Exploration of the cobalt system

Scenarios for a critical metal for the energy transition

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Executive summary

The transition to a low-carbon economy depends on several critical materials, one of which is cobalt. This metal is a main component in batteries, and therefore, demand for cobalt is expected to increase in the coming years. This paper explores future scenarios for the cobalt system, in light of its role in the low-carbon transition. The future of cobalt is characterized by deep uncertainty: it involves uncertainty on how the system is structured, on the values of variables influencing the system, and on the desirability of outcomes of interest. Therefore, this research uses Exploratory system dynamics modelling and analysis as the method, since it allows to explore an ensemble of models, each with different values for the input variables. The results show that cobalt is likely to remain a critical material for the electric vehicle transition, although the demand for the metal could vary greatly, depending on the size of future batteries and how fast the average oregrade of cobalt will decline. The demand scenarios in turn influence the development of industrial and artisanal mining, and recycling in the cobalt system. Depending on the collection rate of batteries and other cobalt-containing goods at the end of their life, recycled cobalt could account for a significant part of the demand. The by-product nature of cobalt makes future industrial mining dependent on developments in the nickel and copper markets. If the demand for cobalt increases sufficiently and its price levels go up, cobalt could become a co-product for nickel and copper. With regards to scarcity and sustainability of the cobalt system, this research examines the influence of the assumptions of the two opposing paradigms in the literature on these two concepts: the Fixed stock paradigm and the Opportunity cost paradigm. While the Fixed stock paradigm warns for eminent physical scarcity, the Opportunity cost paradigm places its trust in the regulating capabilities of the price of metals, the signal for economic scarcity. This paper argues that the continued discussion on the paradigms, divert the attention from the externalities of mining. Cobalt resources are not likely to soon be depleted, but externalities of mining could continue to increase. More cooperation between scientists of both paradigms could help to increase understanding of metal systems, and to produce better advice on policies for decision makers to cope with the externalities. Increased research into understanding how externalities of mining could be mitigated is therefore recommended.

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Acronyms

ASM:	Artisanal and Small-scale Mining
Au:	Aurum, chemical element of Gold
Cu:	Cuprum, chemical element of copper
Co:	Cobalt, chemical element DRC: Democratic Republic of Congo
EMA:	Exploratory Modelling and Analysis
EP:	Equator Principles
ESDMA:	Exploratory System Dynamics Modelling and Analysis
EVs:	Electric Vehicles
ICEs:	Internal Combustion Engines
IEA:	International Energy Agency
IFC:	International Finance Corporation
KDE:	Kernel Density Estimation
Ni:	Nickel, chemical element
SD:	System Dynamics

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Introduction

Climate change mitigation is one of the biggest challenges of our century. A transition to a sustainable, low-carbon economy is necessary in order to keep the earth habitable for future generations. Some scholars argue that the transition to a sustainable system is in fact not sustainable because it needs the input of materials, to put new infrastructures in place that can support a low-carbon economy (Mudd, Weng, Jowitt, & Graedel, 2013; Sverdrup, Ragnarsdottir, & Koca, 2017a; Swart & Dewulf, 2013). The demand for materials, according to them, is so high, that the transition creates scarcity of resources for future generations, which is contradictory to sustainability. This paper researches the sustainability of resource extraction, and the scarcity of resources for the low-carbon transition.

The transition to a low-carbon economy depends on several critical materials. It requires transitioning from a fossil fuel-based energy system to a mainly electricity-based energy system. Fossil fuels are naturally a dense stock of energy, whereas electricity needs to be generated and stored in other ways. Batteries are currently the most common way to store electricity, therefore, the demand for battery metals is rising. Especially the market for batteries for Electric Vehicles (EVs) in the automotive industry is increasing exponentially (Helbig, Bradshaw, Wietschel, Thorenz, & Tuma, 2018; IEA, 2018). Also stationary (grid) storage could become an important source of demand (Campbell, 2019; Helbig et al., 2018). Due to the importance of batteries for the energy transition, the EU, U.S., and China have marked a number of the battery materials as critical materials (European Commission, 2017; Goodman et al., 2018; USA Department of the Interior, 2018).

Cobalt is one of these critical materials. The metal is used in appliances like superalloys, magnets, and batteries (DeCarlo & Matthews, 2019). It has been in use as a metal since the 18th century: before that time, it was thought to be silver bewitched by goblins - a legacy from which it got its current name: *kobald*, which is German for goblin (Emsley, 2011). The past decades of the cobalt system have been characterized by the main trade being between the Democratic Republic of Congo (DRC) and the U.S., and by supply disruptions(Campbell, 2019). Civil wars in the DRC region blocked cobalt trade, up to the point of the occupation of and casualties at one of the biggest mines in the DRC by rebel groups (Alonso, Gregory, Field, & Kirchain, 2007). Consequently, cobalt supply from the DRC was viewed as rather unstable. Nowadays, this characteristic still holds, with the only difference being that the supply chain is dominated by the DRC and China (Campbell, 2019). The DRC dominates cobalt production: it produces 66% of global production, mainly from the Kashanga copperbelt. It also dominates the availability of cobalt in reserves, with 50% being in the country. The DRC has been plagued by challenges like fighting rebel groups, ebola, and an overall low HDI index, making the country rather unstable (Helbig et al., 2018). From the DRC, most of the mined cobalt is exported to China,(Harper, Kavlak, & Graedel, 2012; Simon, Ziemann, & Weil, 2015), where approximately 60% of globally refined cobalt is produced (Brown et al., 2019).

