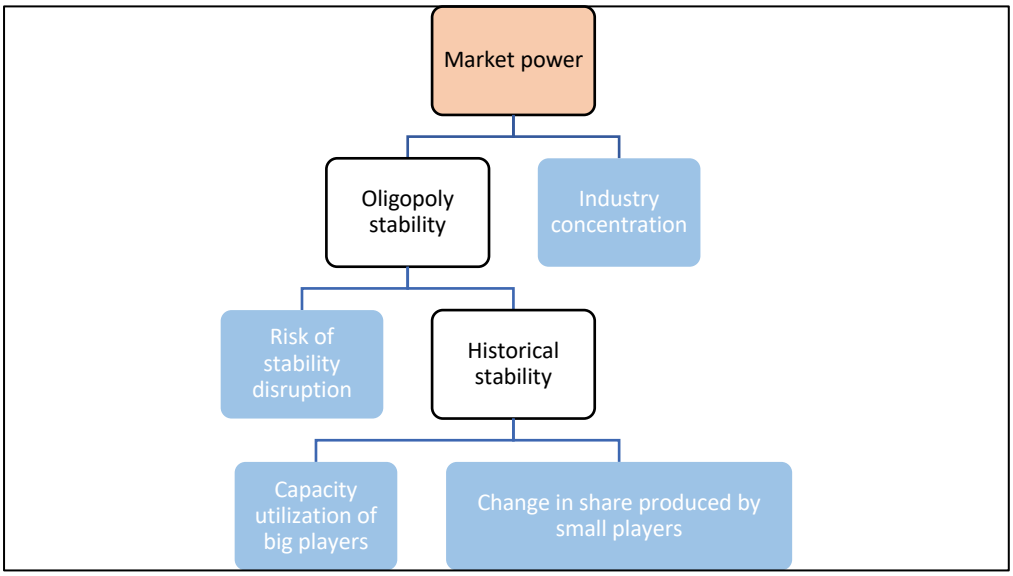

Figure 18: Bottom-up aggregation of driver's flow-chart – Market Power

Market power is quantified through two factors (see **Figure 18** above):

- Industry Concentration: Industry concentration is defined as the share of production detained by the oligopoly players. If there is an oligopoly, it quantifies how dominant its position is currently, and how strong an advantage the oligopoly firms have. A strong industry concentration means that the cost curve will be very convex, entailing high margins
- Oligopoly stability: how long lasting will the margins be? When there is an oligopoly mining a given commodity, the main players extract margins that depend mainly on their ability to maintain just enough room for small players to be profitable. The marginal cost of extraction sets the price, and these small players produce at higher cost, which guarantees high margin for the main players.

III.2.b.(ii) Forces that shape the change in demand

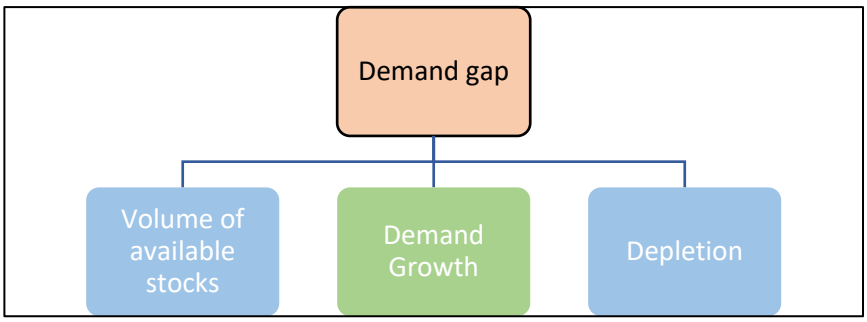

Figure 19: Bottom-up aggregation of driver's flow-chart – Demand gap

The demand gap essentially comes from demand growth, adjusted for structural effects from the supply side (see **Figure 19** above). These structural effects are Depletion, and the volume of available stocks. For instance, a *Depletion* of x between years t and t+1 corresponds to a loss in production capacity of x. So it increases the demand gap by x.

The base case for demand risk forecasts (including substitution and disruption risks) is included in the demand growth input.

III.2.b.(iii) Forces that shape the uncertainty of supply

So far, we described the forces that shape the return on investment (ROI). From a financial investor's perspective, we also want to quantify risk. That is to say, the risk that supply or demand don't behave in an economical way, or as forecasted. Or in other words, the risk that the forecast of the ROI is off because players didn't behave as expected. In order to quantify this risk, we proceed as we did with the attractiveness forces: from elementary drivers, up to the uncertainty of ROI forecast.

In a first step, we assess how uncertain the ROI forecast is. Then, in a later step we combine this measure with a score of risk aversion (which is dependent on the investor's profile), in order to mitigate the next margin forecast.

(i) Uncertainty of ROI forecast

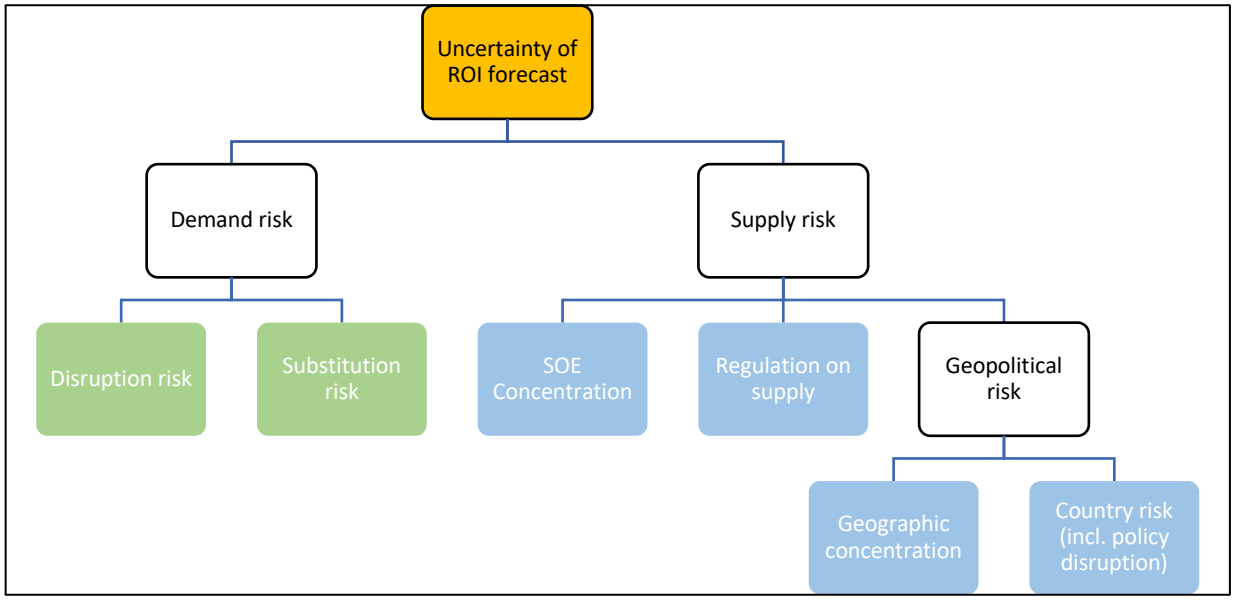

Figure 20: Bottom-up aggregation of driver's flow-chart – Uncertainty of ROI forecast

In order to assess the uncertainty of ROI forecast, we look at the demand and supply risks[16] (see **Figure 20** above).

- *Supply side*

Supply risk[17] comes from the non-economic behavior of firms. While it has been noted earlier (1.b.) that this uncertainty can contribute to margin formation through an increased spikes likelihood, we now consider this uncertainty from a risk aversion perspective.

Three main factors fuel the non-economic behavior of firms:

- State-owned firms (SOEs) have non-economic incentives that may lead them to produce at costs higher than prices

[16] Christoph Helbig et al., *Supply risks associated with lithium-ion battery materials*

[17] Erika Machacek, *Constructing criticality by classification: Expert assessments of mineral raw materials*

- Regulations on some commodities can prevent firms from entering and exiting the market at will, based only on economic profitability.
- Geopolitical risk can materialize in tensions that prevent firm from operating at full capacity

SOE concentration and regulations on supply have already been defined (see 1.b.). Geopolitical risks result from two items: geographic concentration and country risks. Thus, if a commodity is produced mainly in risky locations, it will have a high-risk score.

- *Demand side*

Disruption risk and Substitution risk both factor in the demand growth forecast. They can constitute an opportunity or a threat for growth. In any case, they entail uncertainty, as stressed in the Lithium case study.

(ii) Risk aversion

As announced above, we combine this measure of supply uncertainty with the investor risk aversion's score. Depending on how risk averse the investor is, they will trust or distrust the margin score based on the uncertainty of supply score.

Our modeling of the investor's behavior is comparable to how people purchase apartments. When buying an apartment, the buyer has access to incomplete information only. They know whether it's a rather nice apartment or not, and they know the neighborhood in which the apartment is located. The information on the neighborhood can be very reliable, for instance it is clear that upper-east side is a nice neighborhood in Manhattan, or the information on the neighborhood can also be more speculative. For instance it wasn't clear a few years back that Soho or Chelsea would become such lively and nice places to live.

Knowing whether it's a nice apartment boils down to predicting the ROI for our investor. And the level of certainty the buyer has on the neighborhood corresponds to the degree of uncertainty of supply. If the buyer is risk averse, he will rather buy an apartment in a very certain neighborhood than in a speculative one. Even if the apartment of the certain neighborhood is not as nice. Similarly, a risk averse investor will favor less uncertain commodities although they might have a small predicted ROI, because he doesn't trust enough the information used to predict the ROI of uncertain commodities.

The different possible cases are summed up in **Figure 21** below. The main takeaway is that a risk averse investor will most likely reject investment opportunities in highly uncertain commodities (bottom left quadrant).

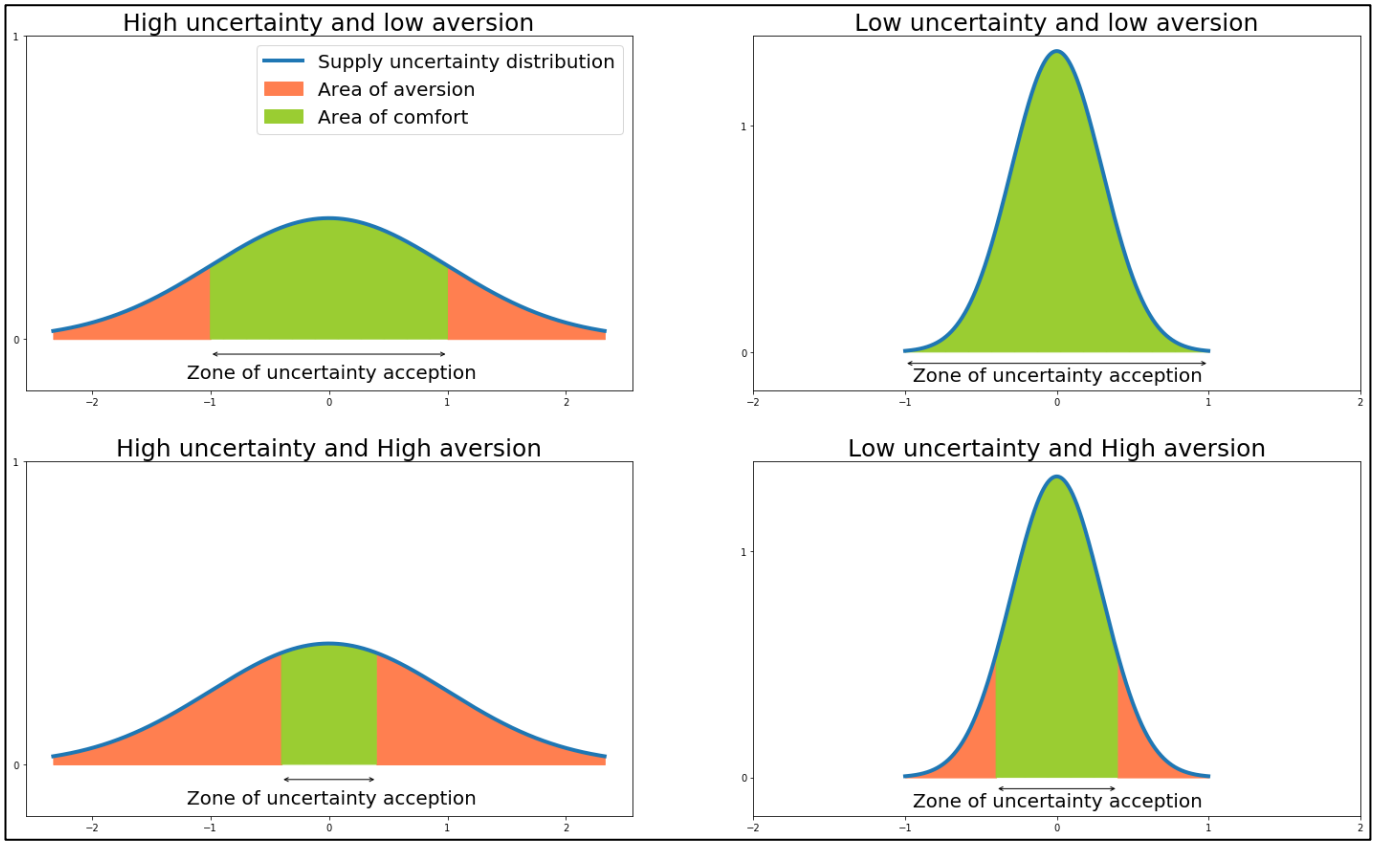

Figure 21: Illustration – Uncertainty and risk aversion

IV. Design of two models based on microeconomics and business economics theories

In section III., we have outlined two frameworks that capture how the elementary drivers from **Table 1** impact industry attractiveness, from an investor's perspective. The first one is based on microeconomics theory, that we introduced in section II.1., and the second one is based on business economics theory, that we introduced in section II.2.

In this section, we suggest one possible implementation for each framework. Our goal is therefore to aggregate the drivers in a measure of attractiveness that is interpretable and scalable to any commodity, by following the frameworks developed in III.1. and III.2. We provide the implementation details of both approaches, and we will then compare the results in section V.

IV.1. Design of a microeconomics model – a *Cost curve model*

In this subsection, we detail further assumptions that enable us to build a *Cost curve model*. It is based on the microeconomics of mining developed in section III.1. It aims at discriminating between commodities, rather than forecasting the margins of a given commodity.

It follows from section III.1. that the long-run margins of a mining industry can be inferred from **Table 1 : Elementary drivers of ROI and risk** by following these 3 steps:

- Computing the supply loss (see **Figure 4**)
- Computing the incentive curve capacity and cost distribution (see **Figure 7** and **Figure 7.**)
- Computing the real demand change (see **Figure 8**)

IV.1.a Computing the supply loss

- <u>Objective:</u>

In this subpart, we are interested in modeling the first transition from **Figure 3**, which is reproduced here, on Figure 22.

- <u>Inputs:</u>

In addition to *Depletion, SOE concentration, Vertical integration* and *Flatness of cost curve,* we use the next price P_{90}^{t+1} and the current consumption Q_{100}^{t} as inputs (see **Figure 4**). P_{90}^{t+1} is also one of the outputs of the model. This is inevitable, as microeconomic theory stipulates that price and demand adjust to reach the equilibrium. Our model will do the same, by iterating with a loop, or in other words: by solving an optimization problem so that the input P_{90}^{t+1} is the same as the output P_{90}^{t+1}.

