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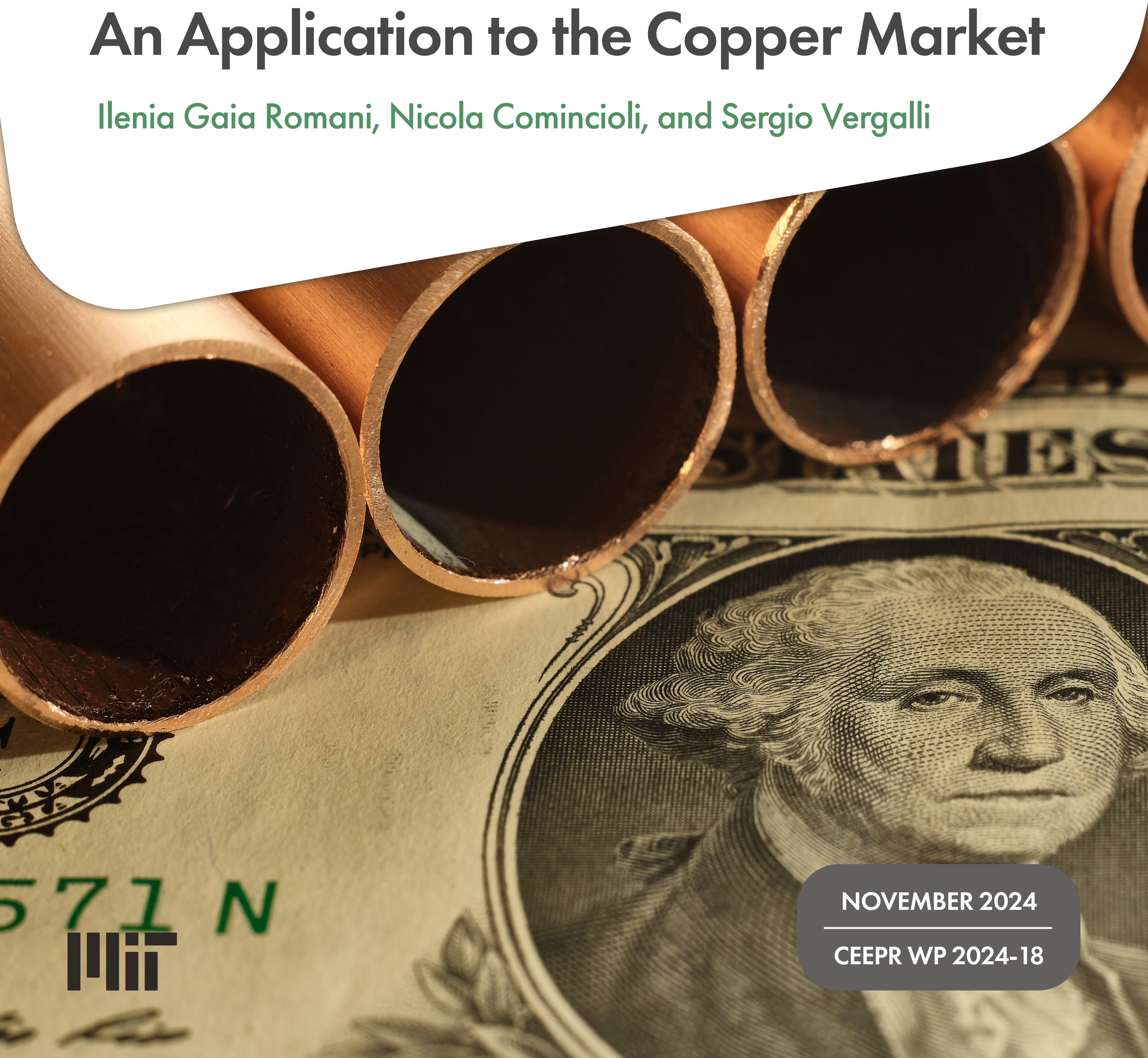

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Climate policy and cartelization risk for critical minerals: An application to the copper market

Ilenia Gaia Romani[1,2,3] Nicola Comincioli[1,2] Sergio Vergalli[1,2]

[1]*Department of Economics and Management, University of Brescia, Italy*
[2]*Fondazione Eni Enrico Mattei, Italy*
[3]*CEEPR, Massachusetts Institute of Technology, USA*

Abstract

Demand for critical raw materials is on the rise, largely due to the energy transition. As demand increases, so do concerns about cartelization attempts, in which some mining countries might organize to control the market by eliminating competition among producers. This would reduce output and thereby force up prices. Quantifying the potential profits of cartelization for specific minerals will help us predict which attempts could succeed. We apply a theoretical model of non-renewable resources extraction to the copper market, and calculate the optimal price, profits and reserves trajectories in a competitive versus a monopolistic market. Our results show that, in the long run, the expected profits of a copper cartel are approximately one and a half times higher than those achieved without market power.

JEL Classification: D43; Q32; C61.

Keywords: Copper; Critical minerals; Cartelization risk; Climate policy; Non-linear dynamic programming.

1 Introduction

Global demand for critical minerals essential to the green transition, such as copper, nickel, cobalt, and Rare Earth Elements (REEs), has experienced unprecedented growth in recent years (Islam et al., 2022; Radetzki et al., 2008). As is common across the mining industry, deposits are often highly localized geographically (Agusdinata et al., 2022). Consequently, a significant portion of the reserves might be controlled by only a few countries or even a single one. Additionally, the mining sector has high barriers to entry that reduce competitiveness, such as substantial fixed capital costs. Taken together, these conditions limit the competitiveness, thus increasing the likelihood of cartel formation (Pindyck, 1978).

Numerous precedents since the 1960's suggest that cartelization of mineral commodity markets is a real possibility. The most notable example is represented by the oil market, where the geographical concentration of deposits has granted near-monopoly power to a group of countries that formed the Organization of the Petroleum Exporting Countries (OPEC). The OPEC has been significantly influencing oil prices since its formation in 1960 (Comincioli et al., 2021). It is currently comprised of 12 member countries, along with 11 non-member countries that voluntarily follow its directives (OPEC+) and 4 observers.[1] As of 2023, the OPEC controls 35.4% of global oil production[2] and, as of 2022, 79% of proven oil reserves.[3] Other notable examples include the Intergovernmental Council of Copper Exporting Countries (CIPEC) and the International Bauxite Association (IBA). The CIPEC, founded in 1967, initially had four members, with four additional countries joining in 1975.[4] At that time, the CIPEC controlled about 30% of world copper refinery production and owned half of the global copper reserves. However, the organization lost effectiveness due to organizational challenges, such as difficulties in coordinating production cuts among members, and geopolitical factors. These issues, along with the higher demand elasticity for copper with respect to oil, ultimately led to CIPEC's dissolution in 1988 (Renner & Wellmer, 2020). The IBA was created in 1974 by seven founding members, with four additional countries joining later that year.[5] Despite excellent results, such as a tripling of bauxite prices by 1979 compared to pre-IPA levels, the organization dissolved after Australia, which alone accounted for 40% of global bauxite production, left the organization, finding no benefit in continued membership (Crasnic, 2019; Hodgkinson, 1980).