Despite its turbulent past, cobalt gained in popularity due to the EV transition, and demand for cobalt is expected to increase substantially, disrupting the cobalt system (IEA, 2018). Most of current battery techniques for EVs are dependent on cobalt. 40 years ago, main end uses were super-alloys and permanent magnets (Statista, 2018). Now, almost half of the demand comes from batteries (DeCarlo & Matthews, 2019). The demand for EVs will probably increase exponentially in the coming decades (Helbig et al., 2018; IEA, 2018).

Given the current policies by countries, the number of EVs could increase from 5 million in 207 to 120 million in 2030 (IEA, 2018). Nevertheless, future battery technology for EVs are not necessarily cobalt-based. Various battery technologies are available, each with a different cobalt content percentage, up to 40%, or without any cobalt content (Bloomberg NEF, 2019). There are technical advantages of using cobalt in its applications, over its potential substitutes (Campbell, 2019; USGS, 2019). Batteries with less cobalt can achieve higher energy and power densities, but the thermal stability of the battery could decrease, increasing the risk of battery explosion (IEA, 2018). However, the high price and potential supply instability cause producers to research low- or no-cobalt battery technologies (Bloomberg NEF, 2019). The supply pf cobalt is charaterized by a by-product nature (Campbell, 2019). Cobalt is largely found in nickel and copper ores and thus jointly mined, almost solely as by-product of these metals, (Sverdrup, 2016; Sverdrup, Ragnarsdottir, & Koca, 2017b; USGS, 2019). Therefore, the cobalt market is largely driven by the copper and nickel markets instead of the cobalt market (Campbell, 2019; Sverdrup et al., 2017b). Given the turbulent past and the coming changes to the system in light of the EV revolution, the future of the cobalt system may prove to be very interesting.

Although cobalt is a critical material for the energy transition, some argue that increased cobalt extraction is undesirable. Increased extraction now might very well lead to scarcity for future generations. Countries in which there is high demand for EVs, focus on decreasing the CO_2 emissions from their transportation sectors. However, this approach could lead to increased environmental and social risks in countries in which the materials necessary for EVs are mined. The battery transition therefore seems to showcase tension between different angles of sustainability, with a potential trade-off between local and global aspects of sustainability (Sovacool, Hook, Martiskainen, & Baker, 2019).

Decision makers on the EV transition include, among others, policy makers, executives in the automotive industry, and banks, in countries that are rapidly adopting electric cars. They likely want to contribute to the transition to a sustainable, low-carbon system. Exploring scenarios for the cobalt system can support their decision making on the cobalt system, and the development of the low-carbon transition. This research therefore researches the following:

In light of the low-carbon transition, how could the cobalt system develop, and what sustainability implications could this have?

This question ties into what is the meaning of *sustainability*. In the literature, there are two paradigms with very different views on how the future of metal systems should develop, each with their own account of scarcity and sustainability: the Fixed stock paradigm and the Opportunity cost paradigm (Prior, Giurco, Mudd, Mason, & Behrisch, 2012; Tilton, 1996, 2003). The two paradigms differ in opinion on whether and how fast resources will become scarce. The Fixed stock paradigm, which stems from research by engineers and environmental scientists, argues that the resources on this planet form a fixed stock, and at current production levels, the stock risks depletion. The paradigm is rooted in the report of the Club of Rome, warning for eminent scarcity and implosion of the economy because of our unsustainable use of resources (Meadows, Meadows, Randers, & Behrens, 1972). Yet, here we are, more than half a century later, and our economy is ever growing. Innovation and discovery of new resources made sure we did not suffer from physical scarcity. This is why the Opportunity cost paradigm argues that demand for metals is driven by economic rather than physical scarcity (Prior et al., 2012; Tilton, 1996, 2003). The economists supporting this paradigm argue that resource availability is determined by what society is willing to give up to produce more metal, rather than physical availability.

In order to understand how the cobalt system could develop, and what sustainability consequences this would have, both the paradigms need to be analysed. The Fixed stock paradigm assumes that the Earth's resources are finite, and the researchers emphasize the possibility of depletion of resources. Consumption of resources by today's society causes resource scarcity for future generations, which makes the system unsustainable. Therefore, this paradigm advocates policies that limit resource extraction, in order to improve the sustainability of the system. The Opportunity cost paradigm assumes that the price reflects economic scarcity. If the price becomes high in comparison with substitute materials, demand will be substituted. In other words: prices will regulate supply and demand dynamics before physical scarcity becomes relevant (Tilton, 1996). Limiting current resource extraction, therefore, is not necessary, since it will automatically be limited when the economic scarcity is high enough. The sustainability of the cobalt system in terms of physical scarcity is regulated by the system, according to the Opportunity cost paradigm scholars. However, sustainability might not just be about scarcity in terms of resource scarcity. Global economic growth of the past 50 years has created scarcity in other ways: one example is the growing scarcity of healthy ecosystems around the globe due to the consequences of accumulating carbon in our atmosphere. The future developments in the cobalt system would have consequences for all aspects of sustainability and scarcity.