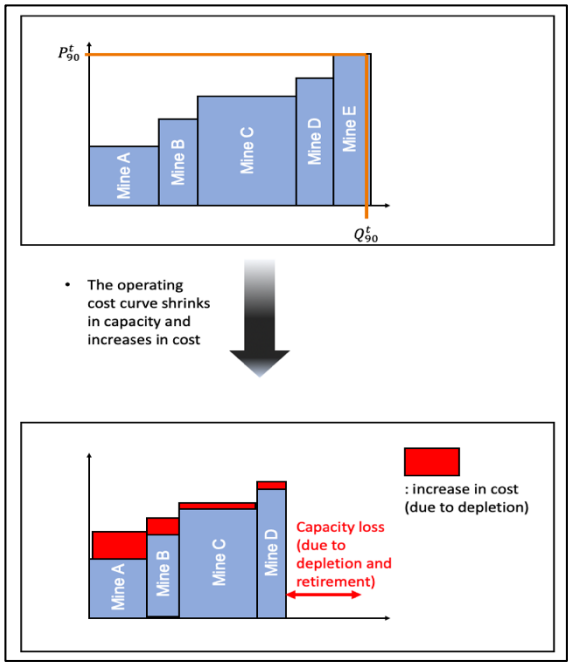

Figure 22: Modeling supply loss

- Assumptions:

When we explained the framework, in part III.2., we justified one assumption, namely that loss of supply comes from one of two reasons: ore grade loss or economic retirement. We make three further assumptions:

- *Depletion* is constant with time and uniformly distributed
- *SOE* and *vertically integrated* firms have uniformly distributed costs
- Mines form a continuum and each mine is punctual (note that this follows from the assumption of linearity based on **Figure 6: Comparison of ICC and OCC, for copper**)

These new assumptions are of course not supported with data, but they are simplifying assumptions, that allow us to model supply loss and to put it in equations.

- Derivation:

The supply loss from ore grade is easily computed as:

$$Supply\ loss\ from\ oregrade = Q_{100}^{t} \cdot ((1 + Depletion)^{years} - 1) \qquad \textbf{(3)}$$

We then compute the supply loss from economic retirement:
The remaining capacity before economic retirement is given, using **Equation 3**, by:

$$q = Q_{100}^{t} - Supply\ loss\ from\ oregrade \qquad \textbf{(4)}$$

From all the capacity q, a fraction doesn't behave economically. State-owned firms and vertically integrated firms are indeed optimizing for goals that go beyond the profitability of a given mine. Therefore, they might not shut down despite being uneconomical.
The total supply that might not behave economically is given, using **Equation 4**, by:

$$q' = q \cdot (SOE\ concentration + Vertical\ integration) \qquad \textbf{(5)}$$

Note that this equation assumes that there is no overlap, we shouldn't double count vertically integrated SOE.

Their incentive to shutdown varies with the slope of the cost curve, as explained in **Figure 17: Illustration - Cost curve flatness is a barrier to exit**. Thus, we quantify which share of q' will actually not behave economically, based on a flatness score, that we design as:

$$flatness = \begin{cases} 0\ if\ \ P90/P25 > 3 \\ 1\ if\ \ P90/P25 = 1 \\ \quad linear \end{cases}$$ (see .**Figure 23**)

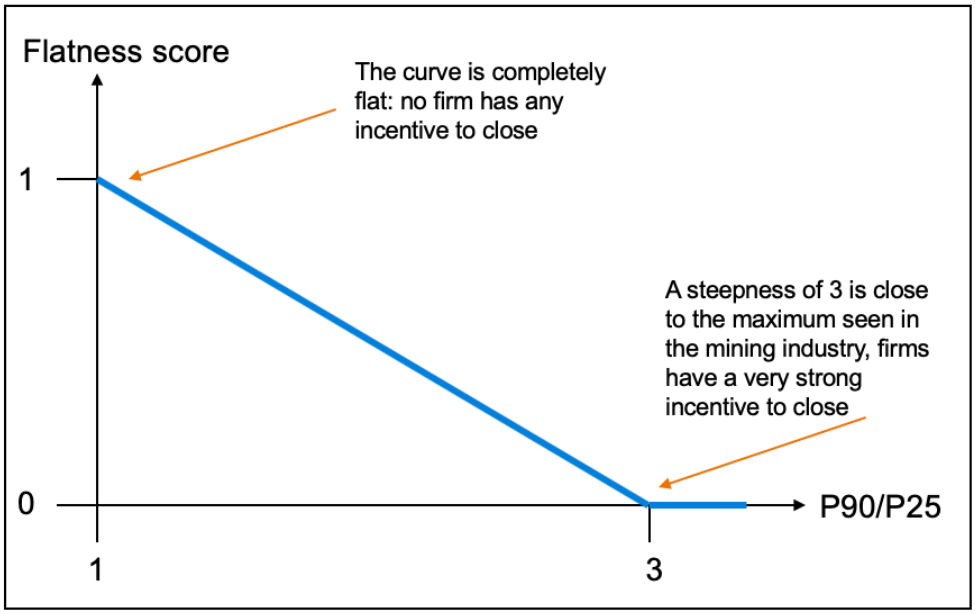

Figure 23: Cost curve model - *Rational for flatness score*

Using **Equation 5**, and the flatness score, we obtain the supply that will behave economically:

$$q_{econ} = q - q' \cdot flatness \qquad \textbf{(6)}$$

For the last step, we use P_{90}^{t+1} to determine the percentile p that separates mines that will still be profitable on the left of cost curve, from mines that will stop being profitable at time t+1, on the right of the cost curve. It is simpler to understand what p is from graph d) of **Figure 24**. p can also be expressed analytically.

First, note that for a given percentile x: its cost at time *t+1* has been increased due to depletion. It is given by

$$C_x^{t+1} = \frac{P_x^t}{(1+depletion)^{years}} \qquad \textbf{(7)}$$

Using the notation in **Equation 7**, it comes that

$$p = 25\% + (90\% - 25\%) \cdot \frac{P_{90}^{t+1} - C_{25}^{t+1}}{C_{90}^{t+1} - C_{25}^{t+1}} \qquad \textbf{(8)}$$

We now have all the pieces, and the supply loss from economic retirement is simply obtained by:

$$Supply\ loss\ from\ economic\ retirement = q_{econ} \cdot (1 - p) \qquad \textbf{(9)}$$

And,

$$Supply\ loss = Supply\ loss\ from\ economic\ retirement + Supply\ loss\ from\ depletion \quad \textbf{(10)}$$

Figure 24, summarizes the main steps we used to compute supply loss.

- It stresses the different assumptions that we have made (namely linearity, and homogeneity of the cost distribution, depletion, SOE concentration and vertical integration).
- It shows how the cost curve shrinks in capacity and increases in cost due to depletion (see graphs **b)** to **d)**) This reflects **Equation 3** and **Equation 7**.
- Graph **d)** shows how we compute the share of supply that might retire, due to economic reasons. It reflects **Equation 8.**

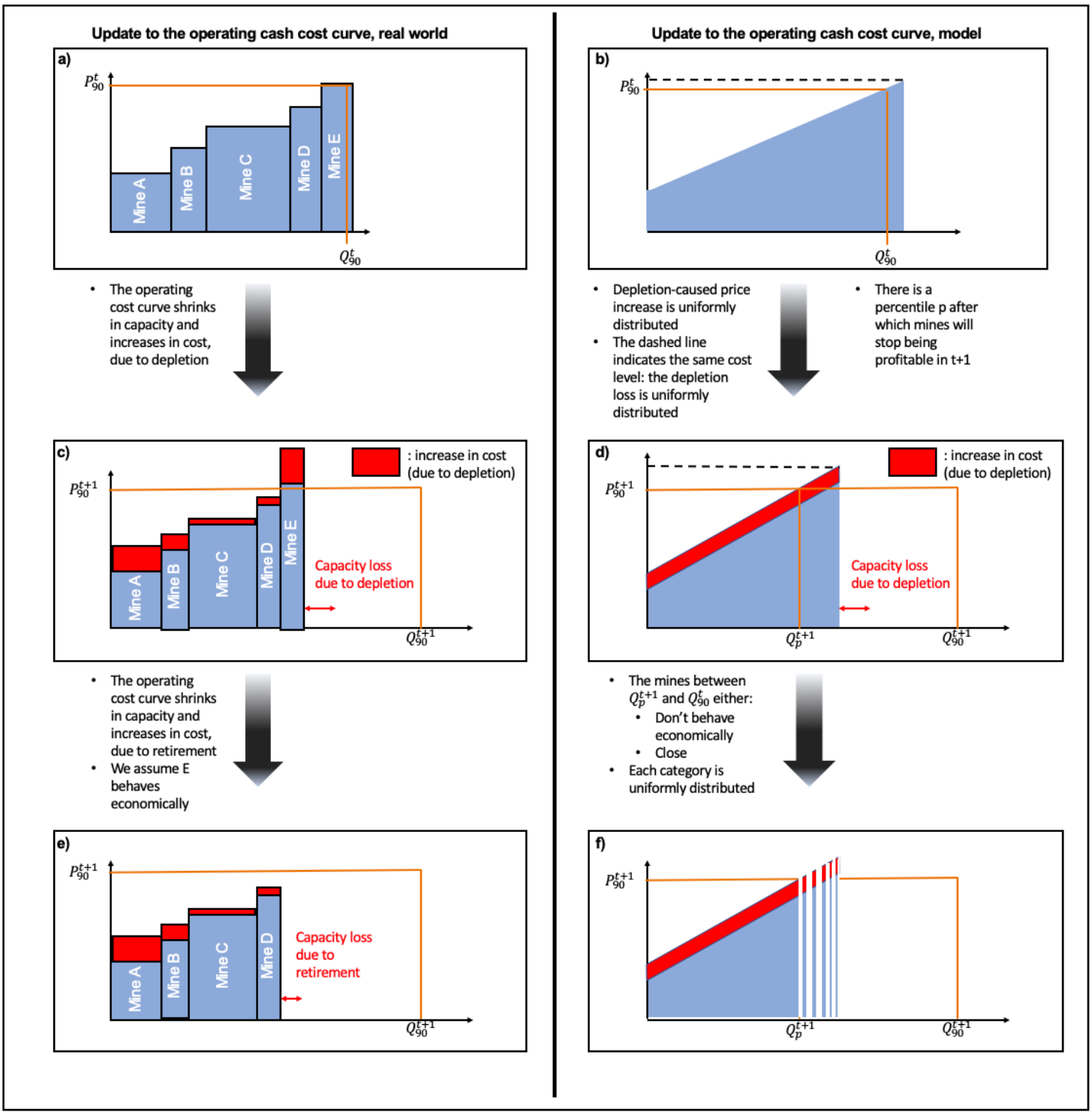

*Figure 24: Cost curve theory (on the left) vs.*Cost curve model *(on the right)*

IV.1.b. Computing the shape and capacity of the incentive curve

- Objective:

In this subpart, we are interested in inferring the incentive cost curve costs and capacity. We base our approach on the framework outlined in III.1.b.

IV.1.b.(i) Capacity of ICC

- Inputs:

For the ICC's capacity, we use the following drivers from **Table 1**:

- *Reserves,*
- Barriers to entry (*Technical complexity, Industry maturity, Intensity of regulation on supply, Geopolitical risk of reserves, Asset concentration, Capital intensity)*,
- *Current Margins.*

For the ICC's cost, we use the *Steepness of cost curve* and *Capital intensity* from **Table 1**, and we use two additional, financial inputs: the CAPEX payback period and the CAPEX interest rate.

- Assumptions:

The main assumption we make was explained in section III.2.b.: the capacity of the incentive curve is a fraction of the size of the reserves, which is increasing in the *Current Margins*, and decreasing in the barriers to entry.

- Derivation:

Given this assumption, the ICC capacity is of the form:

$$Capacity_{ICC} = Ratio \cdot Reserves \quad \textbf{(11)}$$

Therefore, a first approximation could be to use the historical ratio. This could be a sensible guess, because this ratio is constant over time in first approximation, as demonstrated by the following data analysis for copper (see **Figure 25**[18])

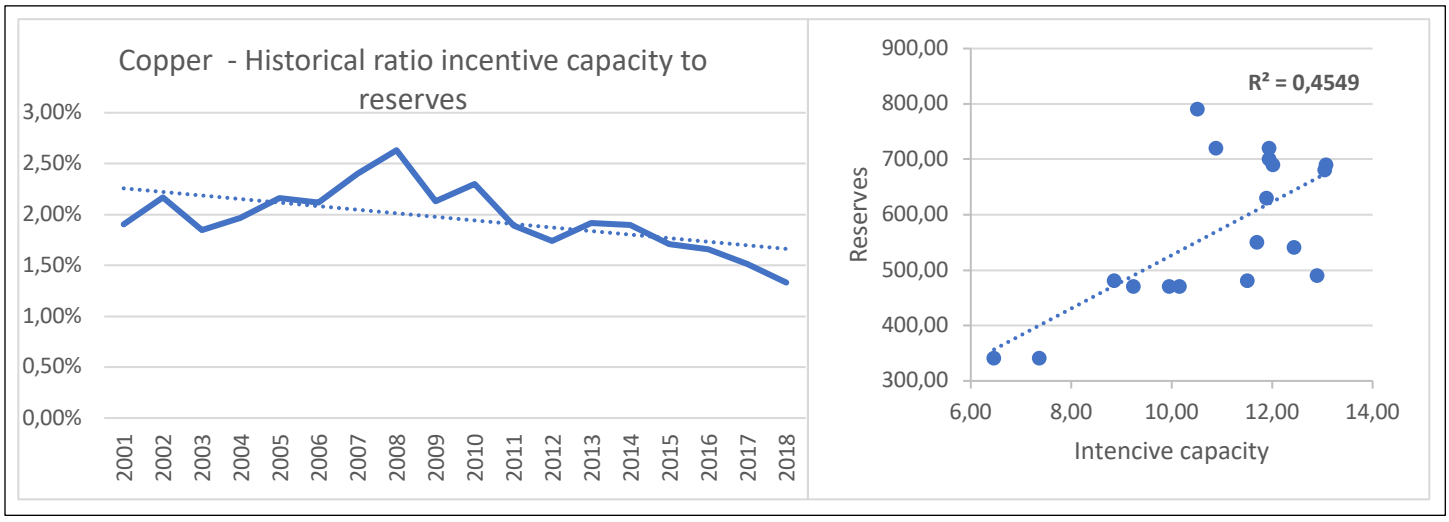

Figure 25: Data analysis for copper - ICC to Reserves ratio

[18] Source : USGS

A more elaborate modeling option is to regress the historical ICC to reserve ratio on the barriers to entry and on the current margins, as in **Equation 12**, below. This allows us to capture dynamically the changes to a commodity's attractiveness caused by barriers to entry and current attractiveness.

Our dependent variable being a ratio, we need too carefully make sure the regression allots values between 0 and 1. We use a least square regression such that the weights sum up to 1. As our regressors stand between 0 and 1, the dependent variable will also be between 0 and 1.

A later step could be to build a more precise learning model, like logistic regression. However, logistic regression would reduce the interpretability of the model.

$$\text{Ratio} = \lambda \cdot Margins + \alpha \cdot Complexity + \beta \cdot Reserve_{risk} + \gamma \cdot Asset\ concentration \quad \textbf{(12)}$$

Such that: $\alpha + \beta + \gamma + \lambda = 1$

Where *Complexity* is a composite measure of barriers to entry related to mining complexity, and that we develop in section IV.2.

We can interpret the regression factors as follows (see **Table 2**):

Factor	Regressor	Sign	Interpretation
α	*Complexity*	-	Share of the reserve that doesn't make it to the incentive curve because of the time it takes to set up operating facilities, once the investment decision is made
β	*Geopolitical risk of reserves*	-	Share of the reserve that doesn't make it to the incentive curve because of the inability to mine in certain areas due to corruption, political instability and safety
γ	*Asset concentration*	-	Share of the reserve that doesn't make it to the incentive curve because good deposits are scarce and only available to big players, given their size.
λ	*Current margins*	+	Share of the reserve that makes it to the incentive curve because the high margins prospect incentivize firms to develop facilities and to be ready to start operations.

Table 2: : Cost curve model - *Interpretation of regression factors*

Given a lack of quality data, we did not seek to obtain numerical values for these factors. Further research could focus on finding a meaningful relation, either based on the approach suggested above, or on other regression techniques. The rest of our work will therefore be based on the first modeling option (see **Equation 11**).

IV.1.b.(ii) Costs of ICC

- Inputs:

For the ICC's cost, we use the *Steepness of cost curve* and *Capital intensity* from **Table 1**, and we use two additional, financial inputs: the CAPEX payback period and the CAPEX interest rate. We also use the price P_{90}^{t}.

- Assumptions:

Again, the main assumption we make was explained in section III.2.b.: the OCC and the ICC are linear and have the same distribution, so the costs of the ICC can be derived from the cost of OCC by **Equation 2**.
We also assume, that CAPEX is uniformly distributed.