Issues arising from high resource concentration are also a concern for critical minerals. For

[1]Current members are Algeria, Equatorial Guinea, Gabon, Iran, Iraq, Kuwait, Libya, Nigeria, the Republic of the Congo, Saudi Arabia, the United Arab Emirates and Venezuela, while Angola, Ecuador, Indonesia and Qatar left the organization. Current OPEC+ members are Azerbaijan, Bahrain, Brunei, Brazil, Kazakhstan, Malaysia, Mexico, Oman, Russia, South Sudan and Sudan while observer countries are Canada, Egypt, Norway, and Oman.

[2]See: https://www.eia.gov

[3]See: https://www.opec.org/opec_web/en/data_graphs/330.htm

[4]Founding countries were Chile, Peru, Zaire and Zambia, later joined by Australia, Indonesia, Papua New Guinea and Yugoslavia.

[5]Founding countries were Australia, Guinea, Guyana, Jamaica, Suriname, Sierra Leone and Yugoslavia, later joined by Ghana, Haiti, the Dominican Republic and Indonesia

example, (i) the Democratic Republic of Congo (DRC) holds nearly half of the world's cobalt reserves, (ii) Mozambique controls more than half of the global graphite reserves, (iii) Argentina, Bolivia, and Chile, known as the "lithium triangle", together hold half of the world's lithium reserves, (iv) China has 34% of the world's copper reserves, and (v) Indonesia controls over 20% of the world's nickel reserves, fundamental for the growing electric vehicle (EV) battery production industry. It is therefore possible that some resource-rich countries or groups of countries may organize to jointly control a significant share of the market in order to gain a strategic advantage. Countries like the DRC, Chile, Peru, China, Russia, South Africa, and Australia could potentially benefit from the increasing demand for critical raw materials. In fact, there are growing concerns that mineral-rich countries could attempt to form an Organization of Metal-Exporting Countries (OMEC).[6] Furthermore, several copper- and nickel-producing countries, led by Indonesia, are considering forming a cartel to control the global supply and pricing of battery metals.[7] Similarly, the countries in the "lithium triangle" have also considered establishing a cartel.[8]

As demonstrated by the historical cases of OPEC, CIPEC, and IBA, having a high concentration of resources alone is not sufficient to form a successful cartel. In addition to this necessary but not sufficient condition, cartel members must also (i) effectively coordinate in controlling production quotas and (ii) ensure that this coordination is enforced and generates sufficient additional profit, compared to a competitive market scenario, to justify the effort. More specifically, since the creation of a cartel is costly in economic, political, and coordination terms, there must be substantial potential gains for a cartel to form and succeed (Pindyck, 1978). These gains must at least offset the significant costs associated with cartelization.

The objective of this study is therefore to assess the potential for cartel formation in critical minerals markets, by analyzing whether a group of candidate cartel members can generate extra profits, compared to a perfectly competitive scenario. Specifically, we focus on the copper market for several reasons. First, copper holds great historical relevance as a key element in technological development since the dawn of civilization, a role it continues to play in modern technologies, e.g. electric vehicles and low-carbon power generation technologies (Seck et al., 2020). Additionally, the availability of long-term and reliable time series makes copper an ideal candidate for empirical analyses. Finally, compared to other critical minerals, the copper market has been extensively studied in the scientific literature, providing a strong foundation for further investigation. We apply a twofold approach. First, using up-to-date data, we calibrate the key equations of the copper market, i.e. demand and supply, distinguishing between primary and secondary supply. Then, we complement these equations with those accounting for the dynamics of reserves and stock, presenting a full model of the copper market. The evolution of this model is then determined under two scenarios: (i) perfect competition, following the Hotelling's rule, and (ii) cartel facing a competitive fringe, solving a dynamic programming

[6]See: https://www.project-syndicate.org/commentary/critical-minerals-metals-from-opec-to-omec-by-ludovic-subran-1-2023-08 and https://www.ft.com/content/394dca37-ac50-4380-9b03-4fdfcef2ff7c

[7]See: https://www.ft.com/content/0990f663-19ae-4744-828f-1bd659697468

[8]See: https://www.forbes.com/sites/eliasferrerbreda/2023/08/08/is-this-the-dawn-of-a-lithium-opec/

problem. The resulting price trajectories and the consequent profits for a group of candidate cartel members are finally used to assess the potential cartelization risk. Substantial gains from cartelization might be sufficient to offset political and organizational costs, and could subsequently be interpreted as a potential driver for cartel formation.

An assessment of the cartelization risk in critical mineral markets provides crucial information to governments and policymakers committed to the green transition. Meeting emissions targets is closely linked to a wide set of actions and investments that in turn depend on a stable and reliable supply chain of critical minerals. Although some copper importers have already put in place plans to secure their access to such minerals, by diversifying the supply and maximizing the recycling,[9] the formation of a cartel could still significantly slow down their progress toward the green transition. This might happen due to, e.g., (i) artificially inflated prices, (ii) reduced production or creation of artificial shortages, (iii) market instability, (iv) decreased innovation and efficiency resulting from the concentration of market power, and (v) geopolitical instability. Therefore, identifying in advance which markets are most at risk of cartelization would allow decision-makers to implement dynamic strategies mitigating potential impacts on the supply chain and, consequently, on the green transition.

The rest of this paper is structured as follows. Section 2 presents a review of the relevant literature on the exploitation of exhaustible resources, first under perfect competition, then in monopolistic or cartel markets. Section 3 outlines the modeling of a commodity market in both these scenarios. Section 4 then presents the application of the model to the copper market. Finally, Section 5 concludes with a discussion of the policy implications.

2 Literature review

2.1 Perfect competition

Most of the scientific literature on the extraction of nonrenewable resources originates from the seminal paper by Hotelling (1931). This study addresses the problem of determining the optimal exploitation rate of an exhaustible resource, considering that over-exploitation, driven by excessively low prices, occurs at the expense of future generations. The basic model is a constrained optimization problem, applied to a perfectly competitive market, which leads to two remarkable implications.