The future of the cobalt system is characterized by deep uncertainty. Deep uncertainty means that various analysts of a system or parties to a decision do not know or cannot agree on 1) the system, its boundaries and the appropriate model to describe the system (structural uncertainty), 2) the prior probability distributions that show uncertainty of the value of parameters in the system (parametric uncertainty), and 3) the outcomes of interest, their desirability and importance (Walker, Marchau, & Kwakkel, 2013). Also, 4) decisions in a system with deep uncertainty are made over time, and in turn influence the system. Therefore, these decisions cannot be considered only external to the system, but need to be considered internally (Haasnoot, Kwakkel, Walker, & ter Maat, 2013). The cobalt system exhibits all four of these characteristics. There is a structural uncertainty on which paradigm provides a better description of the system. There is parametric uncertainty about the main drivers of the cobalt system. Cobalt is mainly produced as a by-product of nickel and copper mining, but in case the future demand of cobalt gets high enough, the price setting might disconnect from the existing price setting relationship between nickel and copper, and a different price setting mechanism may develop (Campbell, 2019). There is uncertainty on the future preferences of decision makers: how fast will the EV transition develop (Goodman et al., 2018; Helbig et al., 2018; IEA, 2018), and how will this impact cobalt demand (DeCarlo & Matthews, 2019; IEA, 2018; Moss, 2017)? Finally, decision makers on global policies for EVs and resource extraction for their batteries are internal to the system, since decisions that are made now, will impact the demand for EVs in the future.

One example of internal decisions on the cobalt system are the decision to finance cobalt extraction. Metal extraction requires high upfront investments, and regular refinancing of existing facilities. Suppliers have operational real options when production is running, such as (temporarily) closing production (Savolainen, Collan, & Luukka, 2017). These real options in turn influence decisions by investors, for example to reinvest in a facility, which in turn influence the decisions made by suppliers. Investors in mining projects, therefore, influence the future cobalt supply. One of the actors with special interest in cobalt is ING Bank, a major bank in the commodity financing sector(van Vliet, 2019). The team in Amsterdam focuses specifically on the metals and mining industry, and they have accumulated knowledge on and experience in the sector. Other ING Bank teams focus on investments further along the supply chain, like commodity trades, and battery factories (Kindt, 2019). ING Bank takes various metrics into account in investment decisions, like the commercial potential of an investment, financial risk and Environmental, Health and Social (EHS) risks (Kindt, 2019). ING Bank committed to steering their loan book towards meeting the Paris Agreement's two-degree goal, in a strategy called the Terra approach (ING, 2019b). Critical materials for the energy transition might, therefore, be interesting to invest in.

Cobalt extraction, however, has often been related to local environmental and social risks. The supply of cobalt in the DRC does not only come from industrial mining, but also from artisanal and small-scale mining (ASM). Although there is no common definition of ASM, one could describe ASM as "mining by individuals, groups, families or cooperatives with minimal or no mechanization, often in the informal (illegal) sector of the market. In the DRC, artisanal mining is widely understood to mean 'mining by hand'. Small-scale mining on the other hand has some mechanization and is on a bit larger scale (Amnesty International, 2016; Hentschel, Hruschka, & Priester, 2003). It is estimated that about 15 to 20% of cobalt production in the DRC is extracted by artisanal miners (Banza Lubaba Nkulu et al., 2018). There are potential local social risks involved with cobalt mining, such as child labor (Amnesty International, 2016; Atibu et al., 2018; Smolders et al., 2019). Also, there are local environmental and health risks: chemicals leaking into rivers causing health risks for local workers (Atibu et al., 2016; Banza Lubaba Nkulu et al., 2018; Pourret et al., 2015), as well as deforestation (Hund, Schure, & van der Goes, 2017).

All of the earlier attempts to quantitatively model the global cobalt system, (and other metals) specifically defend one paradigm (Sverdrup, 2016; Sverdrup et al., 2017b, e.g.), or aim to prove that one paradigm has the most realistic view of reality (Prior et al., 2012; Tilton, 1996). There is hardly any literature that explores the consequences of each paradigms' assumptions. The literature that is available on the influence of paradigms on the cobalt system, is mostly from Fixed stock paradigm scholars. They have made studies of when (rather than whether) 'peak minerals' will occur (Sverdrup et al., 2017a, e.g.), also specifically for cobalt (Sverdrup, 2016; Sverdrup et al., 2017b). van Vuuren, Strengers, and De Vries (1999) researched the differences between the paradigms and applied it to the copper mineral, but the cobalt system's behavior is fundamentally different from the copper system, and the copper system is not influenced as much by the energy transition as the cobalt system, so the conclusions from this research cannot be used in this case.

Other earlier research on the cobalt system was either qualitative, or did not include systematic feedbacks over time. Qualitative assessments of the cobalt system have been made by, for example, Campbell (2019), and Dawkins, Chadwick, Roelich, and Falk (2012). These do not provide quantitative projections of future supply and demand dynamics. Mass Flow analyses are quantitative assessments of flows of goods. For cobalt, Alonso et al. (2007) focused on the supply risks in the cobalt system, while Glöser, Soulier, and Tercero Espinoza (2013) focused on copper and only partially discussed cobalt. Elshkaki and Graedel (2013) made an analysis of global metal flows for electricity generation technologies. Nansai et al., 2014 focused on efficient consumption. Although these models provide a clear overview of the flows of metals, they do not incorporate systematic feedbacks over time. The same holds true for (Harper et al., 2012), although this was no mass flow analysis, this research also focused mainly on the stocks of cobalt over the world, instead of supply demand dynamics. Finally, there is no research on modelling the influence of investors on supply side, and on the market level: Savolainen et al. (2017) researched metal mining investments, but solely on project level.

The objective of this research is to explore the uncertain future of cobalt in light of the low carbon transition. In order to do so, this research develops a model of the global cobalt system. In this model, the most influential uncertainties are analysed. Specific attention is given to gaining more insight in the role of investors in the cobalt system. Finally, this research aims to contribute to the global society's questions on how to develop the low carbon transition as well as its intrinsic sustainability trade-offs.