- Derivation:

We first compute the capital recovery charge (Capex per kg). As we assume it is constant (CAPEX is uniformly distributed), it directly follows from the definition of *Capital intensity* that:

$$Capital\ recovery\ charge = P_{90}^{t} \cdot Capital\ intensity \quad \textbf{(13)}$$

Then, we derive the slope of the ICCC (where ICCC stands for Incentive Cash Cost Curve) from the slope of the OCC by **Equation 2**, which is reminded below:

$$Slope_{ICCC} = Slope_{OCC} \cdot \frac{Capacity_{OCC}}{Capacity_{ICC}} \quad \textbf{(2)}$$

The ICC and OCC having the same cash cost distributions, they have the same extremes. In particular, $P_{50}^{ICCC} = P_{50}^{OCC}$, so it follows that, for any percentile x, the cash cost of the incentive curve at x is given by:

$$P_{x}^{ICCC} = P_{50}^{OCC} + Slope_{ICCC} \cdot (x - 50\%) \quad \textbf{(14)}$$

Lastly, by using **Equation 13** and **Equation 14**, we derive the ICC costs for any percentile x of the incentive cost curve:

$$P_{x}^{ICC} = P_{x}^{ICCC} + Capital\ recovery\ charge \quad \textbf{(15)}$$

IV.1.c. Computing the real demand change

- Objective:

In this subpart, we are interested in predicting the next demand Q_{90}^{t+1}.

- Inputs:

In addition to *Demand growth* and *Stocks,* we use the current consumption Q_{90}^{t} as an input.

- Assumptions:

The only assumption that we use here was made in section III.2.: the use of stocks is proportional to the increase in price.

- Derivation:

The next demand is easily obtained as:

$$Next\ demand\ = (1 +\ Demand\ growth)^{years} \cdot Q_{90}^{t} \qquad \textbf{(16)}$$

We have to adjust this result for stocks. As the use of stocks is considered proportional to the increase in price, we define the used share of stocks s :

$$s = a \cdot \frac{P90_{t+1} - P90_t}{P90_t} \qquad \textbf{(17)}$$

Where a is a coefficient of proportionality between the use of stocks and the increase in price, and where $|s|$. is bounded by some constant below 1 (as less than 100% of the stocks can be used). Because of a lack of data, we don't derive these parameters. They do not affect our results, as we assume the volume of stock was 0 in the following analysis.

Lastly, using **Equation 16** and **Equation 17**, it comes that:

$$Q_{90}^{t+1}\ = Next\ demand\ - Stocks \cdot s \qquad \textbf{(18)}$$

IV.1.d. Conclusion – Computing the next margins

Finally, we put all three previous subsections together, to compute the new margins. This boils down to formulating in equations the last step of our cost curve update model from **Figure 3 : Illustration -Discrete Model for the operating cost curve updates**.

This last step consists in using the remainder of the *time t* operating cost curve, and the incentive curve to build the *time t+1* operating cost curve. Refer to **Figure 27 : Cost** curve ***model*** **- Computing** P_{90}^{t+1} (next page) to follow the graphic interpretations of the quantities that we introduce here.

Using **Equation 10**, the remaining capacity of *OCC(t)* is

$$q = Q_{90}^{t} - Supply\ loss \qquad \textbf{(19)}$$

Therefore, the total new capacity required to satisfy demand is k, defined by:

$$k = Q_{90}^{t+1} - q \qquad \textbf{(20)}$$

k corresponds to a given percentile of the incentive curve, which determines the new price according to:

$$P_{90}^{t+1} = P_{p}^{ICC} \qquad \textbf{(21)}$$

where $p = \frac{k}{ICC_{capacity}}$, $ICC_{capacity}$ is derived in **Equation 11**, and P_{x}^{ICC} is defined for all values of x in **Equation 15**.

<u>Note:</u> P_{90}^{t+1} as obtained in **Equation 21** depends from the supply loss (**Equation 10**) that depends itself from P_{90}^{t+1}, used as an input to **Equation 8**. This translates a real-world circularity: on the one hand, the next price determines whether it is economic or not for firms to continue operating, and on the other hand, if more or less firms continue operating, there will be more or less need for new supply, to meet demand, so the price will more or less increase. (See **Figure 26).**

In other words, we need the k from graph **g)** to be the same as the k from graph **h)** on **Figure 27**. k on graph **g)** is the required new supply to meet demand, while k on graph **h)** is the new supply that can be incentivized because it is economic.

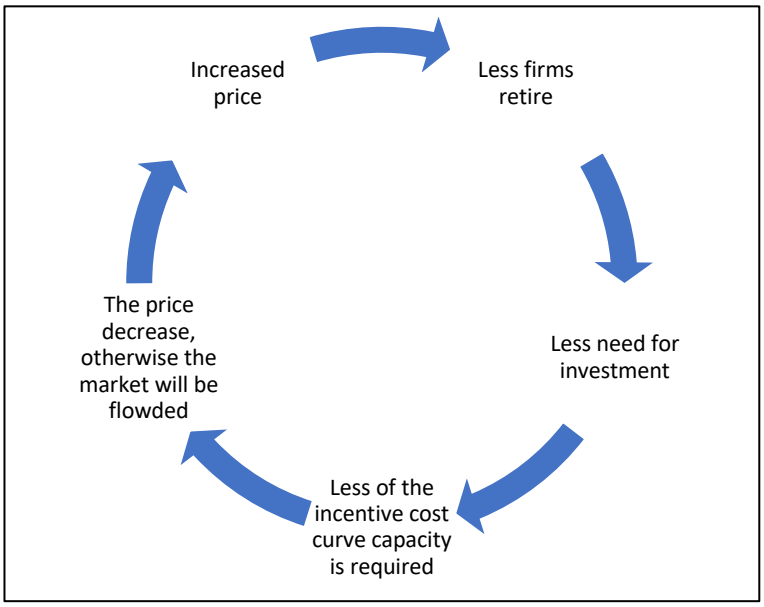

Figure 26: Illustration - Market cyclicality

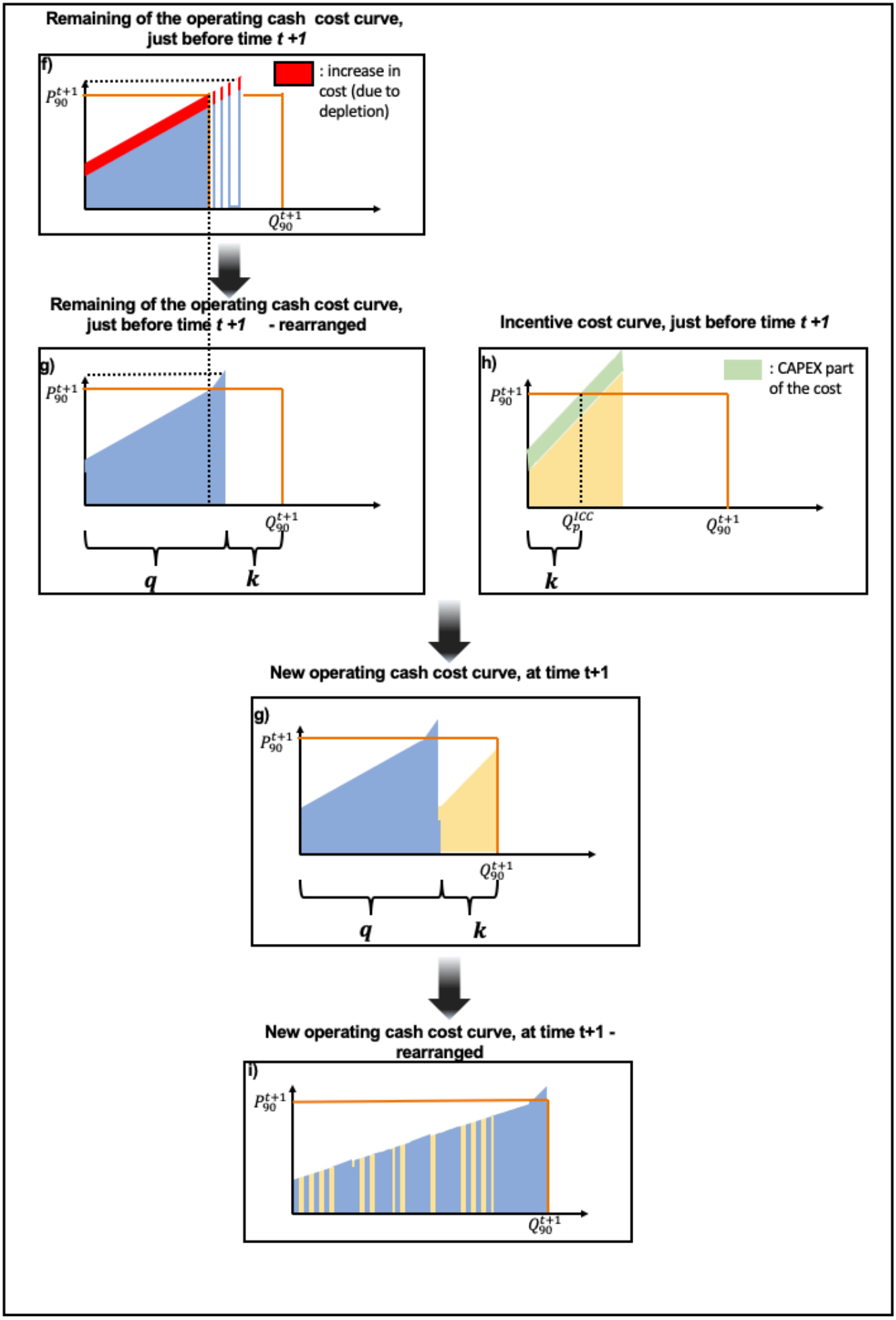

Figure 27 : Cost curve model - *Computing* P_{90}^{t+1}

Note that going from graph **g)** to graph **i)** on **Figure 27** is a linear approximation. This is consistent with our assumptions. The curve should otherwise be piecewise linear, as evidenced by **Figure 28.**

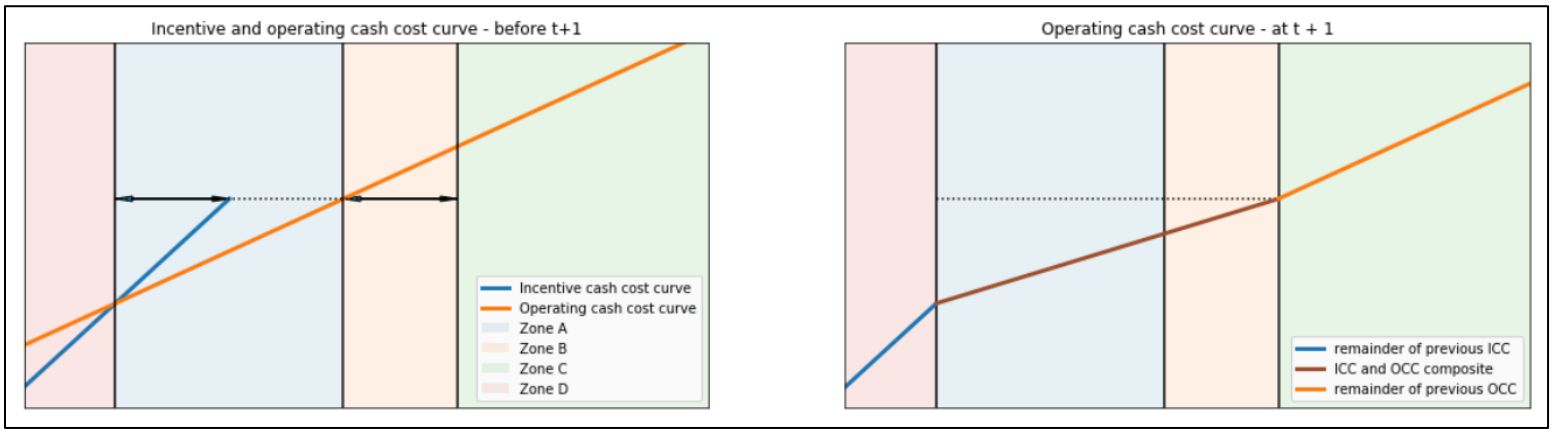

Figure 28: Cost curve model - *Adding the incentive and operating cost curves yields a piecewise linear function*

Given this assumption, the slope of the updated cash cost curve is

$$Slope_{OCC_{t+1}} = \frac{Slope_{OCC_t} \cdot q + Slope_{ICC} \cdot k}{q+k} \quad \textbf{(22)}$$

Also, by definition, $Slope_{OCC_{t+1}} = \frac{P_{90}^{t+1}}{P_{25}^{t+1}}$, hence, using **Equation 1**, we find the next margins:

$$Margins_{t+1} = \frac{P_{90}^{t+1}}{P_{25}^{t+1}} - 1$$

IV.1.e. Next steps – Model enhancement

In addition to refining any of the above-mentioned assumption, a more precise model could take into account the three following ideas for improvement:

- Allow the distribution of the OCC and ICC to differ by a multiplying factor. This wouldn't affect the computation of the ICC slope, but it would allow for a vertical shift up or down.

- Take crisis likelihood into account. As we detailed it in III.2., crisis likelihood can be a reason for attractiveness: it might lead a share of the supply to be idled, which generates price spikes. More generally, one could look at all the different reasons that cause supply to become idle for non-economic reasons (labor, environmental regulations, natural disasters, etc.)

- Forecast commodities' demand growth more granularly, by splitting it between the evolution of material intensity, and the growth of the demand for the manufactured goods.

IV.2. Design of a Business Economics model – a *Logic tree model*

In this subsection, we detail further assumptions that enable us to build a *Logic tree model*. It is based on the business economics of mining developed in section III.2. It aims at discriminating between tier 1 commodities, tier 2 commodities and tier 3 commodities. This high-level screening is useful from an investor's point of view as it enables to focus more in-depth investigations on tier 1 commodities.

So far, we have established that:

(i) from a financial investor's perspective, two KPIs matter for attractiveness: returns on investment (margins) and risk.

(ii) These KPIs are driven by the features defined in Section I.

(iii) These features interact through various mechanisms that create positive or negative forces that shape the future attractiveness by changing the supply or demand aspects of the industry. These forces are barriers to entry, spikes likelihood, market power, demand gap, demand risk (see subsection III.2.).

In this section we rigorously quantify these mechanisms with mathematical functions.

This is done in two steps. We first score each elementary driver based on utility functions, that assigns a utility score to each driver based on real-world data. Then, we quantify each force through a semi-quantitative, bottom up approach, from elementary drivers' scores. This bottom-up approach aggregates root drivers via a logic tree architecture, which we detailed in III.2.b., so we call it *Logic tree model*. Each force is a function of given elementary drivers as discussed in the previous section (IV.2.). We then assemble these drivers through mathematical operations that make qualitative sense, and that represent the causality chain which leads an elementary driver to affect a given force.

IV.2.a. First step: utility functions of elementary drivers

Each elementary driver is scored according to a utility function that has been designed qualitatively. Each function scores the driver between 0 (bad) and 1 (good). Consider the example of *Reserves.* The utility function is given by the blue line in **Figure 29** below.

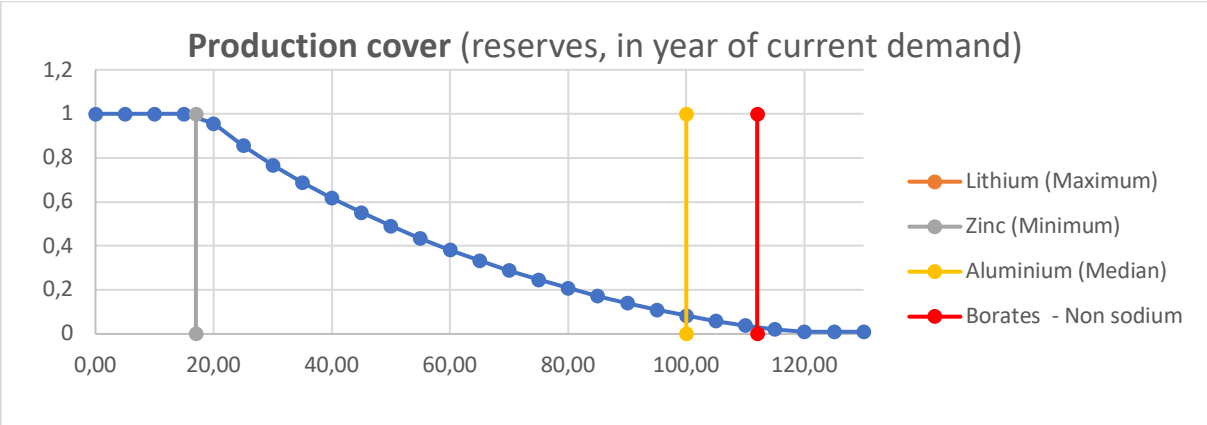

Figure 29: : Logic tree model -*Utility function of Reserves*

A small *Production cover* materializes in an increased attractiveness, because there are less deposits that can turn into prospective mines. In our business economics approach, we consider *Production cover* as contributing to the *Scarcity* barrier to entry (see subsection III.2.).