The first one is that the net price[10] of an irreplaceable finite resource grows at the real rate of interest. Under the constraint of limited reserves, an agent seeking to maximize the Net Present Value (NPV) of future cash flows has to extract a natural resource so that its net

[9] As, for example, the European Critical Raw Materials Act https://ec.europa.eu/commission/presscorner/detail/en/ip_23_1661, or the U.S. Inflation Reduction Act of 2022 https://www.govinfo.gov/content/pkg/PLAW-117publ169/pdf/PLAW-117publ169.pdf and the CHIPS and Science Act https://www.govinfo.gov/content/pkg/PLAW-117publ167/pdf/PLAW-117publ167.pdf.

[10] In the literature, this concept is also referred to by the following terms: scarcity rent, shadow price, royalty, marginal user cost, and in the language of optimal control theory, the costate variable.

marginal value rises at the rate of interest (Levhari & Liviatan, 1977). In other words, the main driver of a resource's price is its own exhaustibility (Gaugler, 2015). The second implication is that, under the hypothesis of time-invariant costs and perfect competition, market price rises over time in real terms. More precisely, if marginal cost is zero (positive) the price's growth rate will be equal to (lower than) the rate of interest.

A substantial body of literature has stemmed from Hotelling (1931), examining the optimal extraction of exhaustible resources from various perspectives. A first stream of literature has focused on extending Hotelling's original model to enhance its realism by incorporating factors such as changing extraction costs, which can be driven down by technological advancements, driven up by physical depreciation, or impacted by expectations about future scarcity (Dasgupta & Heal, 1979; Solow, 1974; Solow & Wan, 1976; Stiglitz, 1974). Other works have instead focused on market structure, going beyond the assumption of perfect competition. In this way, it is possible to consider more realistic structures of the market of non-renewable resources, such as monopoly (Stiglitz, 1976) or oligopoly (Salant, 1976). This strand of literature is treated in detail in Section 2.2.

Finally, beyond the various theoretical advancements, empirical testing of the Hotelling's rule has played a significant role in the development of the related literature. In fact, numerous empirical studies have assessed the validity of Hotelling's theory across different resource markets, e.g., oil, gas, and other mineral resources, mainly testing it in an indirect way, i.e. focusing on trends in market prices instead of the unobservable scarcity rents. However, these studies have yielded inconclusive or inconsistent results (Krautkraemer, 1998; Livernois, 2009). Markets for a large number of mineral resources have been studied, based on nearly a century-long series, finding either the impossibility of making any inference (Smith, 1979) or unexpected U-shaped price trajectories (Slade, 1982). Later studies reached, again, conflicting conclusions (Agbeyegbe, 1989; Berck & Roberts, 1996; Lee et al., 2006). The literature has therefore proposed several factors that might explain the apparent lack of a common price trend. On one hand, even the most advanced versions of the Hotelling's model still rely on strongly restrictive assumptions. On the other hand, there are inherent challenges in the exercise of its empirical validation, such as issues with data availability and consistency. Most importantly, price dynamics are influenced by factors other than scarcity, with extraction costs being particularly relevant (Anderson et al., 2018). To address these limitations, the literature is shifting toward either (i) extending the theoretical model of reference by relaxing its assumptions, such as those related to market structure, or (ii) enhancing empirical methods and focusing on developing particularly precise econometric models of an individual non-renewable resource.

2.2 Market power

The assumption of perfect competition in the Hotelling's basic model has been widely questioned in the literature, as markets for exhaustible resources frequently exhibit monopolistic, oligopolistic or cartel behavior. As a result, a large body of research has focused on how resource depletion and market prices are determined under these different circumstances. Modeling imperfectly competitive resource markets has shown that prices are higher than in competitive equilibrium, regardless of initial conditions, consistent with the allocative inefficiency predicted by microeconomic theory (Stiglitz, 1974; Stiglitz & Dasgupta, 1982). Among possible imperfect competition frameworks, the theoretical development more likely to reconcile Hotelling's rule with the observed market prices seems to be some form of oligopolistic competition (Gaudet, 2007), where the behavior of price and depletion rate can range from being similar to pure monopoly to being similar to perfect competition (Livernois, 2009). The strategic interactions among players with market power, such as cartel members, introduce an additional layer of complexity, which might be addressed through a Nash-Cournot approach, where players ignore each other's strategies (Salant, 1976; Ulph & Folie, 1980), or a von Stackelberg model of pricing behaviour by a dominant firm (Gilbert, 1978), or a model of a monopolist facing a competitive fringe (Cremer & Weitzman, 1976; Pindyck, 1978).

As for the empirical validation of imperfect competition models, the scientific literature has mainly focused on the oil market, given the important role of the resource itself and its cartel, the OPEC, on the global economy. However, the evidence is, once again, that prices do not follow the trajectories predicted by Hotelling's model extensions, likely due to the influence of exogenous factors, e.g. technological advancements (Krautkraemer, 1998), durability of the resource and the uncertainty about their magnitude (Gaudet, 2007), physical constraints of oil extraction (Davis & Cairns, 1999), substitution effects and political influences, or data limitations (Livernois, 2009).

3 Modelling competitive and cartel markets

To assess the potential risk of cartelization, it is crucial to evaluate whether a group of resource-rich countries can exploit their resource endowment for additional profit. For this purpose, we develop a twofold model to describe two alternative market structures, i.e. (i) perfect competition and (ii) a cartel interacting with a competitive fringe. Using two dynamic models, one for each scenario, featuring a set of state equations and proper initial conditions, we derive two optimal price trajectories towards resource depletion. By comparing the profits following the price trajectories in these two scenarios, we identify an additional gain that can be read as an indicator of cartelization risk.

Let us consider a group of countries naturally endowed with a non-renewable resource that has recently gained interest, whose global demand is excepted to grow for, e.g., its role in energy transition or in new technological applications. In light of that, the resource-rich countries aim to capitalize on their favorable position and maximize profits from resource extraction. They face two possibilities. On one hand, each country can play independently in that resource market, facing the competition of all the other actors and taking market price as exogenous, i.e. under perfect competition. On the other hand, resource-rich countries can enter into an agreement to act collectively, exerting market power to influence prices by restricting production, i.e. forming a cartel. In this case, they would act as a monopolistic producer, leaving room for a competitive fringe, comprising either resource-rich countries that remain outside the cartel, or resource-dependent countries. Under the assumption of rationality, the decision between these two options is driven by profit, which is the objective function of our model.