The scope of this research is global, and the time horizon of the research is the period until 2050. For the time horizon, a balance needs to be found that allows for fully exploring the behavior of cycles in the metal industry, while keeping in mind that the further into the future one models, the higher the risk of lower accuracy. The cobalt market experiences spikes and drops in the price with cycles of at least 12 years. From 2019, this research proposes to be able to model at least 2 of these cycles, requiring at least more than 24 years in the future. Furthermore, the duration of an investment in a mining project varies from 3 to 10 years. Taking into account delays and preparation time, also here a minimum period of 12 years of analysis is desirable, from the start moment of an investment. Since it is uncertain whether and when a new spike in cobalt price will occur, modelling a broader time range might be desirable. Therefore, the time horizon of 2050 is chosen.

Considering the existing research gap, and the research objectives, the following research questions arise:

1. How is the cobalt system currently structured?
2. What are the key uncertainties driving change in the cobalt system?
3. Given these uncertainties, what scenarios could the cobalt system exhibit?
4. Given different scenarios, what are the sustainability consequences throughout the cobalt system?
5. Given different scenarios, what are implications for investors in cobalt?
6. How do the assumptions of the two paradigms influence the scenarios in the cobalt system?

The first three research questions are of an exploratory nature. They are intended to find out how the cobalt system actually works, what drives change in it, and what could possible happen in the future in the system. The last three research questions analyse the scenarios more in depth, each from a different angle. The first research question dives into the complex structure of the cobalt system, and the two possible underlying paradigms. The second question zooms in on the uncertain future developments such as supply, demand and countries' policies. Question three explores the various possible futures for the system. The sustainability consequences under the various future scenarios are explored with question four. Question five zooms in on what these future scenarios mean for investors, and especially for ING. Lastly, question six examines the influence of the assumptions made by the two paradigms on the system.

In the remainder of this research, chapter 2 proposes methods and data to answer these questions. Chapter 3 to 5 aim to provide answers to the sub-research questions in order to be able to answer the main question as proposed above. Chapter 6 and 7, finally, present the discussion and conclusion of this research.

2 Methods and Data

This chapter provides an overview of the methods, the data, and the experimental set-up used for this research. The chapter argues that a method is necessary that can cope with all kinds of uncertainty in the cobalt system, and therefore, a combination of methods is presented.

2.1. Methods

In order to cope with all aspects of deep uncertainty of the cobalt system, this research requires a combination of methods. The deep uncertainty can make it hard to fully grasp system behavior in a model: the method needs to be able to consider both structural uncertainty and parametric uncertainty. Furthermore, the research requires a method that acknowledges that although predictions are not possible for a system characterized by deep uncertainty, exploration of the system using multiple models based on the available information is still possible (Kwakkel & Pruyt, 2015).

The combination of System Dynamics (SD) and Exploratory Modelling and Analysis (EMA) into Esploratory System Dynamics Modelling and Analysis (ESDMA) makes this possible (Auping, 2018; Bankes, 1993; Kwakkel, Auping, & Pruyt, 2013). System Dynamics is apt to research structural uncertainty. However, SD does not provide the tools to capture all types of uncertainty (Kwakkel & Pruyt, 2015). The combination with Exploratory Modelling and Analysis (EMA) makes it possible to make multiple models, reflecting the parametric uncertainty and the various decisions that are internal to the model, and thus provides a way to incorporate all aspects of deep uncertainty.

2.1.1. System Dynamics

The cobalt system is characterized by dynamic complexity: it is characterized by, for example, feedback loops, accumulations, delays, and nonlinear, history dependent behavior (Sterman, 2000). SD is tailored to address dynamic complexity in systems (Lane, 2010). Essentially, SD models are systems of differential and/or integral equations (Lane, 2000). Simulating behavior of the system over time provides insight in the dynamics of the system's behavior. SD explores the relation between system structure and the behavior over time that arises out of this structure (Lane, 2000). Therefore, it can be used to research structural uncertainty in a model. Different structures require a different model formulation, and SD explores their effect on consequent behavioral dynamics (Kwakkel & Pruyt, 2015). The differences between the Fixed stock and Opportunity cost paradigm are examples of structural uncertainty.

2.1.2. Exploratory Modelling and Analysis (EMA)

EMA assumes that there is no one single 'correct' model of the world, and therefore, multiple models should be used to explore the future of a system. To do so, EMA uses the XLRM framework: X are uncertain inputs, L are levers, R are relationships in the system (i.e. the model) and M are performance metrics: the results, see figure 2.1. By varying the uncertain inputs, the levers and versions of the model, an ensemble of models is created. Each model run represents the dynamics of the model in case the true values for the input variables would be like the input variables of that model run. Each model run produces data on the performance metrics over the runtime of the model, and all models together thus produce a vast output space of performance metrics. EMA thus explicitly incorporates deep uncertainty in the model (Auping, 2018).

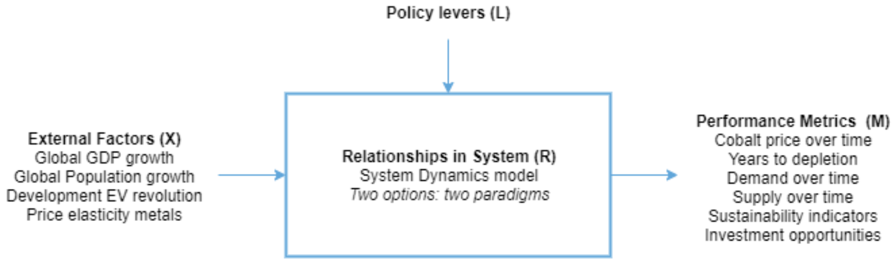

Figure 2.1: The XLRM framework (Lempert, Popper, & Bankes, 2003), applied to the cobalt system with a (highly aggregate level) description of external factors, policy levers, and performance metrics.