Intuitively, *Production cover* has a decreasing marginal utility for a large production cover. In other words, 20 years of production cover is much better than 40, but the difference between 40 and 60 years isn't as important. Hence the curve is convex.

Note: for some drivers, like the intensity of regulation, the input data is already a score between 0 and 1, decided by expert judgment. We use the identity as utility function for these drivers. Likewise, some other drivers, like demand growth and depletion, are aggregated based on their economic significance. For these drivers we also use the identity function.

All the utility functions are available in the appendix for section IV..

IV.2.b. Second step: Aggregations of elementary drivers' scores

In the previous paragraph, we scored each elementary driver based on utility functions, that assign a utility score to each driver based on real-world data.

We now assemble these drivers through mathematical operations that represent the causality chain which leads an elementary driver to affect a given force (see III.2.).

We identified 3 main ways to aggregate individual scores: "barriers averages", "by definition aggregations", and "Expectation aggregations".

<u>Barriers averages:</u>

These aggregation mechanisms apply to barriers to exit and barriers to entry. They consist in a weighted average with a high weight on the biggest barrier and lower weights on other barriers. The rational behind these mechanisms is that the biggest barrier is the limiting factor, that will entail (dis)attractiveness. The other barriers have marginal effects compared to the main one.

For example, assume there are 2 barriers to entry A and B for a set of industries. If one industry has a very high score for A (e.g., .8 out of 1), and average scores for B (e.g., .3 out of 1), most of the barriers to entry will comes from barrier A. For instance, as drawn on **Figure 30** $A = .8$ and $B = .3$ yields a barrier to entry score of $.66$ whereas B= $.6$ yields a score of $.71$. Thus, there is only a small increase of .05.

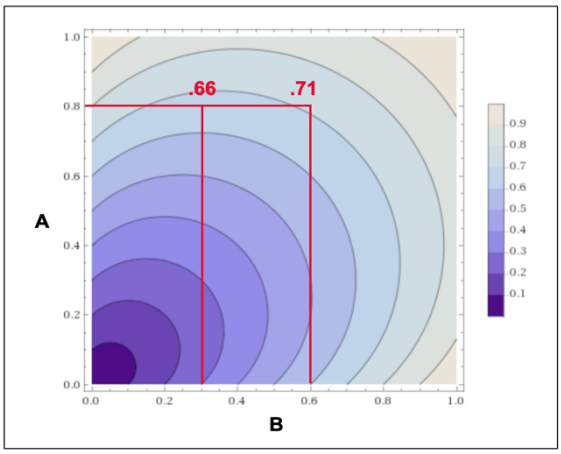

Figure 30: Illustration - "Barriers averages" aggregations

Formally, "Barriers average" can be computed by the following formula:

$$\sum_{barriers\ b} b \cdot \frac{b}{\sum_{barriers\ b'} b'}$$

It can be rewritten as:

$$\frac{\sum_{barriers\ b} b^2}{\sum_{barriers\ b} b}$$

In the case exemplified above with, **Figure 30** the formula becomes $A \cdot \frac{A}{A+B} + B \cdot \frac{B}{A+B}$.

<u>By definition aggregations:</u>

These mechanisms apply to demand gap, demand change, oligopoly stability, market power, and margins sustainability. They consist in subtractions, additions, multiplications of scores (or raw inputs), and exogenous factors. The rational behind these mechanisms is that some forces are naturally defined as functions of drivers.

For example, consider the "demand gap" force. The elementary drivers are the volume of available stocks, demand growth, and depletion. Demand gap is naturally defined as:

$DemandGap = Depletion + DemandGrowth - AvailableStocks$

Expectation aggregations:

These mechanisms apply to the dispersion score, the technical score, the scarcity score, spikes likelihood, supply risk and demand risk. They consist averaging driver's scores, arithmetically or geometrically, and sometimes with weights. The rational behind these mechanisms is that some forces are best captured by looking at its expected value, given drivers.

For example, we take the intermediary computation of the technical score (which in turn is used to compute the barriers to entry score). The associated elementary drivers are the likelihood of a new technology p, and the current technical complexity. We further assume that a new technology could halve the technical complexity in 10 years. Thus the technical score is naturally defined as the expected complexity:

$$Technical\ Score \quad = \quad Current\ complexity \cdot (1 - p) \quad + \quad \frac{Current\ complexity}{2^{\frac{years}{10}}} \cdot p$$

Another example is that of demand risk. Demand risk comes from substitution risk and disruption risk. A natural aggregation mechanism for risk is to compute the arithmetic average. Thus, we get the following formula for demand risk:

$$Demand\ risk = \frac{Disruption\ risk + Substitution\ risk}{2}$$

Note: "Expectation aggregations" mechanisms are the subset of the "By definition aggregations" mechanisms that are based on averages. For the sake of clarity, we explained them separately.

We explained the 3 main ways to aggregate individual scores: "barriers averages", "by definition aggregations", and "Expectation aggregations**". Figure 31**, below summarizes all the mechanisms used in the model

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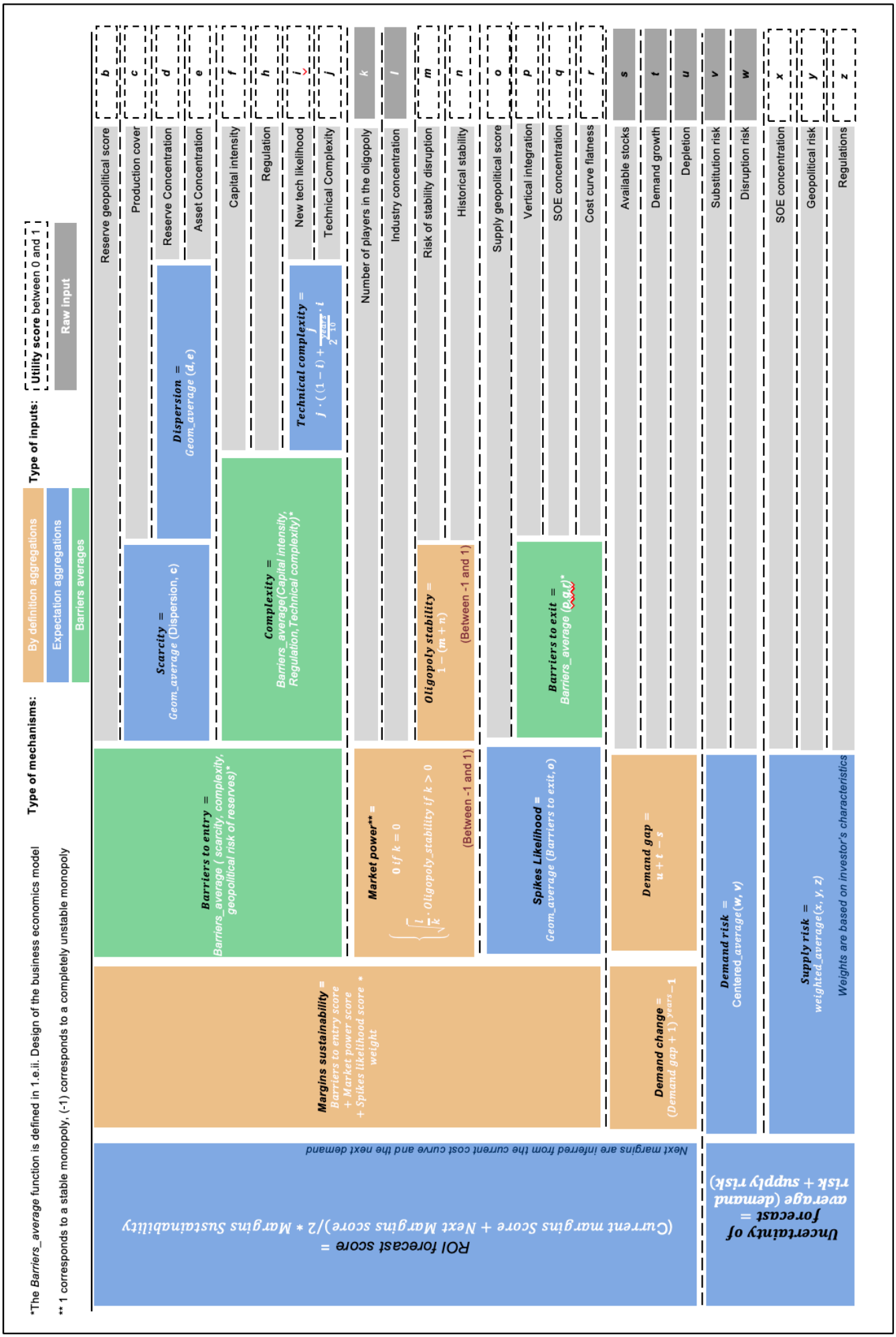

Figure 31: Logic tree model - *Summary of aggregation functions*

V. Results and benefits of the *Cost Curve* and *Logic Tree Models*

We first use the *Cost curve model* with synthetic commodities that have simulated values for the main drivers of the model and fixed value based on copper data for the remainder of the drivers. This allows us to study the long-term effect of various combinations of drivers. Based on these results and the relevant data, one can benchmark how the future margins of a commodity will compare to the future margins of other commodities.

Our industry structure model provides results based on intuition and on expert judgment. We present the result it yields for a subset of synthetic commodities and compare these results with that of the *Cost curve model*.

The insights described in this section can inform decision-makers in how the drivers from section I. impact future margins, in theory. Further research could be done, to directly measure the forecast precision of these models, based on historical data. The rigorous framing and problem-settings we conducted allow to suggest insights on how elementary factors drive attractiveness, without providing a formal proof.

V.1. Results - *Cost curve model*

Which combination of factors are key to attractiveness?

We conduct a full-factorial simulation of the eight main drivers used in the model. These drivers are: *Current Margins, Incentive Capacity, Capital Intensity, Ore Body depletion, Industry depletion, SOE concentration, Growth of Demand*, where *Incentive Capacity* derives from the amount of *Reserves* and the *Incentive capacity to reserves ratio* (see **Equation 11**). For other inputs, we used Copper data. Our full-factorial simulation has three possible inputs for each of the above-mentioned drivers. These inputs are based on data for a set of commodities, including Aluminium, Alumina, Bauxite, Copper, Thermal Coal, Hard Coking coal, Uranium, and Potash. They are presented in **Table 3** below. Each possible combinations of these inputs yields a synthetic commodity with simulated inputs. The model developed in section VI.1. predicts the cost curve of this synthetic commodity in 15 years. From there, we infer the *Next Margins* of the current 25th percentile asset. Thus, we obtain for each synthetic commodity a prediction of how the margins of a first-tier asset evolve in 15 years.

The choice of these inputs, and the design of the model entail inherent biases that suggest the insights we derive from the results shouldn't be considered individually as *Next Margins* forecast. Their purpose is to be used relatively, to compare the contribution to attractiveness of several drivers.

	Steepness of cost curve	Capital Intensity	Reserves	Depletion	Demand growth	SOE concentration	Incentive capacity to reserve ratio	Industry depletion
Low	1.30	1.00	30	0.0%	0.0%	0%	0.50%	0.0%
Interm	2.15	2.25	65	1.0%	1.5%	25%	1.25%	1.0%
High	3.00	3.50	100	2.0%	3.0%	50%	2.0%	2.0%

Table 3 : Cost curve model - *Range and parameter selected for the full factorial simulation of synthetic commodities*

Once we have simulated this data, we analyse it in two different ways:

- We fit it to a regression tree model, with the factor in **Table 3** as explanatory variables and *Next margins* as dependant variable. This analysis reveals which drivers are preeminent according to our model, and which combinations of drivers lead to attractive or unattractive *Next margins*. It shows how some poor scoring drivers can be compensated by other good scoring drivers.
- We analyse what different levels of given combinations of drivers mean for the average *Next Margins* and for the average *Margins Increase*. Where *Margins Increase* is defined as $Margins\ Increase = \frac{Next\ Margins\ (of\ Q25)}{Current\ Margins\ (of\ Q25)}$.

V.1.a. Regression tree analysis

We separate our simulated dataset into training, validation and testing set. We prune the tree using the validation set (20% of the data) (i.e. we limit the tree size by minimizing the MSE on a validation set, in order not to overfit). We then test the prediction power of the tree on the test set (20% of the data). The prediction power of the tree is reported in **Table 4**. These metrics suggest that the tree is good at predicting next margins based on the factor in **Table 3**. This legitimates the following discussion, which drives conclusions on how drivers interact to build attractiveness, based on the tree structure. To enhance interpretability, we combine *Reserves*, and *Incentive capacity to reserve ratio* in one metric: *Incentive capacity*, as in **Equation 11.**

Metric	Value
SSE	908.680305...
MSE	0.34629584...
RMSE	0.58846907...
MAD	0.41697109...
R2	0.94587233...

Table 4: Cost curve model - *Test set metrics for decision tree fit*

The top of the tree is reproduced in **Figure 32**. It is read from top to bottom. Decisions are made at each node, by going left if the node input is smaller than the node value, and right otherwise. The leaves are depicted in red and display the predicted value of attractiveness for synthetic commodities that verify the associated decision path.

Incentive capacity is the most important decision variable, just before current margins. When low, it presumes of much higher next margins (see orange lines, label 1). On the other hand, note that the upside of low incentive capacity can be mitigated by low current margins and low demand growth (see green path, label 2)

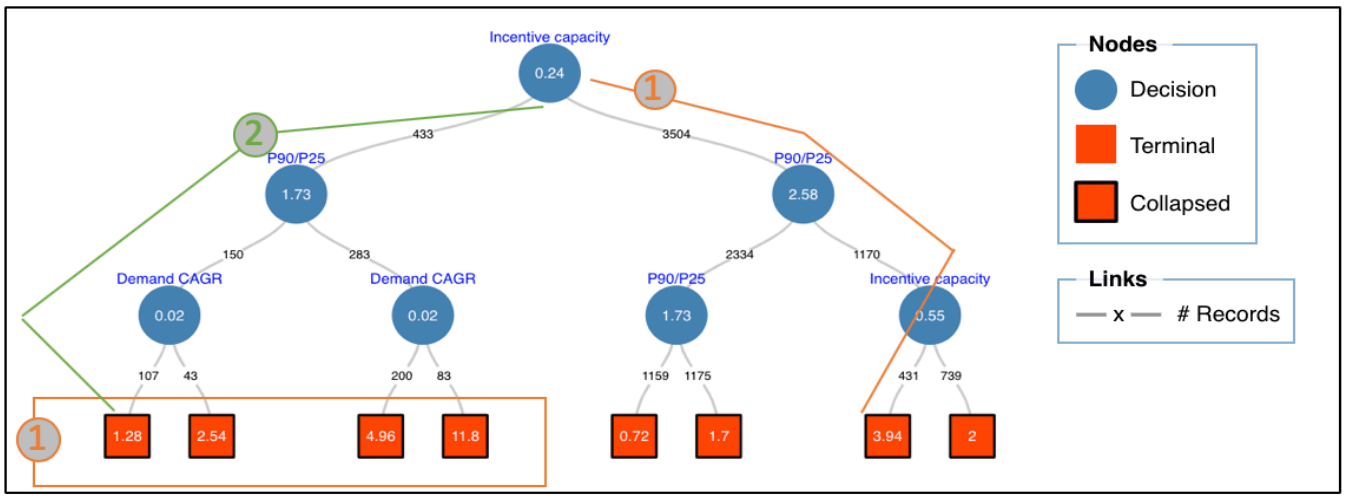

Figure 32: Cost curve model - *Top of the decision tree*

The right branch of the tree is reproduced in **Figure 33.** The left branch is represented in **Figure 34** and **Figure 35.** The tree suggests several ways in which the different elementary factors drive attractiveness. The first thing to note is that not all explanatory variables have the same importance. While *Incentive Capacity*, *Cost curve steepness*, *Demand Growth* and *Current Margins* are of the utmost importance, *Capital Intensity, Ore body depletion* and *Industry depletion* are only secondary drivers, that temper or enhance the outcome of the four main drivers. As for *SOE concentration*, it is not even considered a relevant decision variable by the model.