3.1 Perfect competition

Under perfect competition, numerous producing countries operate in the resource market, all facing equal marginal extraction costs and subject to the same royalties, tax rates and stock constraints. Then, the producers set the same output, Q_t, for any given price, P_t, under the constraint that the change in cumulative output $\dot{x}_t$, i.e. the marginal output, cannot exceed initial reserves, R_0. The market price is exogenous to each producer, who then determines its production plans as a function of price. The problem of each competitive producers is therefore:

$$\begin{aligned} \max_{Q_t} \quad W = \quad & \int_0^T e^{-\delta t}[P_t - C(x_t)]Q_t dt \\ \text{s.t.} \qquad\quad & \dot{x}_t = Q_t, \\ & x_t \leq R_0, \end{aligned} \tag{1}$$

where δ is the discount rate and C is the average cost, which depends on the cumulative output, to reflect higher extraction difficulty, and thus higher cost, as resource exploitations continues. The solution to this dynamic problem is:

$$\dot{P}_t = \delta[P_t - C(x_t)]. \tag{2}$$

This solution, consistent with Hotelling's principles, shows that in a competitive market, marginal revenue equals price. The market net price, defined as market price minus marginal cost, increases at the rate of interest (Hotelling, 1931). To compute the optimal competitive price trajectory, we discretize the solution in Eq. (2) over the interval $[t-1, t]$:

$$P_t = (1+\delta)P_{t-1} - \delta C(x_{t-1}) \tag{3}$$

where $C(x_{t-1})$ can also be expressed in terms of m/R_{t-1}, with m being the initial average cost. As reserves decrease over time, costs rise accordingly, as mentioned above.

Finally, the market is assumed to always be in equilibrium, with a clearing price that rises monotonically over time. It is worth noting that if demand drops to zero before profits do, some of the resource will be wasted, yielding no profit. Profits would, in fact, be higher if the resource were depleted more rapidly at a lower price. Conversely, if profits reach zero before demand does, it indicates that depletion is occurring too rapidly.

3.2 Cartel

In the cartelized scenario, member countries act collectively as a monopolist (Cremer & Weitzman, 1976; Pindyck, 1978). Given their market power, they adjust their output to obtain an optimal profit-maximizing market price, also taking into account the competitive fringe consequent output decision. Compared to the perfect competition case, supply is reduced so that cartel's marginal revenue equals marginal cost. It is important to note that marginal profit, rather than net price or royalty, should increase at the rate of interest in order to maximize the discounted profits over time (Hotelling, 1931).

Let $Q_{tot,t}$ be the total amount of a non-renewable resource exchanged in the market during year t. Since the market is assumed to be in equilibrium, this quantity equals both demand and supply. The total output is influenced by market price and has an autoregressive component, i.e. $Q_{tot,t} = f\left(P_t, Q_{tot,t-1}\right)$. As mentioned above, the market supply is divided between cartel countries (c) and the competitive fringe (f). Therefore, the total output supplied, $Q_{tot,t}$, is shared between the two players, such that:

$$Q_{tot,t} = S_{c,t} + S_{f,t}. \tag{4}$$

The output of the competitive fringe can be further split into primary from mineral ores (p) and secondary, i.e. recycled from scrap (s):

$$S_{f,t} = S^p_{f,t} + S^s_{f,t}, \tag{5}$$

where primary supply depends on the price and on an autoregressive component, i.e. $S^p_{f,t} = f\left(P_t, S^p_{f,t-1}\right)$, while secondary supply is also influenced by the previous and contemporaneous level of stock, i.e. $S^s_{f,t} = f\left(P_t, S^s_{f,t-1}, K_t, K_{t-1}\right)$. The stock K_t represents the total amount of a mineral in product form, and depends on an autoregressive component as well as on total quantity supplied on the market net of its secondary component, i.e. $K_t = f\left(K_{t-1}, Q_{tot,t}, S^s_{f,t}\right)$. The cartel's output is finally found by difference from Eq. (4) given Eq. (5). Moreover, cartel supply is constrained by its reserves, evolving according to:

$$R_{c,t} = R_{c,t-1} - S_{c,t}, \tag{6}$$

The objective of the cartel is to determine the optimal price trajectory $\{P_t\}_{t=1,\dots,T}$, towards reserves depletion, such to maximize the present value of all future cash flows. Thus, the cartel's problem is:

$$\max_{P_t} W = \sum_{t=0}^{T} \frac{1}{(1+\delta)^t} \left(P_t - \frac{m}{R_{c,t}}\right) S_{c,t}, \tag{7}$$

where δ is the discount rate, $m/R_{c,0}$ is the initial production cost which is then monotonically increasing over time, as from Eq. (6). It is worth noting that, as resource depletion approaches, production costs tend to infinity, and so should the price in order to make extraction viable. For this reason, the resource-exhaustion constraint does not need to be explicitly stated.

4 Copper Market Application

In this Section, we apply the models detailed in Section 3 to the copper market. Given the extensive body of studies on this topic, Section 4.1 provides a brief survey of the main empirical contributions, identifying key equations and comparing their main features, which will guide the development of our model. This model will be informed based on the up-to-date database presented in Section 4.2. Estimation of key equations and the definition of our model for copper market are presented in Section 4.3, while the solution for both the competitive and cartelized markets is shown in Section 4.4.

4.1 Empirical studies on the copper market

The empirical models of the copper market can be classified according to different criteria. In terms of geographical focus, some employ a global lens (Pindyck, 1978), others aggregate equations estimated at the country-level (Fisher et al., 1972; Valencia, 2005) or focus on a specific country, typically the U.S. (Shojaeinia, 2023; Slade, 1980). Another possible categorization is based on which market side is considered. Some works estimate demand, primary and secondary supply equations (Fisher et al., 1972; Valencia, 2005), while others focus on the supply side, specifically on its secondary component (Fu et al., 2017; Gomez et al., 2007; Slade, 1980). In addition, some studies explicitly test the market power in the copper market, focusing on the price estimation only (Agostini, 2006; Zhang & Lawell, 2017).

The work by Fisher et al. (1972) is the most seminal contribution in the econometric literature applied to copper market, and served as foundation or as a benchmark for numerous other studies. For example, Pindyck (1978) draws heavily from Fisher's work, and so does Valencia (2005), who proposes a new model by merging the approaches of Fisher and Slade (1980). In addition, Hu and Zandi (1980) re-estimate Fisher's model and compare it with two other econometric models, using 1957-1973 data. Rivera et al. (2021) also compare it with other models, using 1960-2016 data.