Scenario discovery is one application of EMA, in which the aim is to identify the influence of combinations of uncertainties on the behavioral landscape of model outcomes (Kwakkel et al., 2013). Scenario discovery traditionally focused on the influence of combinations of uncertainties on the terminal values of outcomes of interest. To go a step further, one could also focus on the influence of combinations of uncertainties on the dynamics of outcomes of interest throughout the individual model runs.

In order to do so, a variety of machine learning techniques can be employed. The choice of technique depends on the focus on the terminal value or the dynamics over time of the outcome of interest. In this paper, the dynamics over time are considered most interesting.

First, instead of static clustering techniques that focus on the terminal value of outcomes of interest, a time series clustering technique is used to organize the output data into groups that contain runs with similar behavior over time (Kwakkel et al., 2013). Second, a dynamic sensitivity analysis is used to assess the individual effect of each input variable on specific outcomes of interest. Due to the relatively large size of the input and output space, the computational cost of sensitivity analysis could be high. Traditional sensitivity analysis techniques, like Sobol, require many model runs in order to perform a global sensitivity analysis. Jaxa-Rozen and Kwakkel (2018) present a technique that allows global sensitivity analysis to be performed, and that requires less model runs for meaningful results: Extra trees feature scoring. The resulting feature scores provide an accurate approximate of Sobol indices. Since the influence of the input variables on the outcomes of interest is likely to vary over time, this paper uses dynamic Extra trees feature scoring. The feature scores are examined for multiple time-steps in the model. The results of Extra trees feature scoring can be shown in heatmaps, in which the individual effects of input variables on outcomes of interest are visuatliezd.

2.2. Experimental set-up

The SD model is implemented in the Vensim modelling software (Ventana System, 2010), which is software tailored specifically for SD models. The model is simulated for 50 years (2000 - 2050), with a time step of 0.0078125, using the Euler numerical integration method. This model is thereafter tested in the Python environment using the Exploratory Modelling Workbench, a library which was created specifically to perform EMA (Kwakkel, 2017). For the 67 uncertainties, Latin Hypercube sampling is used, with uniform distributions between the minimum and maximum as described in table 4.2. Furthermore, 5 switches were included, to switch on and off scenarios, and to provide insight in structural uncertainty. These switches are also sampled over using Latin Hypercube sampling, except for the switch for the paradigm. This is sampled using the Partial Full Factorial approach, making sure that every combination of all parameters is run for both paradigms, in order to improve comparison of the influence of the paradigms. In this way, 30,000 samples are generated. The files for the analysis can be found on https://github.com/erikavdlinden/CobaltModel.

2.3. Data

This research uses data from diverse sources. There are various publicly available sources on cobalt supply, production, and demand, like USGS (2019), Brown et al. (2019), and Statista (2018). Furthermore, there are certain organizations that specifically collect industry data, like Bloomberg, and AME. These sources are available through ING subscriptions. Also, literature on system parameters can be used as sources. Finally, expert interviews can fill in data gaps. The experts can be found within ING Bank, since the knowledge of their Metals, Mining and Fertilizers team provides insight in how decisions on investments in mining projects are made. Also, experts at Delft University of Technology are consulted, and various other organizations active in the field of cobalt mining or the EV industry.

3

Structure of cobalt model

The cobalt model consists of a supply chain, demand dynamics, and conomics and price dynamics. This chapter presents the main assumptions concerning the structure of this model.

3.1. Cobalt in the Earth's crust

In the field of resource extraction, often a distinction is made between the resource base, resources, the reserve base, and reserves, depending on the project feasibility, geological knowledge, and socio-economic viability (UN, 2010). The *resource base* is calculated by multiplying its elemental abundance in grams per metric ton times the total weight in metric tons of the earth's crust (Tilton, 2003). A *resource* is a concentration of a material "in such a form and amount that economic extraction of a commodity from the concentration is currently or potentially feasible" (USGS, 1980, p. 1). A distinction can be made between inferred, indicated, and measured resources. The first is an estimated which may not be supported by measurements, whereas for indicated resources some measured information has been used. The quantity of measured resources has been computed from the results of detailed sampling. The *reserve base* meets specified minimum physical and chemical criteria, and encompasses "those parts of the resources that have a reasonable potential for becoming economically available within planning horizons (USGS, 1980, p. 2). *Reserves*, finally, are "that part of the reserve base which could be economically extracted or produced at the time of determination" (USGS, 1980, p. 2). The price level thus influences the classification of ores: resources become reserves when the price levels are high enough, and higher prices lead to more exploration, moving ores from the resource base to resources or reserves. Figure 3.1 shows a graphical representation of these definitions, and the implementation in the model is visualized in figure 3.2.