For the 90% of the synthetic commodities that don't have a very small incentive capacity (see **Figure 33**), *Current Margins* is the most important driver, after *Incentive Capacity*. *Demand Growth*, and to a lesser extent, *Capital Intensity* exacerbate or temper the high or low prediction of *Next Margins.*

Very high *Cost curve steepness* (i.e. *Current Margins* of 200%) leads to *Next margins* more than two times higher than when *Cost curve steepness* is low to average (271% vs. 121% in the model). These high *Next Margins* can be enhanced by a 1.5 factor with high demand growth (3% CAGR leads to *Next Margins* of 396% in the model), or tempered by a 1.3 factor with low to average *Demand growth*.

Very low *Cost curve steepness* (i.e. *Current Margins* of 30%) leads to *Next margins* about three times lower than when *Cost curve steepness* is average to high (72% vs. 221% in the model). These low *Next Margins* can be enhanced by a 1.4 factor when *Capital intensity* is high (3.5 *Capital intensity* leads to *Next Margins* of 98% in the model), or tempered by a 1.2 factor with low to average *Capital Intensity*. *Demand growth* can further enhance margins by another 1.2 factors (3% *Demand growth* enhances *Next Margins* from 98% to 121% in the model).

The most important results outlined in this discussion are summed up in **Table 5**. While *Current Margins* dictate the order of magnitude of *Next Margins*, other factors amplify or mitigate them, the most important factors being *Capital Intensity* and *Demand Growth.*

Next margins - for commodities with low to high incentive capacity (>.25 years)

Current Margins					
Low (30%)		Mid (115%)		High (200%)	
72%		170%		271%	
Capital intensity		**Demand Growth**			
Low to mid (1 to 2.25)	High (3.5)	Low to mid (0 to 1.5%)	High (3%)	Low to mid (0 to 1.5%)	High (3%)
59%	98%	136%	242%	212%	396%

Table 5 : Cost curve model - *Next margins for commodities with low to high incentive capacity*

For the remaining 10% of the synthetic commodities that have a very small incentive capacity (see **Figure 34** and **Figure 35**), *Current Margins* is again the most important decision factor, after *Incentive Capacity*. *Demand Growth*, and to a lesser extent, *Capital Intensity*, *Ore Body* Depletion and *Industry* depletion exacerbate or temper the high or low prediction of *Next Margins.*

Medium to high *Cost curve steepness* entails *Next Margins* to be more than four times higher than when *Cost curve steepness* is low, on average (697% vs. 164% in the model). These

high *Next Margins* can be enhanced by a factor of a 1.5 with high demand growth (3% CAGR leads to *Next Margins* of 1180% in the model), or tempered by low *Demand growth*, low *Capital intensity* and low *Ore Body Depletion*. For instance, *Demand growth* of 0% and *Ore Body Depletion* of 0% will lead to tempering the *Next Margins* by a factor of 4, (from 697% to 166% in the model)

On the other hand, low *Cost curve steepness* can be mitigated by high demand growth, high capital intensity or high *Industry Depletion*. For instance, *Demand growth* of 3% and *Industry Depletion* of 2% will lead to increase the *Next Margins* by a factor of 2, (from 164% to 307% in the model).

The main results are summed up in **Table 6** and **Table 7.** While *Current Margins* dictate the order of magnitude of *Next Margins*, other factors amplify or mitigate them, the most important factors being *Demand Growth, Capital Intensity, Industry Depletion* and *Ore Body depletion.*

Next margins - for commodities with low to high incentive capacity (<.25 years)

Current Margins										
Low (30%)						Mid to High (115% to 200%)				
164%						697%				
Demand growth										
Low (0%)		Mid (1.5%)		High (3%)		Low (0%)	Mid (1.5%)		High (3%)	
87%		166%		254%		326%	681%		1180%	
Capital intensity										
Low (1)	Mid to High (2.25 to 3.5)	Low (1)	Mid to High (2.25 to 3.5)	Low (1)	Mid to High (2.25 to 3.5)		Low to Mid (1 to 2.25)	High (3.5)	Low to Mid (1 to 2.25)	High (3.5)
57%	103%	141%	180%	227%	268%		524%	866%	882%	1517%

Table 6 : Cost curve model - *Next margins for commodities with very low incentive capacity – option 1*

Next margins - for commodities with low to high incentive capacity (<.25 years)

Current Margins														
Low (30%)							Mid to High (115% to 200%)							
164%							697%							
Demand growth														
Low (0%)		Mid (1.5%)			High (3%)		Low (0%)		Mid (1.5%)			High (3%)		
87%		166%			254%		326%		681%			1180%		
Ore Body depletion		Industry depletion					Ore Body depletion					Industry depletion		
Low (0%)	Mid to High(1% to 2%)	Low (0%)	Mid to High(1% to 2%)	Low (0%)	Mid (1%)	High (2%)	Low (0%)	Mid (1%)	High (2%)	Low (1)	Mid to High (2.25 to 3.5)	Low (0%)	Mid (1%)	High (2%)
76%	113%	133%	180%	215%	258%	307%	166%	298%	498%	518%	759%	1004%	1167%	1360%

Table 7 : Cost curve model - *Next margins for commodities with very low incentive capacity – option 2*

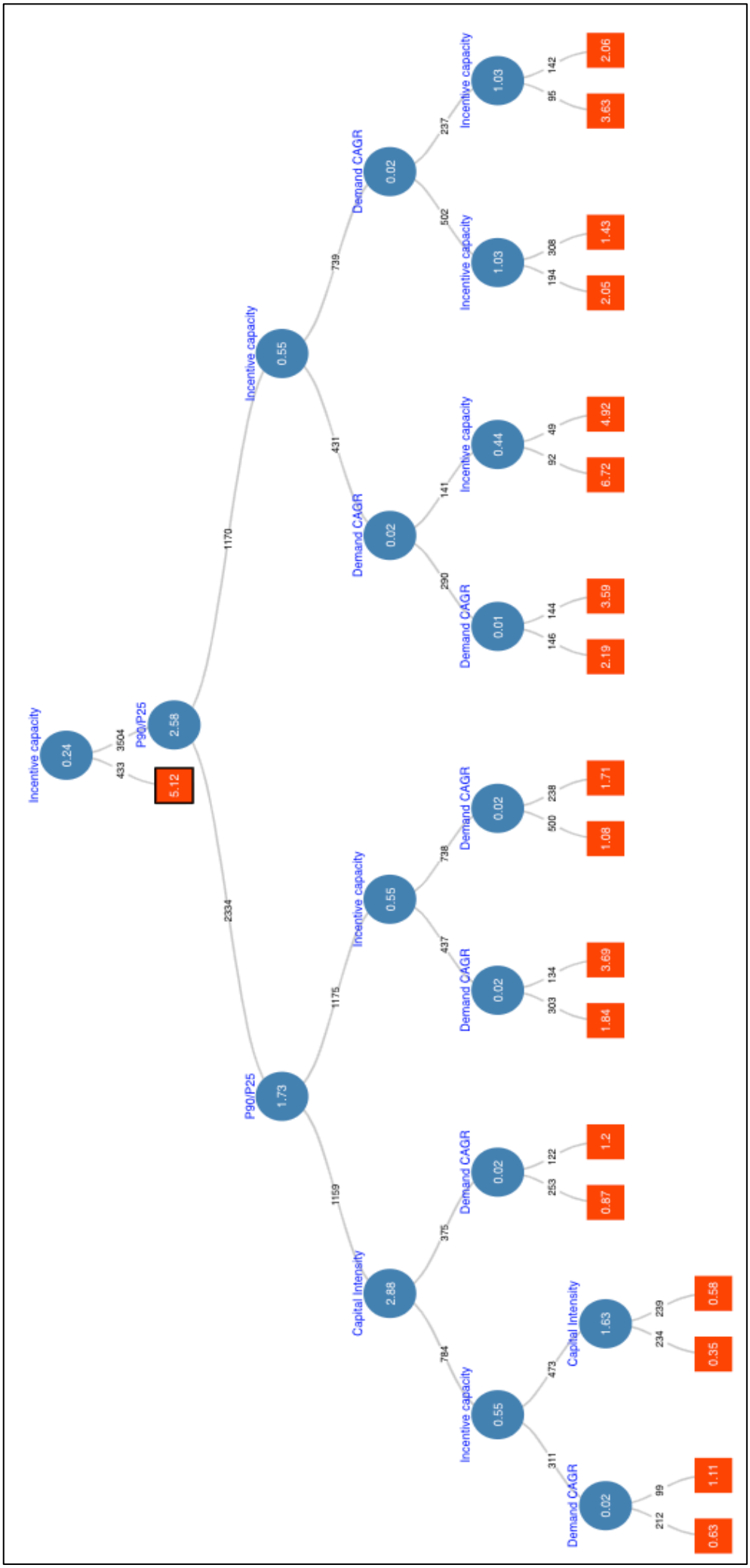

Figure 33: Cost curve model - *Decision tree - Right Branch*

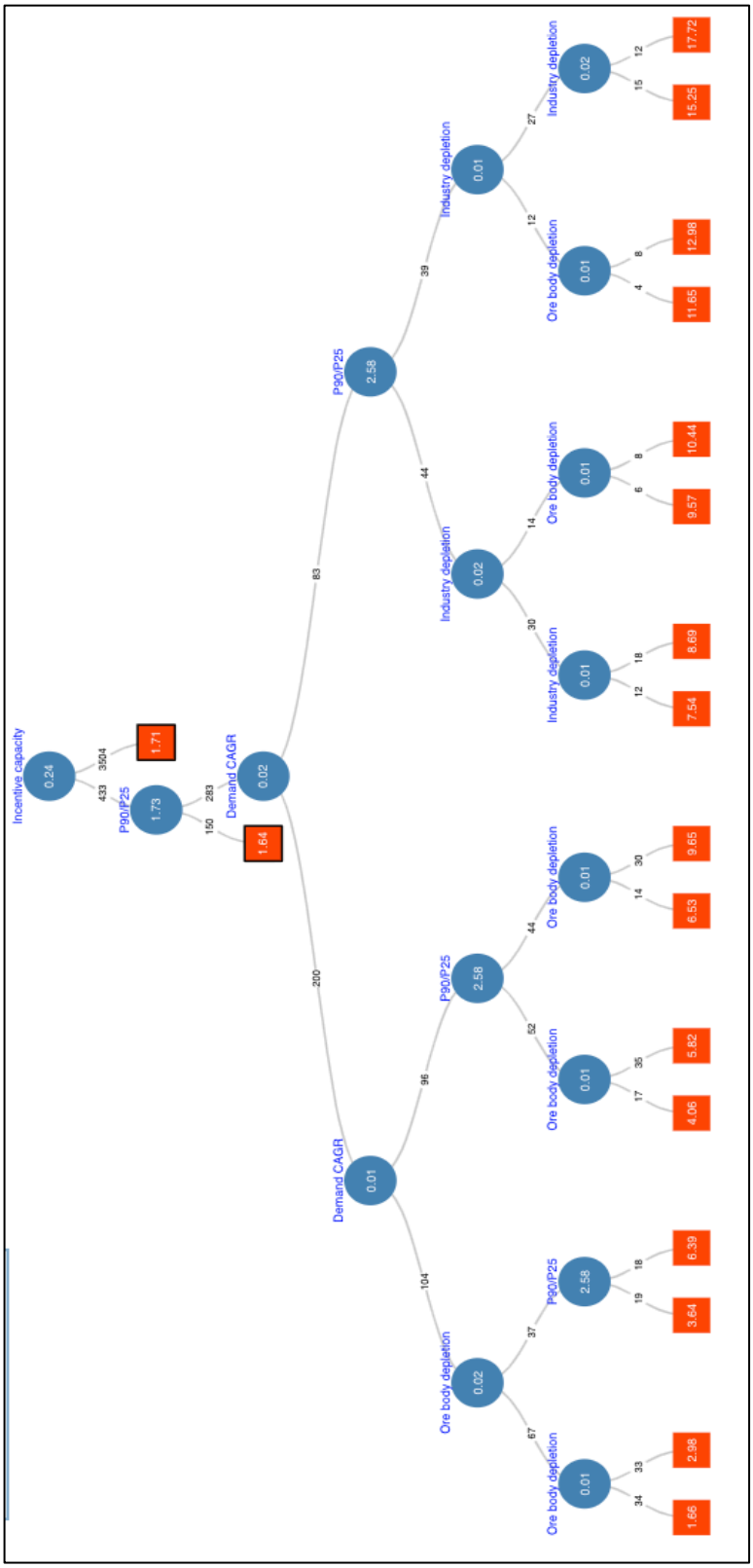

Figure 34: Cost curve model - *Decision tree - Left Branch (part 1)*

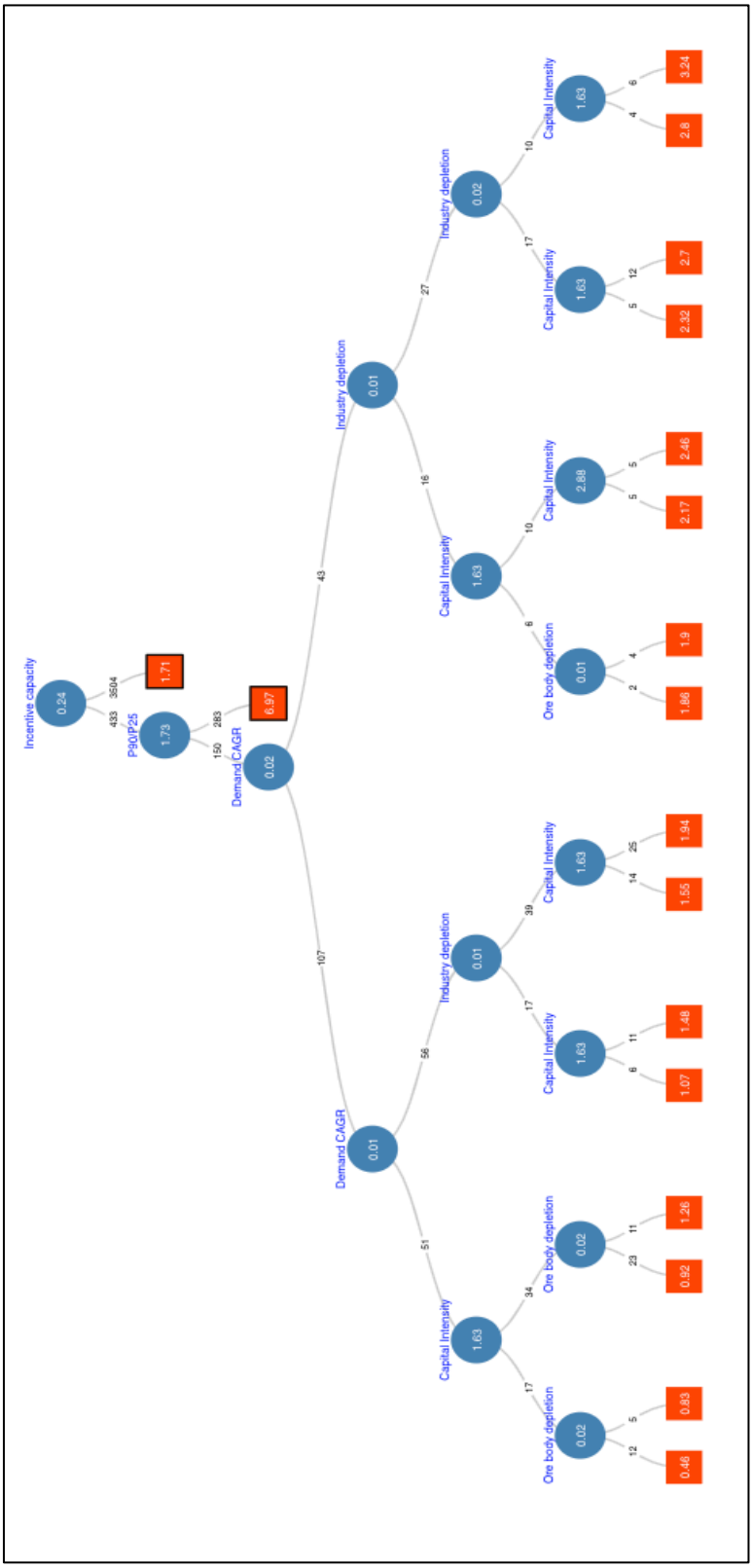

Figure 35: Cost curve model - *Decision tree - left branch (part 2)*

V.1.b. Impact of different drivers

Another way to analyse the results from the simulation is to look directly at how the average *Next Margins* varies depending on a selection of interest parameters. The discussion that follows is based on **Figure 36** to **Figure 38**, below.