The fundamental equations of these relevant contributions are summarized in Table 1. Copper demand equations are quite homogeneous across these studies. Their main determinants are its autoregressive component, the price of copper and of its possible substitutes, e.g. aluminum P^{Al} (Fisher et al., 1972; Valencia, 2005), and measures of economic activity, e.g., the industrial production index IP (Fisher et al., 1972; Valencia, 2005), or household income Y (Shojaeinia, 2023). Some models also add a time trend t, to take into account economic cycle, changes in consumption preferences or technological progress. The equations of primary supply are also fairly similar across models. Some analogies with demand equations are, e.g., the use of an autoregressive component and copper price. Other distinctive variables are, instead, the cumulative primary supply CSP (Pindyck, 1978), the capacity of copper production C used both as an independent or as an additional endogenous variable (Valencia, 2005), the industrial price of electricity EP, as the input price to measure the impact of energy cost on supply of copper (Shojaeinia, 2023), and time trend. Secondary supply equations, on the other hand, show a higher level of heterogeneity. Common drivers include an autoregressive component, the price of copper, and the current stock of copper products available for collection, i.e. to be converted into scrap K. However, the relationship between secondary supply and K can be expressed in different ways. For example, the dependent variable can be either secondary supply (Slade, 1980; Valencia, 2005) or its ratio to the stock (Pindyck, 1978), both in absolute terms or in logarithmic form (Fisher et al., 1972). In addition to the stand-alone stock K, some studies also model secondary supply using its flow, KF (Gomez et al., 2007). Another variable that can be included in modeling secondary supply is production cost CP, accounting for, e.g., the deflated indexes of capital, labor, energy, industrial chemical and transportation costs (Slade, 1980). Furthermore, the industrial production index IP and the Electrical Equipment, Appliance, and Component Index $EEAC$ can also serve this purpose (Fu et al., 2017).

The last row of Table 1 presents the functional form of the key equations we estimate to calibrate the dynamic programming problem. While the main determinants of demand, primary and secondary supply are in line with the other models, a few adjustments are necessary due to the new dataset on which our estimation is based. Details of the estimation process are provided in Section 4.3. For the demand, we retain the equation of Pindyck (1978), except for linearizing the relationship between $Q_{tot,t}$ and t, as the exponential form is not found to be significant. The functional form of primary supply by Fisher et al. (1972) yields instead consistent and significant estimates, so it remains unchanged. Lastly, due to the lack of significance in the updated estimations of the secondary supply equation, in the dynamic programming problem we use the results by Fu et al. (2017).

Reference	Focus	Demand $Q_{tot,t}$	Primary supply $S^p_{f,t}$	Secondary supply $S^s_{f,t}$
Fisher et al. (1972)	Global	$Q_{tot,t} = \beta_1 P_t + \beta_2 Q_{tot,t-1} + \beta_3 P^{Al}_t + \beta_4 IP_t$	$S^p_{f,t} = \beta_1 P_t + \beta_2 S^p_{f,t-1}$	$\ln \frac{S^s_{f,t}}{K_t} = \beta_1 \ln P_t + \beta_2 \ln \frac{S^s_{f,t-1}}{K_{t-1}}$
Pindyck (1978)	Global	$Q_{tot,t} = \beta_1 P_t + \beta_2 Q_{tot,t-1} + (\beta_3)^t$	$S^p_{f,t} = (\beta_1 P_t)(\beta_2)^{-\frac{CSP}{4}} + \beta_3 S^p_{f,t-1}$	$\frac{S^s_{f,t}}{K_t} = \beta_1 P_t + \beta_2 \frac{S^s_{f,t-1}}{K_{t-1}}$
Slade (1980)	U.S.	–	–	$\ln S^s_{f,t} = \beta_1 \ln P_t + \beta_2 \ln K_t + \beta_3 \ln CP_t$
Valencia (2005)	Global	$Q_{tot,t} = \beta_1 P_t + \beta_2 Q_{tot,t-1} + \beta_3 P^{AL}_t + \beta_4 IP_t$	$\mathrm{S}^p_{f,t} = \beta_1 P_t + \beta_2 C_t + \beta_3 t$	$S^s_{f,t} = \beta_1 P_t + \beta_2 \frac{S^s_{f,t-1}}{K_{t-1}} + \beta_3 K_t$
Gomez et al. (2007)	Global	–	–	$\ln S^s_{f,t} = \beta_1 \ln P_t + \beta_2 \ln SS_{t-1} + \beta_3 \ln K_t + \beta_4 \ln KF_t$
Fu et al. (2017)	Global	–	–	$S^s_{f,t} = \beta_1 P_t + \beta_2 SS_{t-1} + \beta_3 IP_t + \beta_4 EEAC_t + \beta_5 t$
Shojaeinia (2023)	U.S.	$\ln Q_{tot,t} = \beta_1 \ln P_t + \beta_2 \ln CS_t + \beta_3 \ln Y_t$	$\ln S^p_{f,t} = \beta_1 \ln P_t + \beta_2 \ln EP_t$	–
Our proposal	Global	$Q_{tot,t} = \beta_1 P_t + \beta_2 Q_{tot,t-1} + \beta_3 t$	$S^p_{f,t} = \beta_1 p_t + \beta_2 S^p_{f,t-1}$	$\frac{S^s_{f,t}}{K_t} = \beta_1 P_t + \beta_2 \frac{S^s_{f,t-1}}{K_{t-1}}$

Table 1: Summary of equations for global demand, primary and secondary supply, as proposed by the most relevant scientific contributions (top) and as estimated in this study (bottom). Constant and error terms are omitted to lighten the notation.

Variable	Description	Unit of measure	Mean	Median	Std. dev.	Min	Max	Source
P_t	London Metal Exchange (LME) copper cash	USD per mt	$4,156$	$3,042$	$2,654$	$1,321$	$9,741$	lme.com
$Q_{tot,t}$	Global refined copper traded quantity	$mt \times 10^6$	13.793	13.700	4.559	7.580	21.900	icsg.org
$S_{c,t}$	Share of global demand met by cartel	$mt \times 10^6$	6.008	5.812	2.855	2.653	10.930	usgs.gov
$S_{f,t}$	Share of global demand met by competitive fringe	$mt \times 10^6$	7.785	7.776	1.750	4.891	10.970	usgs.gov
$S^p_{f,t}$	Primary share of competitive fringe's supply	$mt \times 10^6$	6.499	6.414	1.930	3.370	9.925	usgs.gov
$S^s_{f,t}$	Secondary share of competitive fringe's supply	$mt \times 10^6$	1.286	1.213	0.246	0.878	1.640	usgs.gov
K_t	Global stock of copper in product form	$mt \times 10^6$	253.60	235.10	93.81	131.90	439.50	internationalcopper.org
GDP_t	World gross domestic product (GDP)	2015 USD$\times 10^{12}$	53.854	50.455	18.981	26.929	89.814	worldbank.org
IP_t	Industrial Production (IP) Total Index	–	82.73	89.98	18.14	48.33	103.20	fred.stlouisfed.org (`INDPRO`)
$COMEX_t$	London Metal Exchange (LME) copper 3-month futures	USD per mt	$4,078$	$2,702$	$2,603$	$1,355$	$9,358$	refinitiv.com
TDI_t	Nominal Advanced Foreign Economies USD Index	–	119.00	116.50	18.30	91.36	172.30	fred.stlouisfed.org (`DTWEXAFEGS`)
TB_t	Market yield on 10-year U.S. Treasury Bond	%	5.395	4.795	3.065	0.889	13.010	fred.stlouisfed.org (`DGS10`)
C_t	Global copper mine production capacity	$mt \times 10^6$	15.327	13.869	5.811	9.136	26.894	icsg.org

Table 2: Description, key features, and sources of the variables in our dataset. The upper (lower) section details dependent and independent (instrumental) variables.