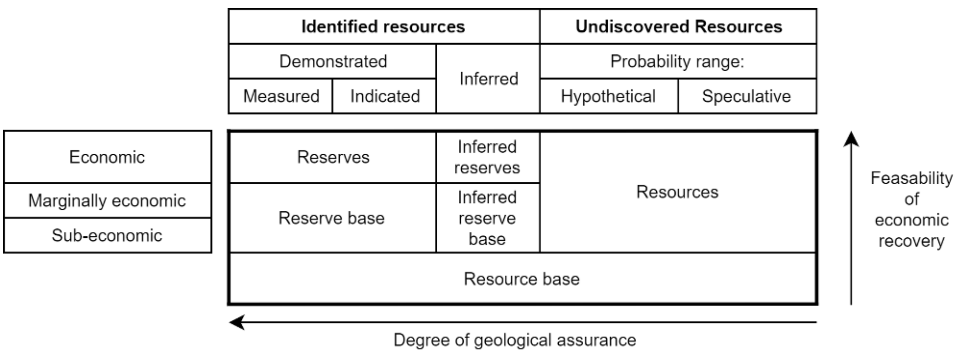

Figure 3.1: General relationship between Exploration results, Resources, and Reserves, based on McKelvey (1972), Tilton (2003)

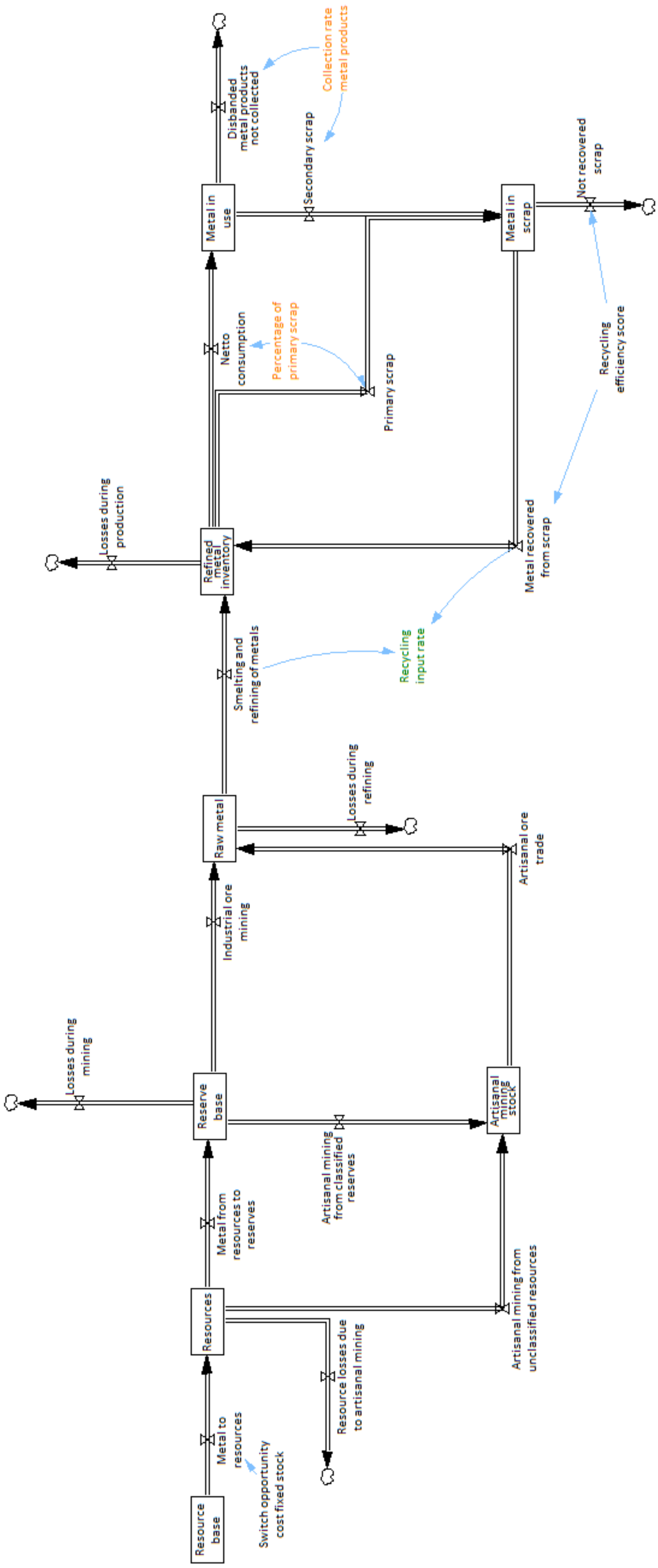

Figure 3.2: Stocks and flows of the metals copper, nickel and cobalt.

3.2. Cobalt's supply chain

The supply chain of copper, nickel and cobalt consists of a number of phases: mining from ore deposits, smelting and refining (Moskalyk & Alfantazi, 2002; Reck, Müller, Rostkowski, & Graedel, 2008), and use of recycled scrap (ICSG, 2019; Usanov, Ridder, Auping, & Lingemann, 2013), see figure 3.2. Industrial ore mining depends on the available reserves, the industrial mining capacity, the forecasted consumption, and the recycling input rate. Since reserves represent the deposits of a mine that are economically viable to win, the absence of reserves means that there are no deposits that are economically viable to win, and mining would not take place. The reserves increase in size when the price levels are high, and vice versa, since the reserve base represents the ore that is both geologically and economically viable to mine. The resources are either static, in the Fixed Stock paradigm, or dynamic in the Opportunity Cost paradigm. Ore in the resource base can turn into resources when they become more geologically assured, which is assumed to happen when price levels are high. Industrial cobalt mining depends on industrial nickel and copper mining because of its by-product nature (Shedd, McCullough, & Bleiwas, 2017; Sverdrup et al., 2017b).The industrial mining capacity depends on the profitability of the deposits that a metal ore is mined from. The forecasted consumption is based on the current demand.