We have looked at combinations of variables based on our regression tree analysis (see previous section). As *Current margins* stood out as the main decision variable, we also consider *Margins Increase* as a dependent variable. This allows us to analyze the impact of individual drivers on *Next Margins* independently from the starting point.

- *Incentive capacity & Cost curve steepness* (**Figure 36**)

Both low *Incentive capacity* and high *Cost curve steepness* drive *Next Margins* and *Margins Increase* down. Extremely high *Cost curve steepness* and high *Incentive capacity* is more desirable than extremely low *Cost curve steepness* and extremely low *Incentive capacity*. For instance, a *Cost curve steepness* of 3 and an *Incentive capacity* of 2 years yields *Next margins* of ~140% while a *Cost curve steepness* of 1.3 and an *Incentive capacity* of .4 years yields *Next margins* of ~95%.

If the incentive pool capacity is high enough (i.e. >= 1.5 years of production (~ 65 years of production cover and ~2% of IC/ reserves ratio)), and if the cost curve is steep, then margins stop increasing, and might decrease. This decrease in margins happens much sooner if the *Demand growth* or *Capital intensity* is low and much later if one of these drivers is high. It happen a little bit sooner if *Industry depletion is low* and a little bit later if it is high. (See Appendix for section V.).

Low *incentive capacity* and Low *cost curve steppness* lead to smaller *next margins* (~100%) than high *incentive capacity* and high *cost curve steppness* (~140%). In other words, the curve is steeper as a function of *cost curve steppness* than as a function of *incentive capacity*. **Figure 39** provides an exhaustive one to one comparison of drivers. This higher importance of *cost curve steppness* is hindered in the absence of *Ore body depletion*. SOE concentration has little impact, all else equal

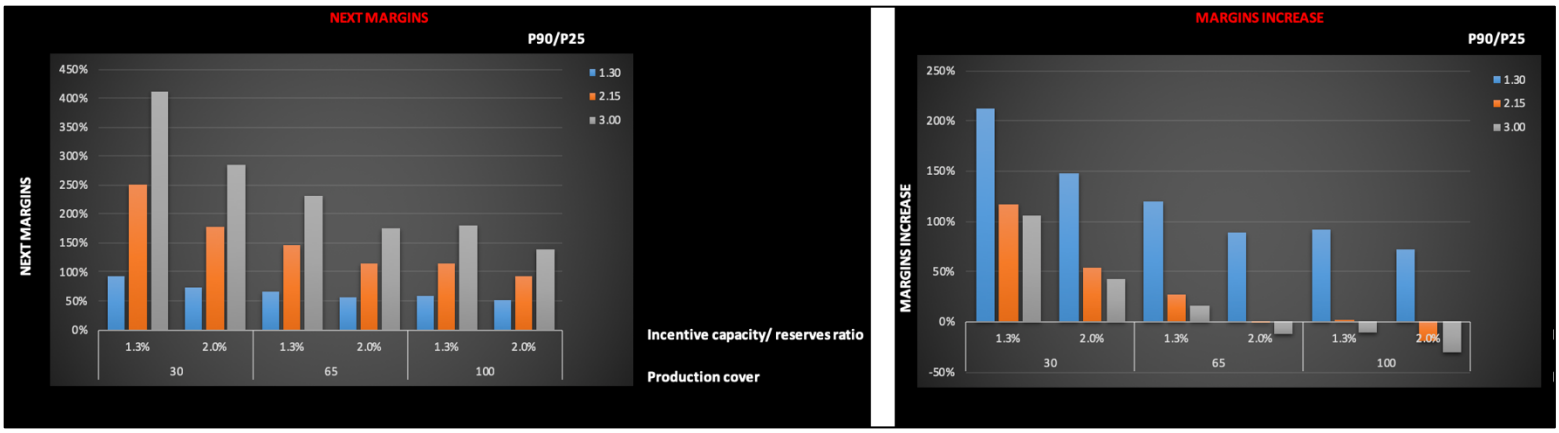

Figure 36: Cost curve model - Average next margins (left) and margins increase (right) in function of Current margins and Incentive Capacity

- *Incentive capacity & Capital intensity* (**Figure 37**)

At equal *incentive capacity*, *capital intensity* increases next margins by a constant increment.

Margins start decreasing when the *incentive capacity* is large enough and the capital intensity isn't large enough to compensate. At low *capital intensity*, low *demand Growth* entails a shrinkage in margins increase for almost all size of incentive capacity, while high *demand growth* entails an absence of margins increase shrinkage, even at low *capital intensity* (See Apendix 2.2). At low *capital intensity*, high *cost curve steepness* entails a shrinkage in *margins increase* for almost all sizes of *incentive capacity*, while low *cost curve steppness* entails an absence of *margins increase* shrinkage, even at low *capital intensity* (High *demand growth* approximately compensates for High *Cost curve steepness*)

The contribution of *capital intensity* is less important than that of *incentive capacity*. In other words, the curve is steeper as a function of *incentive capacity* than as a function of *capital intensity* (**Figure 39** provides an exhaustive one to one comparisons of drivers).

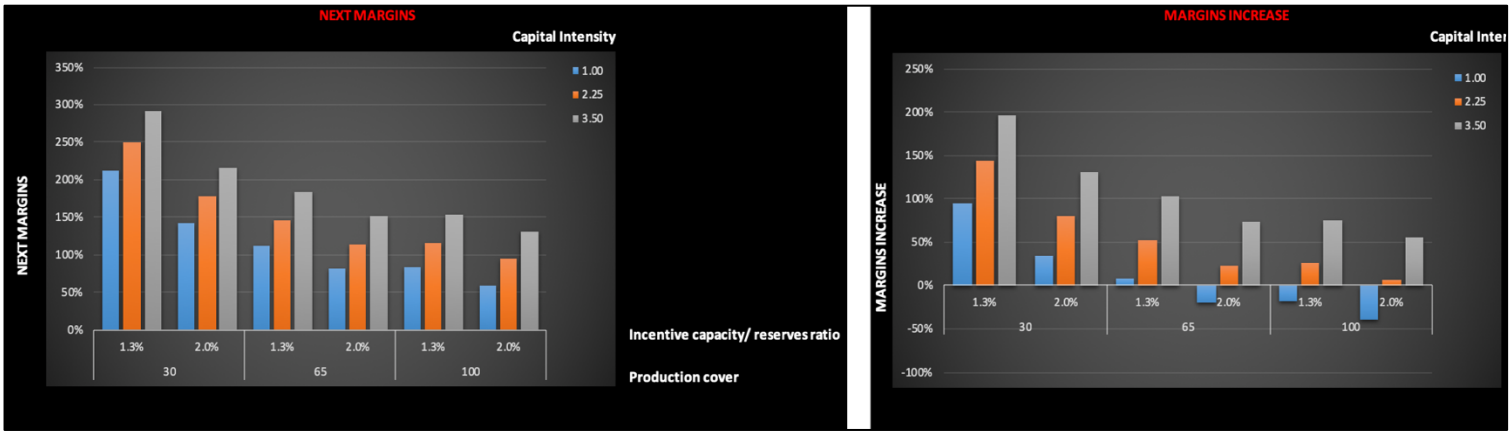

Figure 37: Cost curve Model - Average next margins (left) and margins increase (right) in function of Capital Intensity and Incentive Capacity

- *Investment need & Production cover* (**Figure 38)**

There are 2 drivers of investment need: *Ore body depletion* and *Demand Growth*. *Demand Growth* is more important for next margins (see **Figure 39**)

The increase in margins depends mostly on the *Production Cover* ; *Ore body depletion* and *Demand Growth* play less important roles. High *Industry Depletion* homogeneously increases next margins

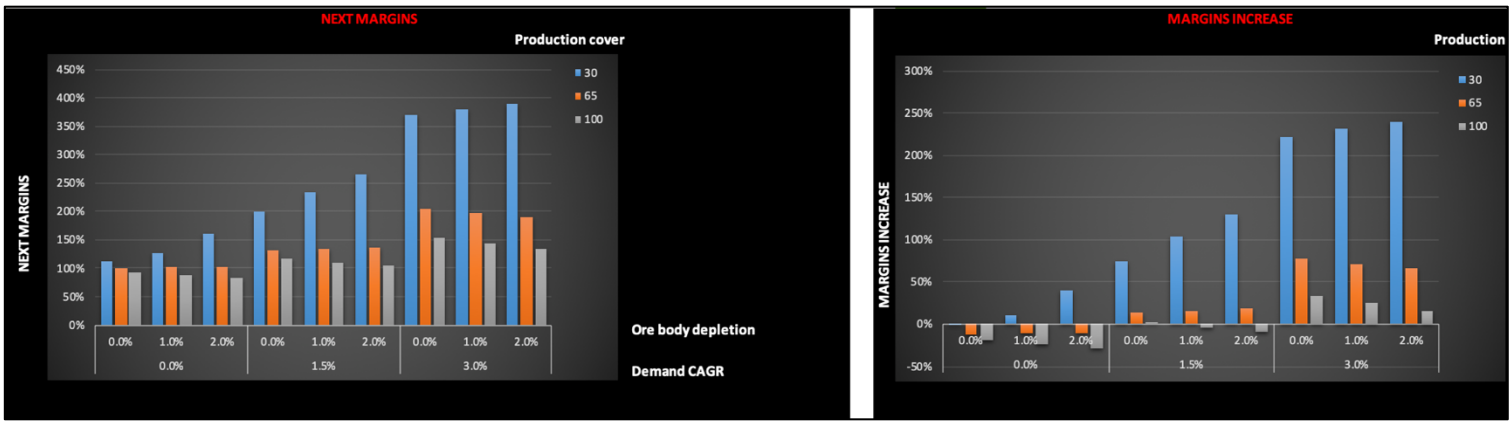

Figure 38: Average next margins (left) and margins increase (right) in function of Ore body depletion, Demand CAGR and Production Cover

	Steepness of cost curve	Capital Intensity	Incentive Capacity	Depletion	Demand growth	SOE concentration	Industry depletion
Steepness of cost curve		+	+	+	+	+	+
Capital Intensity	-		-	+	-	+	+
Incentive Capacity	-	+		+	+	+	+
Depletion	-	-	-		-	+	-
Demand growth	-	+	-	+		+	+
SOE concentration	-	-	-	-	-		-
Industry depletion	-	-	-	+	-	+	

'+' : the row driver leads to higher next margins, in average
'-' : the row driver leads to lower next margins, in average

Figure 39: Summary of 1 vs.1 predominance of individual drivers

Figure 39 provides a one vs one predominance comparison of individual drivers. Green square signify that the row driver is more important than the column driver in average. For instance, it is preferable for *Next* Margins to have high *Steepness of cost curve* and low *Capital Intensity* than the contrary.

V.2. Results – *Logic Tree Model*

Our *Logic tree model* provides result that are summarized in **Figure 41**. As these results were obtained with proprietary data, we have anonymized them. One way to confirm is expert judgment. This model was designed to assess the high-level attractiveness of any commodity, in an intuitive and transparent manner. The conformity of the attractiveness scores to expert judgment for the commodities that are well understood therefore indicates that the model can be used as a starting point to assess the attractiveness of commodities which are less understood. This model also allows decision-makers to visualize the main driver of attractiveness for each commodity (see
Figure 42 and **Figure 40** for instance).