4.2 Dataset

To estimate the key equations of our model, detailed in the last row of Table 1, we have constructed a database covering the period from 1982 to 2022, with annual frequency. Table 2 provides a description of the variables involved, including those later used as instruments, along with their key features and sources.

A key aspect to explore is the division of global supply between the cartel and the competitive fringe. Specifically, a group of countries must be identified as potential cartel founders, based on their copper reserves. By aggregating the country-specific supply of these countries, we obtain the cartel's supply, i.e. $S_{c,t}$, while its complement to the global traded quantity level is the supply of competitive fringe, i.e. $S_{f,tot}$. For this purpose, we selected Chile, Peru, Zambia, and the DRC as potential cartel members. As highlighted in Section 1, these countries were founders of CIPEC in the late 1960s and currently control 50% of global primary supply, 29% of secondary supply and 17% of global reserves, positioning them to exert potential market power. Additionally, with the only exception of China, whose strength lies primarily in refining rather than mining, the rest of the market is highly fragmented. Therefore, there are no other realistic options for potential cartel members at present.[11]

Further assumptions are then needed due to the lack of global data for certain variables. First, to partition the competitive fringe's supply into primary and secondary components, i.e. $S^p_{f,tot}$ and $S^s_{f,tot}$, we applied the U.S. ratio between primary and secondary copper to the global competitive supply.[12] Second, to obtain the global stock of copper in product form K_t we used the state equation most commonly used in the literature (Pindyck, 1978) to update prior estimates.

4.3 Model calibration

In this Section, we present the estimation of the key equations of our model based on the dataset described above. Since observed equilibrium prices and quantities are simultaneously determined by the matching of demand and supply, a classical identification problem arises. Therefore, to account for endogeneity, we use a set of instrumental variables (IVs) that enter the supply but not the demand equation, and *vice versa*.[13] Our choice of IVs is in line with other empirical studies of the copper market (Fisher et al., 1972; Shojaeinia, 2023; Valencia, 2005; Zhang & Lawell, 2017). Estimation is then carried out using the two-stage least squares estimator (2SLS).

To ensure the correct application of 2SLS, the following specification tests are executed. The Hausman test allows to verify whether there is statistical difference between an OLS and

[11] See: https://pubs.usgs.gov/periodicals/mcs2021/mcs2021-copper.pdf

[12] To the best of our knowledge, U.S. Geological Survey (USGS) is the only data provider that includes data on recycled copper alone, i.e. old scrap. See, for example: https://pubs.usgs.gov/periodicals/mcs2021/mcs2021-copper.pdf

[13] An appropriate instrument must be correlated with the endogenous regressor only through its correlation with the dependent variable, and must be uncorrelated with the error term.

Independent variables	Dependent variable		
	$Q_{tot,t}$	$S^p_{f,t}$	$S^s_{f,t}K_t^{-1}$
Constant	1.7139***	0.4548**	−0.0009
	(0.5561)	(0.2169)	(0.0006)
P_t	−0.0083*	0.0086**	0.0000
	(0.0044)	(0.0041)	(0.0000)
First lag	0.7300***	0.8974***	1.0364***
	(0.0978)	(0.0530)	(0.0493)
t	0.1238***	–	–
	(0.0387)	–	–
Hausman test p-value	0.0033	0.0006	0.1128
Sargan over-identification test p-value	0.2912	0.1832	0.4590
Weak instrument test F-statistic	11.2126	6.6602	15.3779

Notes: $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 3: Results of 2SLS estimation for key model equations.

a 2SLS estimator. A small p-value justifies the use of an IV approach. The Sargan test is then used to test the over-identification of the model, by estimating it with all instruments, then regressing the residuals on the instruments. With a large p-value the null hypothesis that the over-identifying restrictions are valid cannot be rejected, thus the instruments are determined to be valid. Finally, the weak instrument test regresses each independent variable likely to be contemporaneously correlated with the error onto all of the instruments.[14] A large F-statistic indicates that the hypothesis of weak instruments is rejected.

Table 3 presents the results of the estimation of the key equations of the model. The coefficients of the total demand equation are significant, and the three specification tests validate both the use of 2SLS and the choice of the instruments. A similar outcome is observed for the primary supply equation, though the instruments used might be weak. For secondary supply, however, the estimates are not significant, except for the autoregressive component. Moreover, the Hausman test indicates no advantage in using 2SLS over OLS. As a consequence, when setting up the dynamic programming problem, we substitute the secondary supply results shown in Table 3 with the most recent values proposed in the literature (Fu et al., 2017).

A word of caution is however necessary. As mentioned in Section 4.2, the dataset on which our estimation is based includes only 40 observations for each variable. Therefore, given the restricted size of our sample, we use the results in a descriptive fashion and not for causal inference.

[14] Weak instruments are those weakly correlated with endogenous variables. This can cause issues such as biased or inconsistent estimates, or hypothesis tests with large size distortions as well as wrong confidence intervals.

4.4 Results

The basic model outlined in Section 3 is now parameterized for the global copper market, based on the approach suggested in the literature and our estimates described above. The state equations of the model are as follows:

$$Q_{tot,t} = 1.7139 - 0.0083P_t + 0.7300Q_{tot,t-1} + 0.1238t \tag{8}$$
$$S^p_{f,t} = 0.4548 + 0.0086P_t + 0.8974S^p_{f,t-1} \tag{9}$$
$$\frac{S^s_{f,t}}{K_t} = -0.0033 + 0.0029P_t + 0.0073\frac{S^p_{f,t-1}}{K_{t-1}} \tag{10}$$
$$S_{f,t} = S^p_{f,t} + S^s_{f,t} \tag{11}$$
$$K_t = 0.98K_{t-1} + Q_{tot,t} - S^s_{f,t} \tag{12}$$
$$S_{c,t} = Q_{tot,t} - S_{f,t} \tag{13}$$
$$R_t = R_{t-1} - S_{c,t} \tag{14}$$

In line with Eq. (7), candidate cartel members solve the following problem, which highlights the potential gain from cartelization:

$$\max_{P_t} W = \sum_{t=0}^{T} \frac{2204}{(1+\delta)^t}\left(P_t - \frac{m}{R_{c,t}}\right) S_{c,t}. \tag{15}$$

where the coefficient 2204 allows to convert metric tons to pounds. By contrast, the price trajectory in the competitive scenario follows Eq. (3).