Recycling depends on how much cobalt is collected after the use phase, and how much of the collected metal is actually recycled, see figure 3.2 and table 3.1. These two variables determine the recycling input rate: the percentage of input metal for the smelting and refining processes that is recycled scrap (Glöser et al., 2013). Currently, only some of the end uses of cobalt can be recycled (Sverdrup et al., 2017b), and only 29% of cobalt is recycled (collection rate * recycling efficiency score, see table 3.1) (USA Department of the Interior, 2018). In the model, the collection rate is assumed to be an input variable, since it is essentially a decision that needs to be made by external decision makers. The recycling efficiency score depends on the attractiveness of recycling scrap compared to mining new cobalt. As the average oregrade of cobalt declines, scrap recycling becomes more attractive, and the recycling efficiency rate increases. Furthermore, the recycling efficiency rate depends on the percentage of demand that comes from EVs. With increasing dominance of EV batteries as end use, the volumes available for recycling can increase as well, since the organized collection and recycling of EV batteries is assumed to be better than collection and recycling of other cobalt products.

Table 3.1: Recycling indicators. Based on: Glöser, Soulier, and Tercero Espinoza (2013)

Indicator	Formula	
Recycling Input Rate	$\frac{R}{SR+R}$	R = Metal recovered from scrap
		SR = Smelting and refining of metals
Recycling Efficiency Score	$\frac{R}{NR+R}$	R = Metal recovered from scrap
		NR = Metal not recovered from scrap
Collection rate	$\frac{S}{S+D}$	Ss = Secondary scrap
		D = Disbanded metal products not collected

Smelting and refining also depends on the forecasted consumption and the recycling input rate, and on the smelting and refining capacity. The use of recycled scrap depends on a number of recycling indicators, see table 3.1. Refined metal is sold for production of end uses, after which the metal enters the use phase. Primary scrap is scrap that is recycled during the fabrication of end uses, before it has entered the use phase, while secondary scrap is recycled after it has been used (ICSG, 2019). Primary scrap immediately enters the smelting and refining process again. The availability of secondary scrap for recycling depends on the end of life collection rate, and the recycling efficiency score Glöser et al., 2013. Throughout the phases of the supply chain there are losses (Glöser et al., 2013; ICSG, 2019).

3.2.1. Metal production capacity of mines from deposit types

Metals are not found in isolation: specific deposits contain groups of metal ores which may or may not be economically interesting to mine (Dill, 2010; Verhoef, 2004). Mining facilities therefore often mine multiple metals from one deposit, with the maximum production depending on the nameplate capacity: the capacity the facility theoretically is capable of delivering yearly (Moskalyk & Alfantazi, 2002).The production of a facility is not necessarily the same as, but often lower than the nameplace capacity. The mining capacity in the model represents how much contained metal in the ores can be processed. Preparation of new mining capacity depends on the profitability of the current mining capacity, the part of the demand that cannot be satisfied by recycled scrap, and the availability of reserves. Mining capacity can be mothballed, or parked, for a while, in order to be recommissioned when the price levels are more advantageous.

Table 3.2: Cobalt production (2000) from deposit types with respective Cu, Ni and Co average oregrades, and by-products. N.B.: Classification of deposits, oregrades and by-products are a simplification of the actual wide variety of deposit types. Sources: (Mudd, 2010; Mudd & Jowitt, 2018; Mudd, Weng, Jowitt, & Graedel, 2013; Northey, Mohr, Mudd, Weng, & Giurco, 2014)

Deposit type	Cu oregrade	Ni oregrade	Co oregrade	By-products	% of Co production
Sediment hosted	2.70 %		0.55 %	Au	71
Ni laterite		1.46 %	0.13 %		18
Magmatic sulfide	1.56 %	1.54 %	0.05 %	Au	11

Copper is primarily mined from porphyry deposits (60% of production) and sediment-hosted deposits (20%) (ICSG, 2019). The average oregrade of porphyry deposits is rather low, but they appear in large quantities. Sediment hosted deposits have a higher average oregrade and are therefore more profitable, but their quantities are lower. Porphyry deposits often contain various minerals that can be produced as by-product, for example, gold (Au). When mined, its production contributes to the profitability of the deposit. The majority of sediment hosted deposits is found in the Katanga copperbelt in the DRC. Nickel is primarily mined from nickel laterite deposits and sulfide deposits (Mudd, 2010; Mudd & Jowitt, 2014). Nickel laterite deposits can occasionally contain Cobalt. Sulfide deposits contain nickel, copper and occasionally cobalt. In terms of cobalt production, the majority is produced from the Katanga copperbelt. The rest is mined from nickel laterite and magmatic sulfides in which both nickel and copper occur. Table 3.2 presents the average oregrades of cobalt containing deposits. The selection of these deposits, the average oregrades of the deposits as well as the selection of the by-products are a simplification of the actual wide variety of deposits, oregrades and by-products. The simplification is done because of computational limitations, and to minimize modelling complexity. The profitability of a mining facility depends on the type of deposit it mines from, with each metal contained in the deposit contributing to the costs and the revenues of the mine. The profitability of the individual metals mined from a deposit determine which are the primary metals for a mine. Since a mine's primary product can change over time in reflection of fluctuating commodity prices, this research focuses on the deposits of a mine, rather than on what the primary commodity of a mine is. The cobalt recovery rate refers to the percentage of cobalt content in a deposit that is recovered, and depends on the profitability of cobalt mining (Mudd et al., 2013). Cobalt, nickel and copper could also be mined from manganese nodules on the sea-floor. However, this is assumed to be outside the scope of this research, since production from these nodules is projected to become relevant only after 2050 (Sverdrup et al., 2017b). Due to the fact that tailings of mines contain possibly economically viable metals, tailings are assumed to become part of the reserve again after mining.