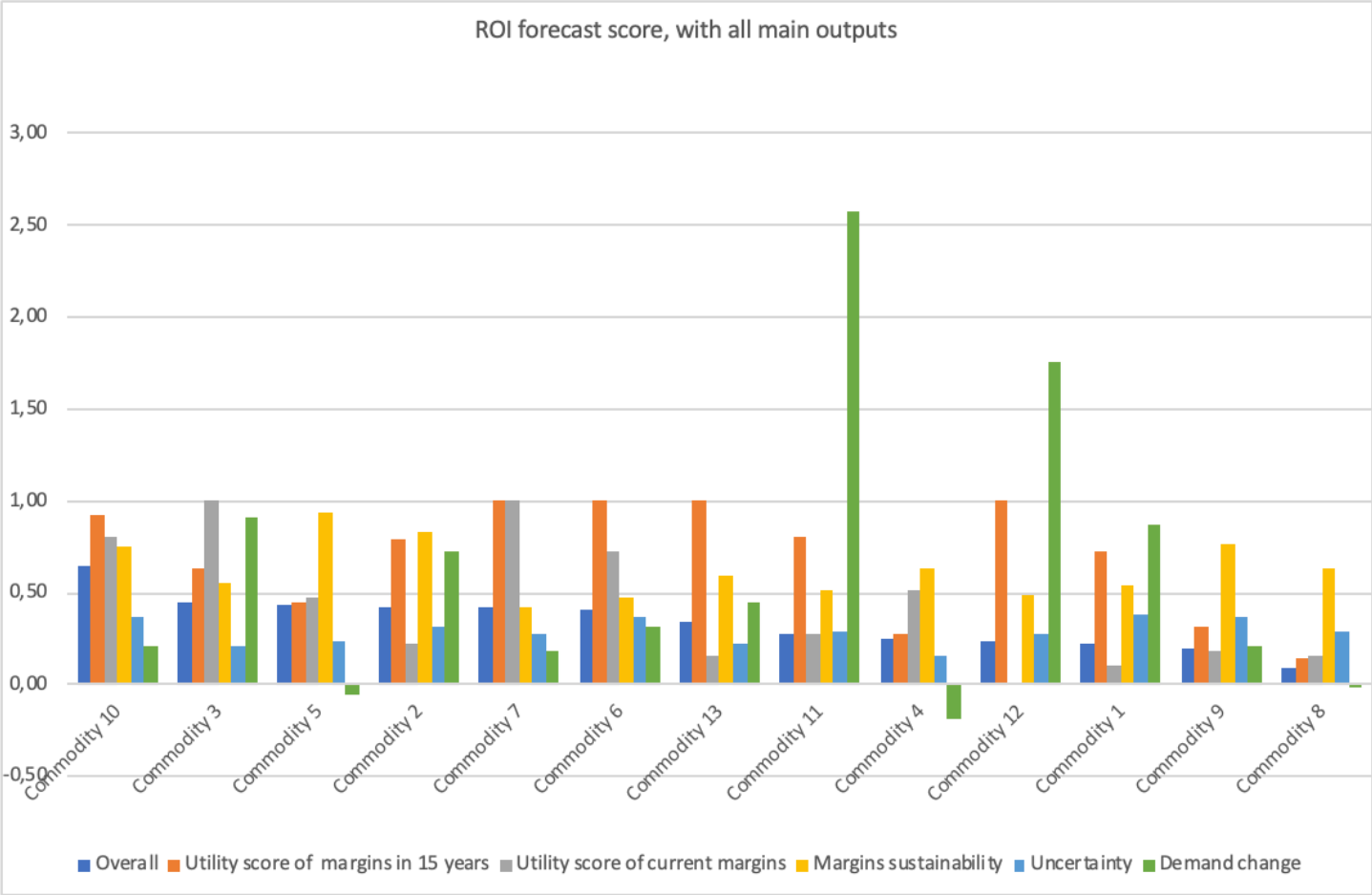

Figure 41: Logic tree model - *ROI score for real world commodities*

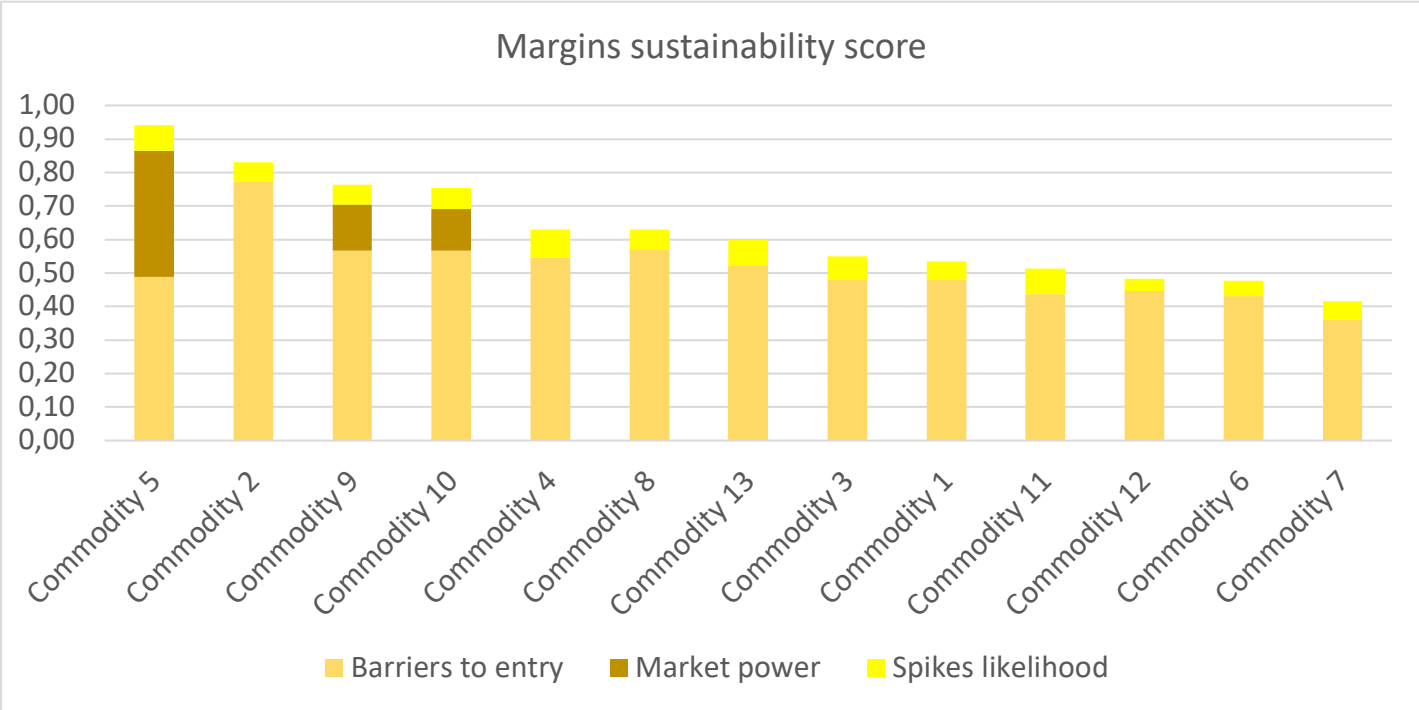

Figure 40 : Logic tree model – *Margins sustainability score for real world commodities*

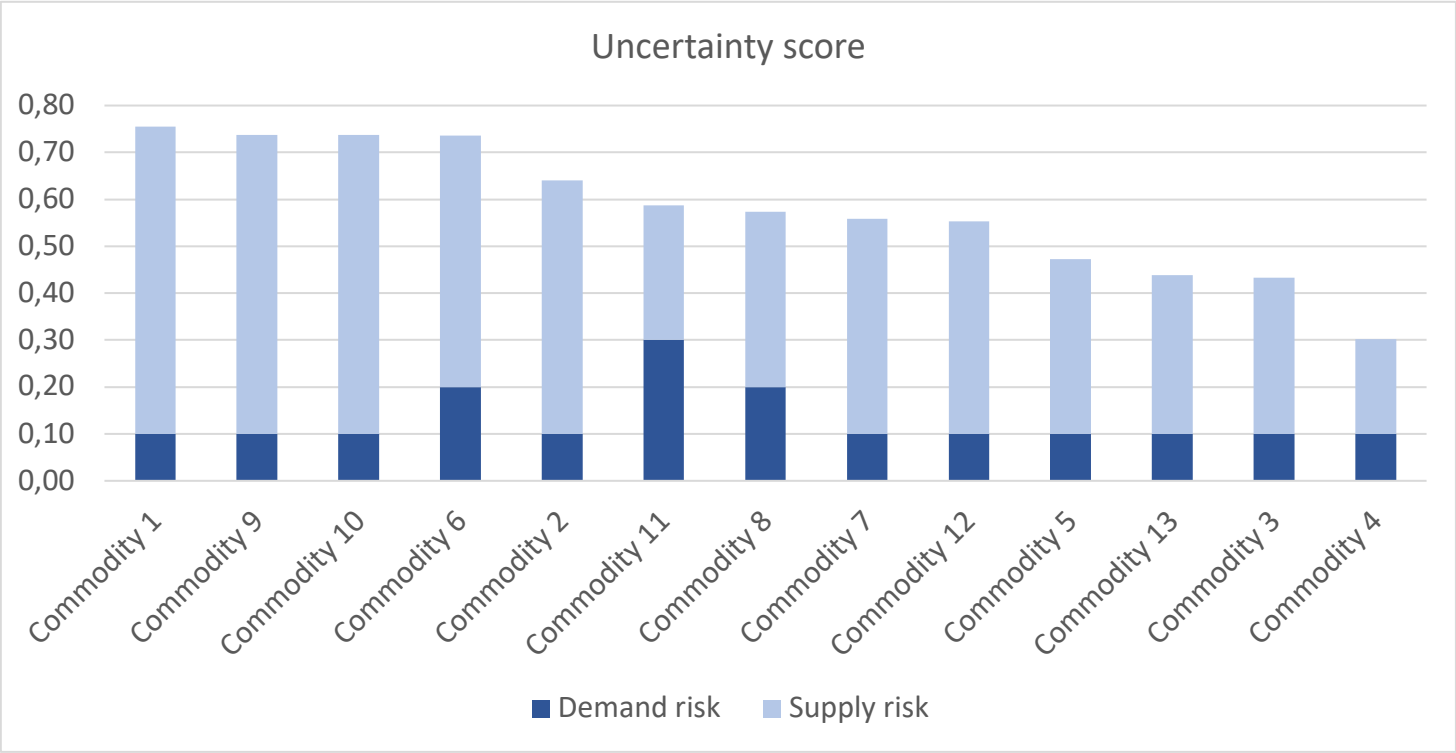

Figure 42: Logic tree model – *Uncertainty score for real world commodities*

V.3. – *Logic tree model* vs. *Cost curve model*

Another way to test the insightfulness of the *Logic tree model* is to benchmark it against our *Cost curve model*. For this purpose, we considered a subset of the synthetic commodities introduced in the previous section. **Table 8** summarizes the main inputs, and the results obtained with the *Cost curve model.*

	Synthetic commodity 1	Synthetic commodity 2	Synthetic commodity 3	Synthetic commodity 4	Synthetic commodity 5	Synthetic commodity 6	Synthetic commodity 7	Synthetic commodity 8	Synthetic commodity 9	Synthetic commodity 10
Description	**Worst case:** all drivers indicate poor performance, and current margins are low	**Bad case 1:** drivers indicate poor performance, but current margins are average	**Bad case 2:** great grivers mitigate poor drivers, and current margins are average	**Intermediate-bad case 1:** drivers indicate great performance, but current margins are low	**Intermediate-bad case 2:** great grivers mitigate poor drivers, and current margins are average	**Intermediate-bad case 3:** great grivers mitigate poor drivers, and current margins are average	**Intermediate-good case 1:** most drivers indicate average-to-great performance, and current margins are only average	**Intermediate-good case 2:** great grivers mitigate poor drivers, and current margins are very high	**Good case:** most drivers indicate great performance, although current margins are only average	**Best case:** all drivers indicate great performance, current margins are great
Current Margins	30%	115%	30%	30%	115%	115%	115%	200%	115%	200%
Next Margins	3%	50%	50%	100%	100%	100%	150%	150%	200%	820%
Margin increase	-89%	-56%	68%	232%	-13%	-13%	30%	-25%	74%	310%
P90/P25	1.3	2.15	1.3	1.3	2.15	2.15	2.15	3	2.15	3
Capital Intensity	1	1	1	3.5	3.5	1	1	1	3.5	3.5
Reserves	100	100	30	100	100	100	65	100	30	30
Ore body depletion	2%	2%	2%	0%	2%	0%	2%	0%	2%	2%
Demand growth	0.0%	0.0%	0.0%	3.0%	0.0%	1.5%	3.0%	1.5%	0.0%	3.0%
SOE concentration	50%	50%	0%	25%	25%	0%	0%	25%	0%	0%
Industry depletion	0%	1%	2%	0%	0%	2%	1%	2%	1%	2%

Table 8 : Description of 10 synthetic commodities chosen to span the range of next margins prediction

Table 9 reports the ROI score that synthetic commodities 1 to 10 are given by the *Logic tree model,* and compares it to the forecast of the *Cost curve model*. **Figure 43** and **Figure 44** provide additional details regarding the ROI and uncertainty scores.

	1	2	3	4	5	6	7	8	9	10
Score, Business economics model	**0.02**	**0.39**	**0.07**	**0.17**	**0.53**	**0.48**	**0.48**	**0.69**	**0.61**	**0.66**
Next margins - Microeconomics model	3%	50%	50%	100%	100%	100%	150%	150%	200%	820%
Margin increase - Microeconomics model	-89%	-56%	68%	232%	-13%	-13%	30%	-25%	74%	310%

Table 9 : Comparison of Logic tree *and* Cost curve *models for synthetic commodities of Table 8*

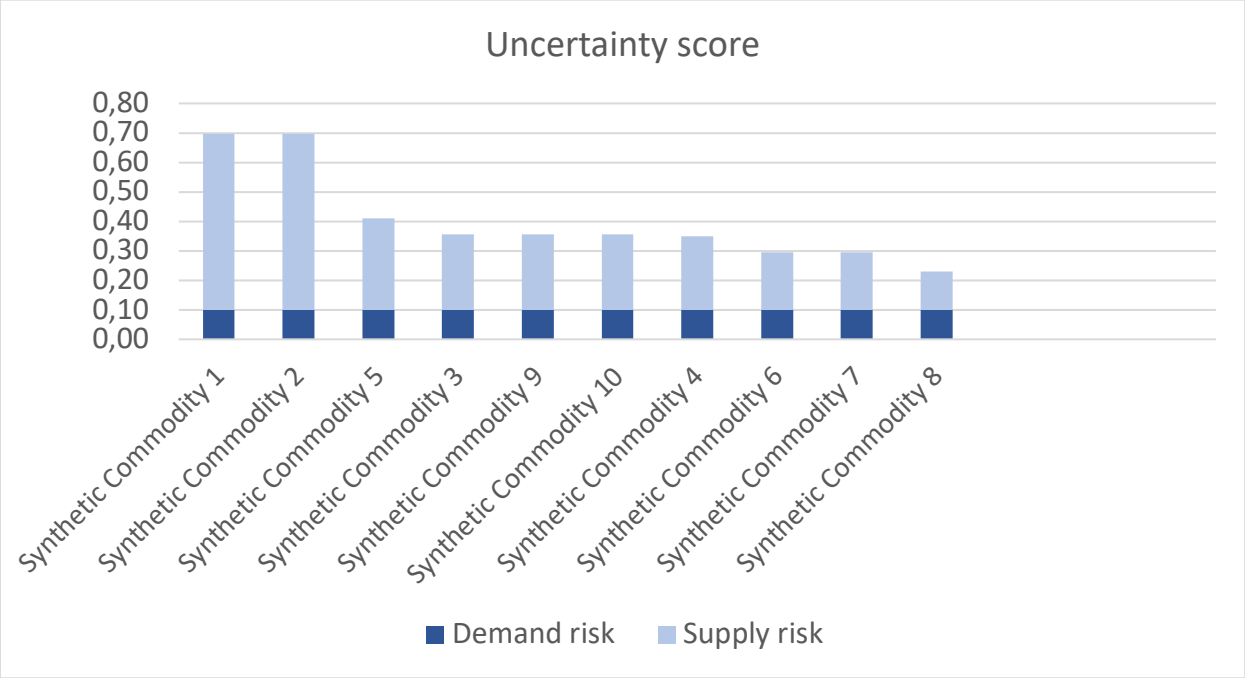

Figure 43: Logic tree model – *Uncertainty score for synthetic commodities of Table 8*

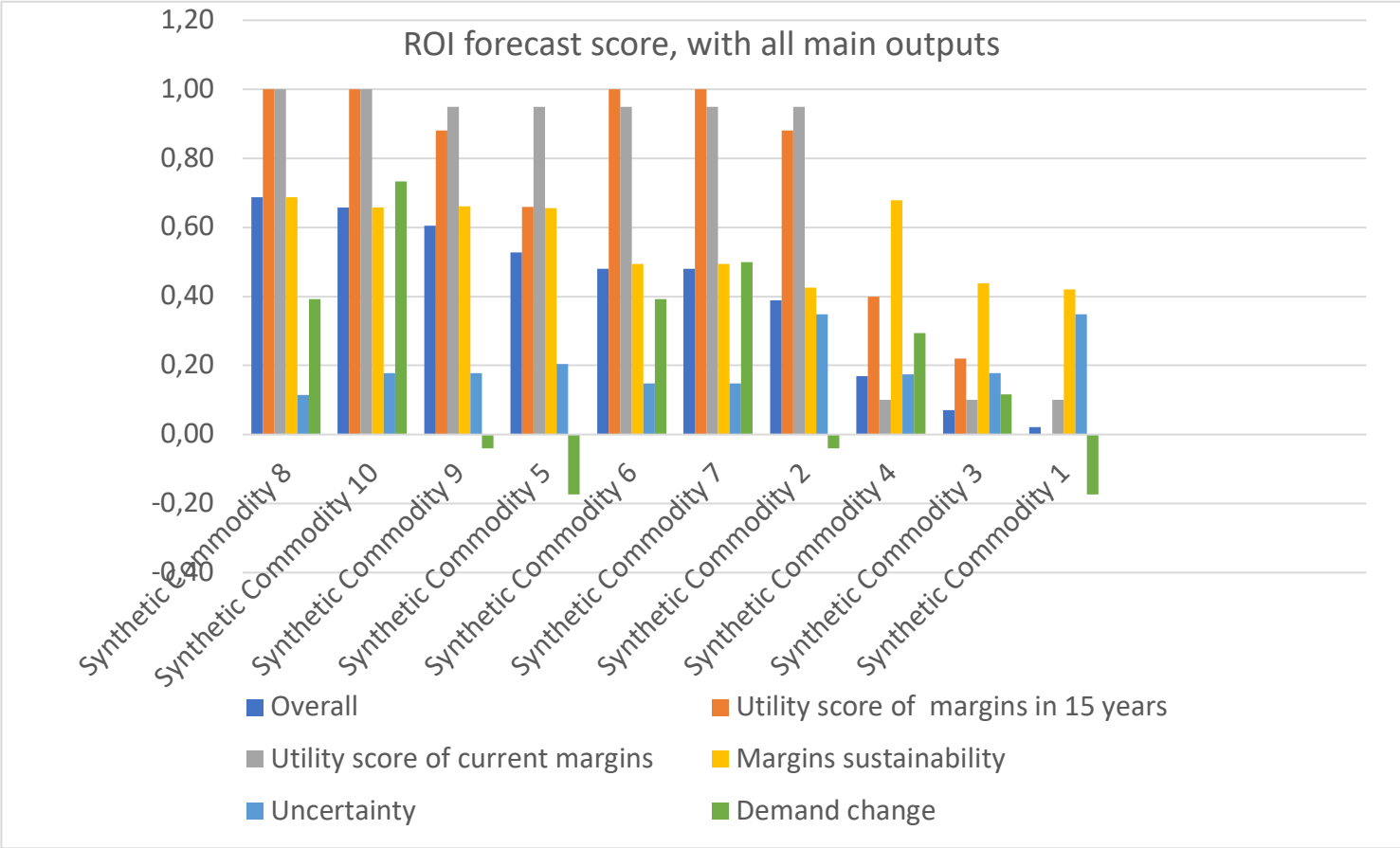

Figure 44 : Logic tree model – *ROI score for synthetic commodities of Table 8*

The results of our two models are mostly aligned. Synthetic commodities 2 and 8 are the major discrepancies. While synthetic commodity 2 (SC2) is supposed to be very unattractive based on the *Cost curve model*, the *Logic tree model* gives it an average score. On the other hand, the *Logic tree model* overrates synthetic commodity 8 (SC8) compared to the *Cost curve model.*

Going back to **Table 8**, the good drivers are *Ore body depletion* and *Current Margins* for SC2 and *Industry depletion* and *Current Margins* for SC8. On the other hand, the bad drivers are *Capital Intensity, Production Cover, Demand Growth* and *SOE concentration* for SC2, and *Capital Intensity* and *Production Cover* for SC8. This indicates that the *Logic tree model* may overestimate the long-term impact of *Current Margins* and an underestimation of the impact of low barrier to entries due to low *Capital Intensity* and high *Production cover*, compared to the *Cost curve model*. Further work could be done to tune parameters in the *Logic tree model*, in order to enhance the consistency of the *Logic tree model* with the *Cost curve model.* However, we do not want to alter the insights of this model, coming from qualitative case studies and expert interviews, based on such little evidence (10 synthetic commodities). Moreover, the results from **Table 9** show a correct amount of consistency across the two models.