This finite-horizon, nonlinear, multi-stage deterministic dynamic programming problem is finally solved using `Dynaprog`, a `MATLAB` toolbox designed to optimize an objective function in problems where decisions must be made at each stage in a system that evolves through a finite number of stages (Miretti et al., 2021). For the initial conditions in `Dynaprog`, we use the state variables values as of 2022. Specifically, for quantities traded on the market, we use $Q_{tot,2022} = 26$ million metric tons, divided into $S_{c,2022} = 15.027$ and $S_{f,2022} = 10.973$. For the stock of copper in product form and cartel reserves, we use $K_{2022} = 470$ and $R_{2022} = 4.11 \times 10^8$ million metric tons, respectively.[15] The initial price in the competitive scenario is $P_{2022} = 3$ USD per pound, derived by converting the most recent market price from metric tons to pounds, as shown Table 1, while it is endogenous in the cartelized world. The computational framework is completed by the discount rate $\delta = 0.05$ (Zhang & Lawell, 2017) and the initial average cost $m/R_{2022} = 2$ USD per pound.[16]

Figure 1 shows the optimal price trajectory, the consequent profit dynamics, and the evolution of the state variables from Eq. (8) to (14), over a 45-year time horizon, for both the competitive and cartelized scenarios. In the scenario where a cartel is formed, all state variables exhibit high volatility, due to the endogenously determined price, which is particularly

[15] See: https://pubs.usgs.gov/periodicals/mcs2021/mcs2021-copper.pdf

[16] The cost is sourced from the financial statements of major copper mining companies, such as Alta Copper, Ero Copper, Ivanhoe Mines, Lundin Mining.

high and volatile in the first stages. This initial instability, likely resulting from the algorithm's warm-up phase, quickly subsides, offering valuable insights into long-term trends, which are most relevant for informing the decision on whether to form a cartel.

Market price (panel a) is almost always higher in the cartelized scenario than in the competitive one, signaling the market power exerted by cartel members. Moreover, despite the initial cartel volatility, in both cases the market price exhibits an upward trend. This dynamic is in line with the Hotelling's rule, according to which the price of an exhaustible resource rises as its depletion nears.

As for yearly profit (panel b), despite the initial price-induced volatility in the cartelized scenario, we observe that, for the first two decades, potential cartel members would make higher gains in the competitive scenario. Only around the midpoint of the depicted time frame, a flip occurs. Although profit is closely linked to market price, the dynamics of these two variables are not identical, as profit also depends on the quantity supplied to the market. Moreover, it is important to note that profits in the cartelized scenario exhibit fluctuations that cartel members would probably prefer to avoid, and that consuming countries could anticipate and counteract through stockpiling. Finally, another important information is provided by the cumulative profit over the considered time horizon. Specifically, over the depicted time frame of 45 years, the cumulative profit of potential cartel members is 3.47×10^{11} USD if they act as competitive players, compared to 5.41×10^{11} USD if they actually form a cartel. Given that the decision to form a cartel is a lengthy process based on long-term projections, the fact that cartelization yields higher gains than perfect competition in the long run might provide valuable insights to potential cartel members. Instead, for policymakers and countries located downstream in the copper supply chain, this information could be valuable in assessing the risk of supply shortages due to potential cartelization.

The market power of potential cartel members also affects their supply (panel c). In the cartelized scenario, cartel supply remains very low during the first half of the depicted time frame, contributing to the profit dynamics described above. Notably, cartel supply stays below the competitive market trajectory for most of the period, underscoring the allocative inefficiency of a cartelized market structure. When the market is cartelized, its members reduce their supply while the competitive fringe increases its production to meet demand, also benefiting from the higher market price. This dynamic is represented by both primary and secondary competitive supply (panels d and e) and their combined value (panel f).

Finally, cartel reserves (panel h) exhibit a monotonically decreasing trend, in line with (14), which is designed to reflect the depletion of a nonrenewable resource. An important result is that reserves' trajectory in the competitive scenario is consistently lower than in the cartelized one. This indicates that potential cartel members extract less copper when they form a cartel, once again confirming the lower allocative efficiency of this market structure compared to perfect competition. The stock of copper (panel g) shows only modest fluctuations, partly due to the strong autoregressive component of Eq. (12). As another consequence of the lower allocative efficiency in the cartelized market, stock levels are higher in the competitive scenario, as more

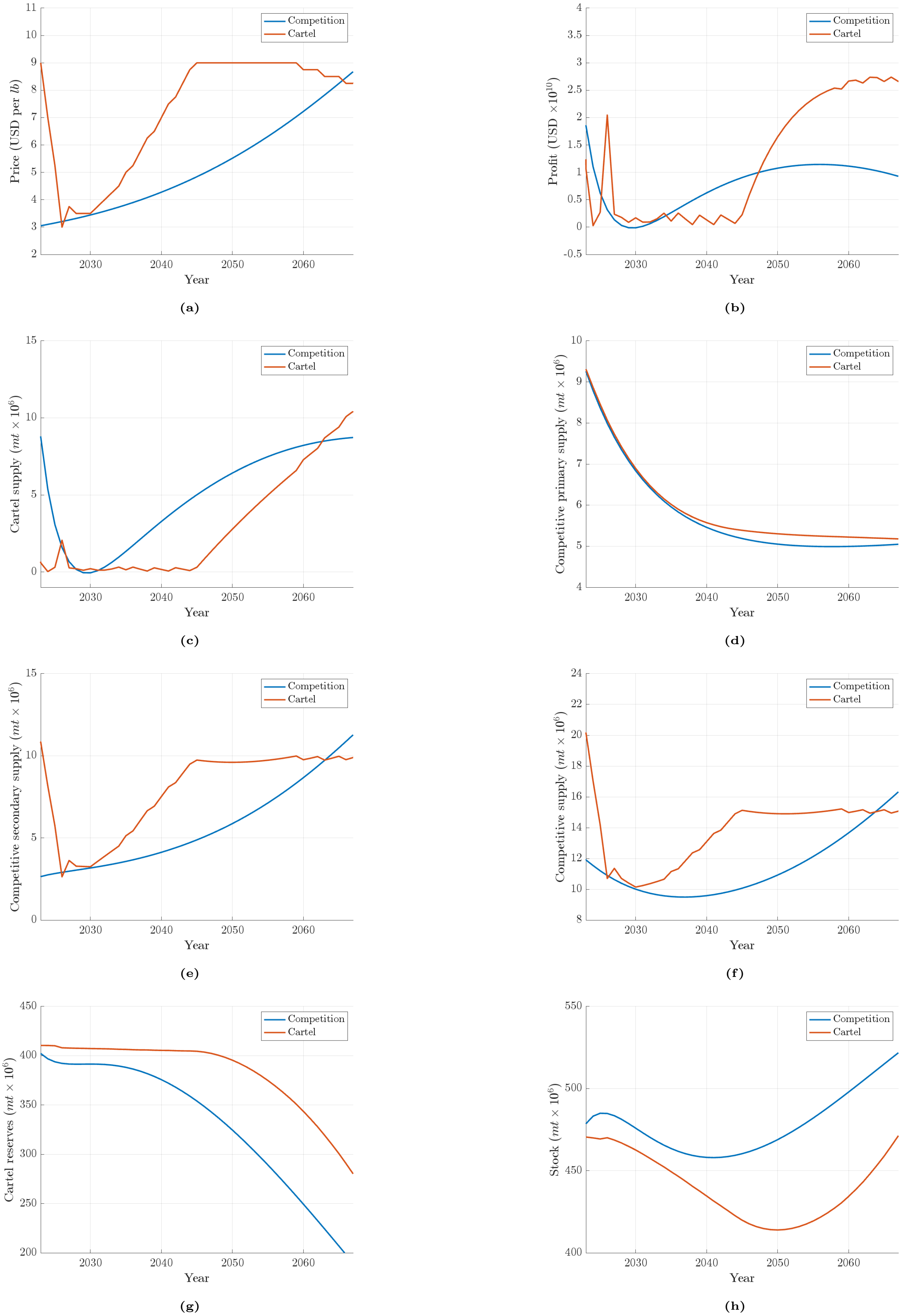

Figure 1: Optimal price trajectory and evolution of model state variables for both competitive and cartelized scenarios.

copper is extracted and subsequently enters the market.

5 Concluding remarks

In this paper, we assess the risk that a group of copper-rich countries might form a cartel to achieve higher profits than under perfect competition. To this end, we employ a twofold approach. First, we empirically calibrate theoretical models of an exhaustible resource, i.e. copper, under both perfect competition and market power. Then, we set up and solve a nonlinear dynamic programming problem to simulate the future profits of this group of countries in both scenarios, with endogenous output or endogenous price, respectively. Our results not only describe the long-term evolution of key market variables, but also indicate that if copper-rich countries form a cartel, their market control yields additional gains compared to a competitive scenario. Specifically, over 45 years, their expected profits are approximately 50% higher than those achieved without market power. However, the profit difference between the two scenarios does not grow linearly over time. After a decade during which cumulative profits are fairly similar, we observe a period when cumulative profits under perfect competition exceed those of the cartel. It is only in the long term, after about 25 years, that this gap shifts in favor of the cartel, steadily widening thereafter.

What conclusions can we then draw regarding the risk of cartelization? On one hand, if cartel members adopt a long-term time horizon, waiting decades to realize greater gains could be feasible and sustainable, as our results indicate. This is particularly likely when reserves are substantial, delaying depletion far into the future (Holahan, 1978). On the other hand, cartels might adopt a shorter-term perspective due to heightened risk of exogenous shocks, which is more pronounced when reserves are located in less developed countries (Osborne, 1976; Porter, 1983). Political shifts, difficulties in maintaining agreements among members, or even coups, all of which are well-documented historical examples, can reduce the expected lifespan of a cartel and, therefore, its outlook. In conclusion, predicting with certainty whether a cartel will form in the global copper market is challenging. Rather, our contribution demonstrates the existence of conditions that could support its formation. This finding aligns with previous literature, which highlights the presence of oligopolistic behavior in the copper market (Zhang & Lawell, 2017).

The potential formation of a copper cartel provides relevant information to a variety of stakeholders, such as governments, regulators and private companies, especially in the context of the energy transition. The allocative inefficiency introduced by a cartel would create substantial uncertainties about meeting Net Zero Emission (NZE) goals. It could, indeed, lead to shortages or bottlenecks, particularly given the projected 2.7-fold increase in global copper demand from 2020 to 2040.[17]

The policy implications of cartelization risks are multifaceted. Governments and regulators can, in fact, consider both immediate and long-term actions to protect the market from potential

[17] Source: https://www.iea.org/reports/the-role-of-critical-minerals-in-clean-energy-transitions

distortions. One strategy is to foster the resilience of supply chains. For example, where feasible, developing new sites in other countries (Moats et al., 2021; Mudd & Jowitt, 2018) or forming strategic partnerships as anti-cartel measures (Kang et al., 2023) can help dilute a potential cartel's market power, as well as promote trade diversification. Another option is to encourage the substitution of copper with alternative materials, where possible. However, due to copper's unique properties, finding suitable substitutes for many of its major applications is particularly challenging (Elshkaki et al., 2016). In fact, copper often serves as a substitute for more expensive metals, such as silver, in specific applications (García-Olivares, 2015). Given copper's essential role in the energy transition, investment aimed at reducing the copper intensity of current technologies (Watari et al., 2022) or making more deliberate choices of sub-technologies, such as the type of solar PV, could have a significant impact on reducing demand (Månberger & Stenqvist, 2018). Finally, the development and better exploitation of secondary supply could also play a crucial role. Increasing domestic copper scrap smelting capacity would prepare for potential international shortages. Moreover, copper needs could be met more sustainably by raising recycling rates and exploiting copper stocks currently in hibernation (Yuan et al., 2023). Besides helping to meet copper demand, these actions could also have positive spillover effects in terms of circularity (van Oorschot et al., 2022).

Our conclusion should, however, be interpreted with caution, in light of those elements that could not be embedded into the model. First, cartels are strongly politicized entities; therefore, geopolitical dynamics should not be disregarded. Second, while we have quantified the potential benefits, it is not possible to quantify the potential political and organizational cost of cartelization. Therefore, there is no clear indication about whether the additional gains are sufficient to justify cartel formation. Third, we consider a case in which cartel members are countries. Instead, companies who own deposits, invest in mining and processing capacity, and market those materials internationally can form a cartel too, and they are typically controlled by foreign entities. The case of cobalt is particularly illuminating in this regard; as 69% of global production originates in the Democratic Republic of Congo (DRC), only a small part is controlled by local companies, while 80% of the DRC's cobalt output is owned by Chinese companies, refined in China, and then sold to battery makers around the world.[18] For this reason, our future research will extend the application of this model to other critical mineral markets, such as cobalt and nickel.

[18]Source: https://www.cecc.gov/events/hearings/from-cobalt-to-cars-how-china-exploits-child-and-forced-labor-in-the-congo

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Massachusetts Institute of Technology
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Cambridge, MA 02139-4307
USA

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