In a nutschell, there is a good fit between both models and when there are discrepancies, they can be attributed to the specific weaknesses of each models. These discrepancies can indicate ways in which both model could be improved. For instance, the discrepancies for SC2 and SC8 could be eliminated by relaxing the linearity assumption in the

cost curve model. Real world cost curves tend to have concave slopes, which would entail a more positive *Next Margins* forecast for SC2 and SC8 in the *Cost curve model*, because these two synthetic commodities both have high *Cost-curve steepness*. For a given *Cost-curve steepness*, the current margins of the 25th percentile asset is lower when the cost curve is modeled as concave rather than linear. Thus when *Cost-curve steepness* is high, the spread, or the utility of high current margins is higher in the concave case. Thus relaxing the linearity assumption should help reconcile discrepancies and improving the models fit.

Conclusion

In this thesis, we determined which forces drive commodity attractiveness, and how a general framework could assess the attractiveness of mining commodities.

We identified with 18 key drivers of attractiveness, and we aggregated them following two concurrent approaches. The first approach, based on microeconomics theory, led us to developing the *Cost curve model*. The second, based on business economics theory, led us to developing the *Decision tree model*. The first model allocates a score to each commodity and the second one provides a forecast of what the next margins are. This forecast is not meaningful out of context and has to be used only to compare a commodity's attractiveness, based on a benchmark against forecast for other commodities by this same *Cost curve model*.

The limitations of each model come from very different sources. On the one hand, the *Logic tree model* is based mostly on intuition, thus it might miss some of the mechanical interactions linked to the cost curve structure the industry. On the other hand, the *Cost curve model* accounts for these structural details, but it misses some insights because of the simplifying assumptions on which it relies. Thus, the two models are complementary.

Possible next steps include tuning the models based on historical data and improving them by relaxing assumptions. For instance, the *Cost curve model* could be made more precise by allowing non-linearity. Another major improvement would consist in better understanding the relationship between incentive capacity and barriers to entry.

The results presented in subsections V. provide:

(i) a high-level tool to assess mining commidity attractiveness based on very little data points (See V.1.), and
(ii) a high-level description of which drivers are the most important, in relative terms, and of how drivers interact to mitigate or enhance attractiveness (See V.3.).

(i): With a reduced number of data points (see **Table 3**) for a given commodity, a quick-way to assess it's attractiveness at a high level is to fit these data points to **Table 5**, **Table 6** and **Table 7**. If *Incentive Capacity* is higher than .25 years of current production, one should look at **Table 5** and discriminate attractiveness based on *Cost Curve Steepness, Demand Growth* and *Capital intensity.* Otherwise, one should look at **Table 6** or **Table 7** and discriminate attractiveness either based on *Cost Curve Steepness, Demand Growth* and *Capital intensity,* or based on *Cost Curve Steepness, Demand Growth, Ore Body depletion* and *Industry depletion.*

In order to conduct a more thorough assesment, one can follow the decision trees (see **Figure 33**, **Figure 34**, and **Figure 35**). A more complete assessment would require using the *Cost Curve model* and conducting a sensitivity analysis.

(ii): The decision trees and the results in section V.3 provide insights as to which drivers are the most important on average. *Incentive capacity* and *Cost curve steepness* come out as the two most important drivers of attractiveness. *Demand growth* and *Capital intensity* play a major part in mitigating or enhancing attractiveness. *Industry depletion* and *Ore body depletion* also have mitigating or enhancing roles, although to a lesser extent.

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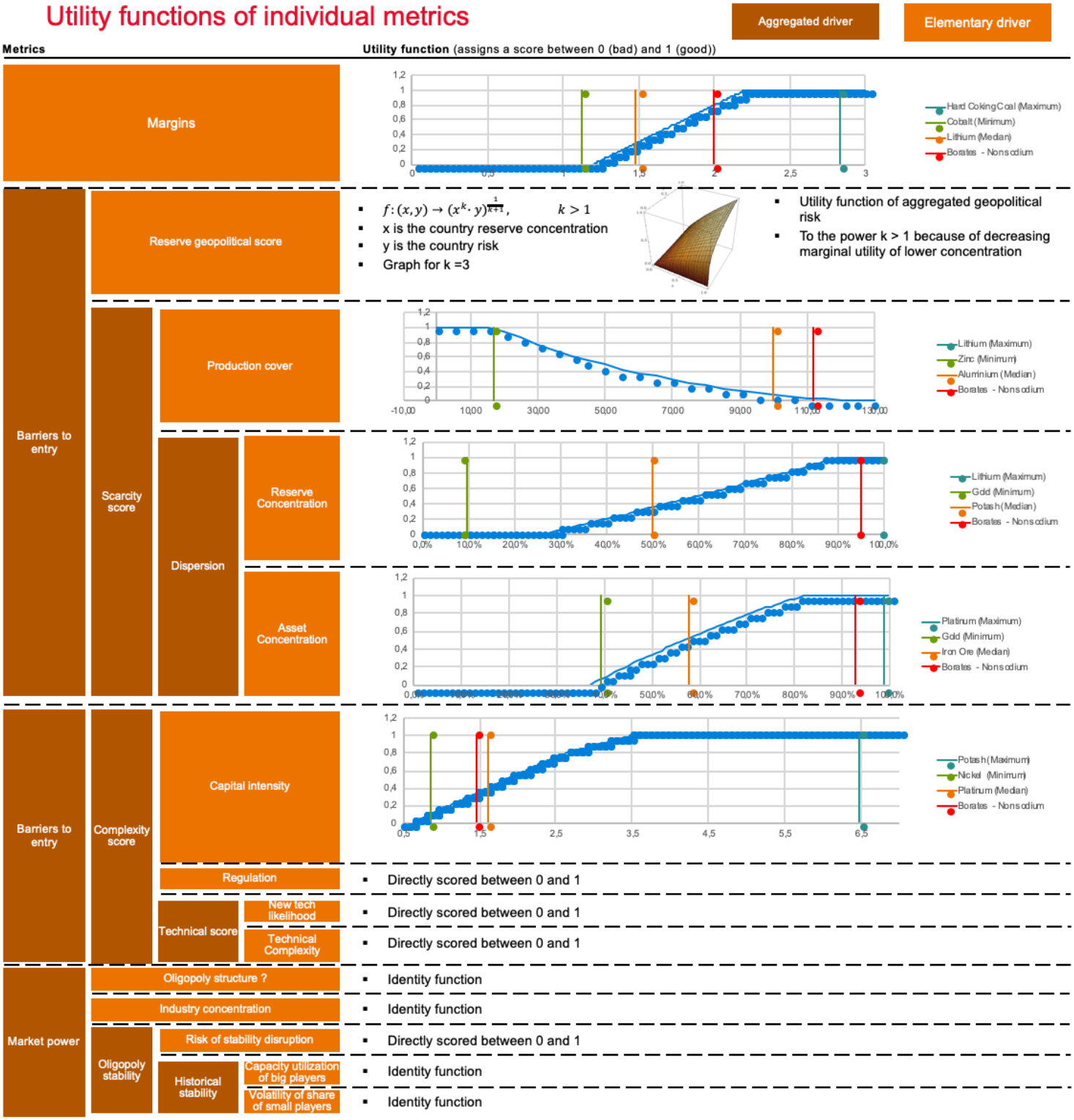
Appendix

Appendix for section IV.

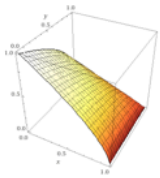
- <u>Utility function for all drivers (see IV.2.a.):</u>



Spikes likelihood

Supply Geopolitical risk

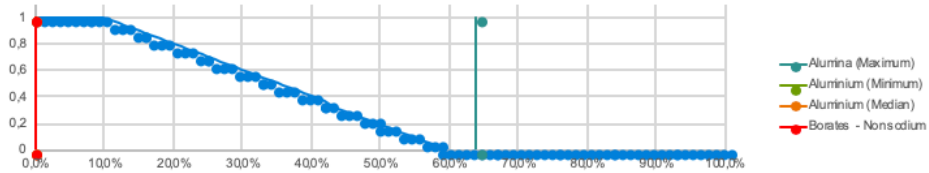
- $f:(x,y) \rightarrow 1-(x^k \cdot y)^{\frac{1}{k+1}} \qquad k>1$
- x is the country supply concentration
- y is the country risk
- Graph for k =2



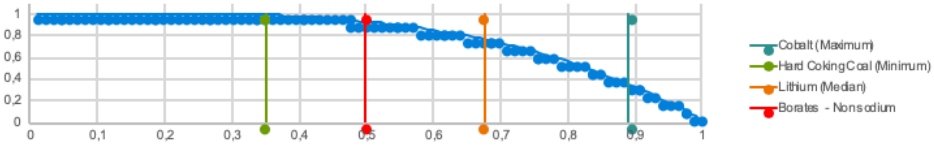
- Utility function of aggregated geopolitical risk
- To the power k > 1 because of decreasing marginal utility of lower concentration

Barriers to exit

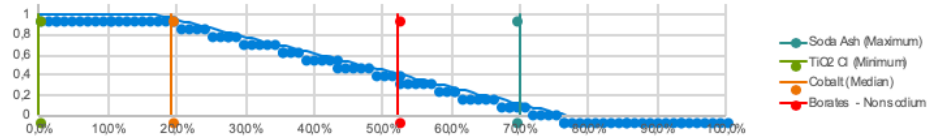
Vertical integration



Cost curve flatness



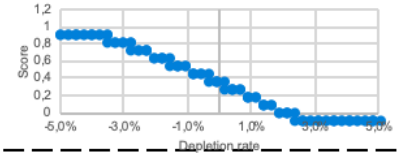
SOE concentration



Investment need

Depletion

- Identity function (this is an exception as it is not scored between 0 and 1)



Capacity Utilization

- $f: x \rightarrow 1-x$

Volume of stocks

- Identity function

Demand growth

Growth of volume drivers

Growth of material intensity

- Identity function

- Utility function of aggregated demand growth
- Reproduces utility function of previous version

Demand risk

Substitution risk (incl. regulations)

- Directly scored between 0 and 1

- Reproduces utility function of previous version

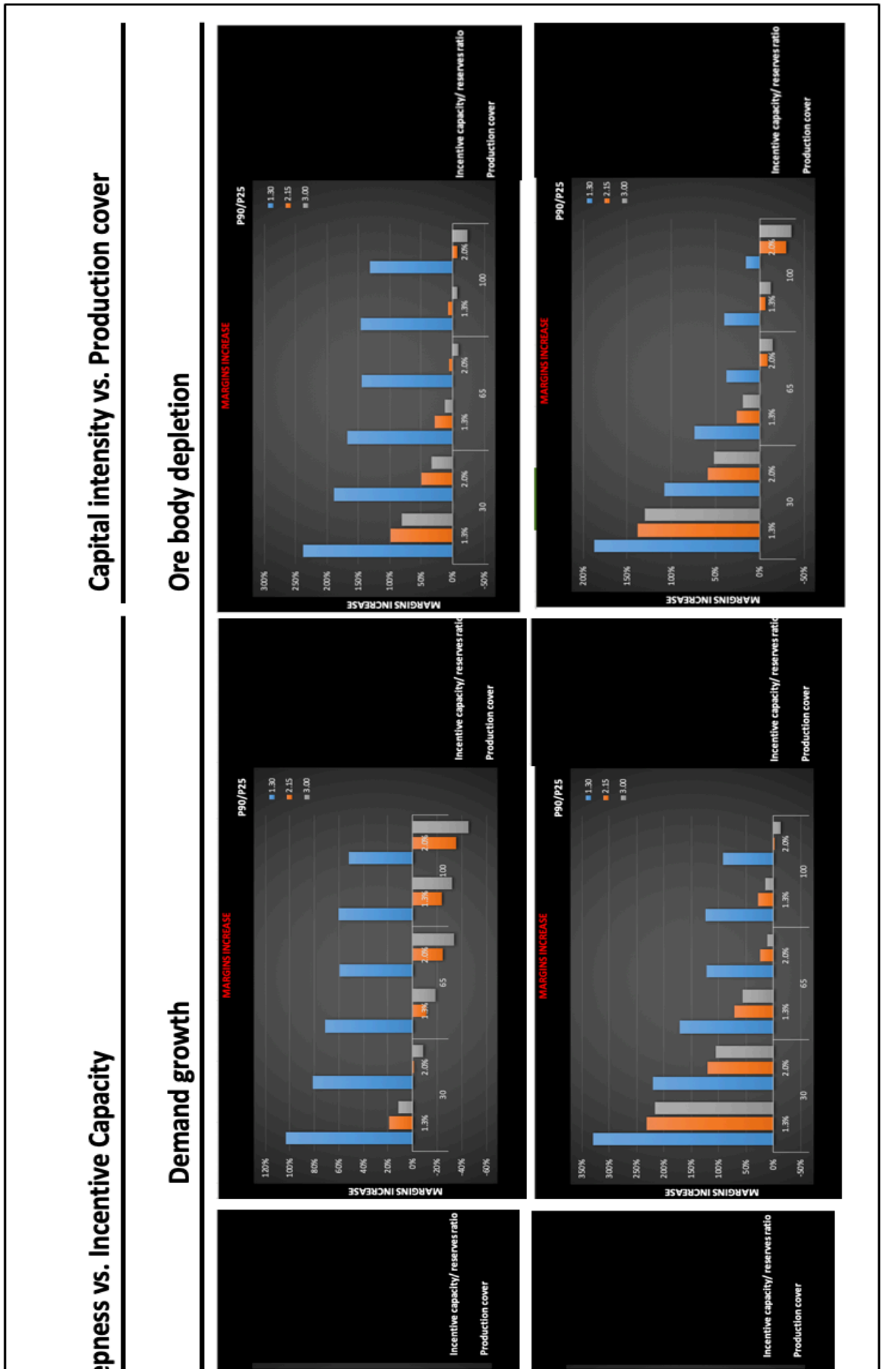
Negative disruption risk

- Directly scored between 0 and 1

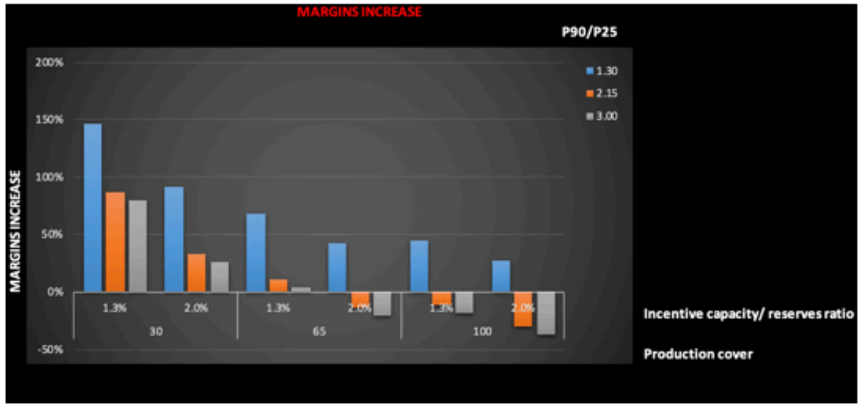
- Reproduces utility function of previous version

Appendix for section V.

- <u>Comparison of next margins across drivers, in function of incentive capacity and current margins (see V.1.b.):</u>



Margins increase for varying level of Industry depletion, Capital Intensity and Demand Growth - Current Steep

Variable	Industry depletion	Capital Intensity
Low		
High