Smelting and refining facilities also have a nameplate capacity, which is not necessarily the same as their production. The total smelting and refining capacity of a metal depends on the mothballed capacity, the decommissioning, and the preparation of new capacity, see figure 3.4. Preparation of new smelting and refining capacity depends on the percentage of capacity in use, and the profitability of the current capacity.

3.2.2. Artisanal mining

Artisanal cobalt mining is poverty, and cobalt price dependent. For artisanal miners, cobalt is the primary ore to mine instead of a by-product, and they are more flexible in ramping up and down production in response to prices, which makes them swing producers in the cobalt system (USGS, 2019). Artisanal mining capacity consists of people living in the region in which artisanal mining could take place. The number of people interested in artisanal mining is poverty driven (Barreto, Schein, Hinton, & Hruschka, 2018), with influencing factors begin proximity of people to mines, their income level, and metal price fluctuations (Amnesty International, 2016; Faber, Krause, & Sánchez de la Sierra, 2017). When people live in extreme poverty, defined as having an income of less than US$ 1.90 per day, making US$ 3 a day from artisanal mining makes it a relatively attractive livelihood, even if it is related with increased health risks (Banza Lubaba Nkulu et al., 2018; Faber et al., 2017; Tsurukawa, Prakash, & Manhart, 2011). For example, in 2000, 97% of the people in the region of the Katanga copperbelt lived in extreme poverty; in 2018, this had decreased to 69.1% (World Bank,

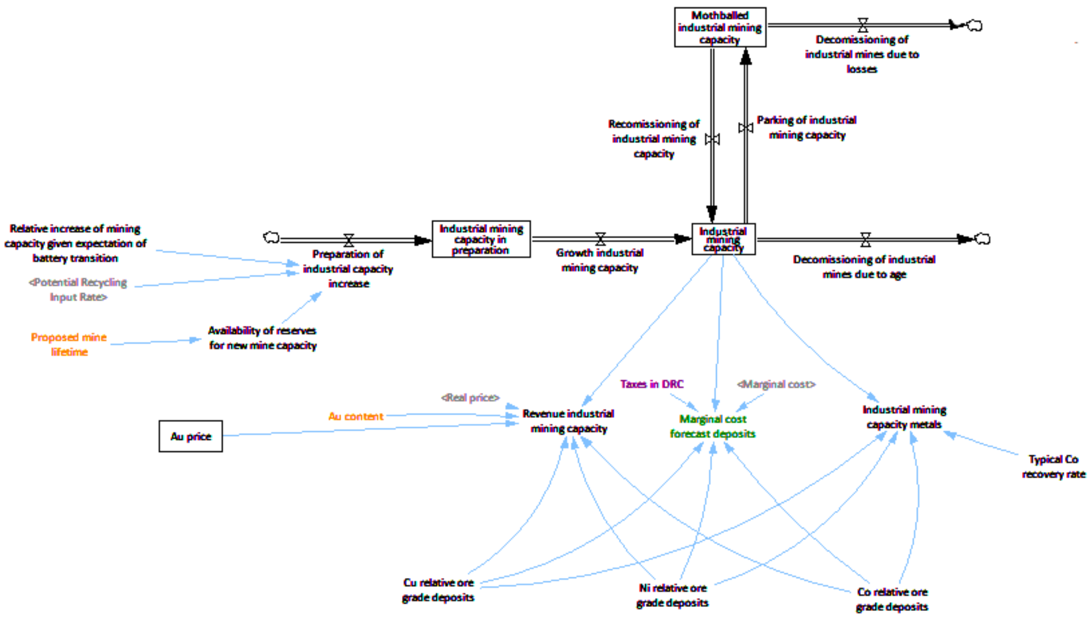

Figure 3.3: Industrial mining capacity of copper, nickel and cobalt. Orange variables are input variables, green variables are output variables, and purple variables are switches in the system.

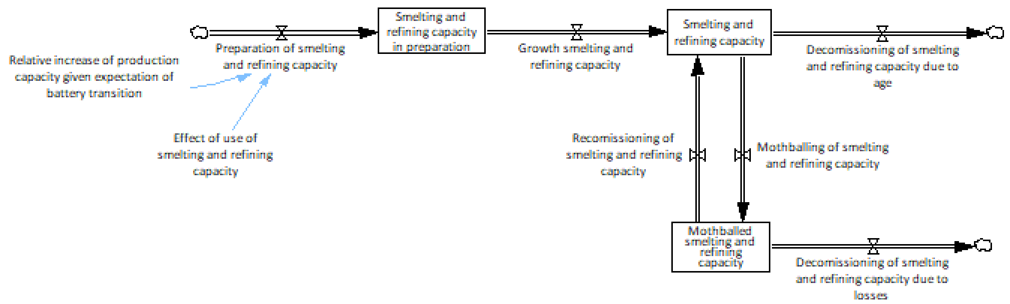

Figure 3.4: Smelting and refining capacity of copper, nickel and cobalt. Orange variables are input variables, green variables are output variables, and purple variables are switches in the system.

2019). This research, therefore, assumes that the maximum potential artisanal mining capacity depends on the minimum of the available resources and reserves, and the number of people available in the region to do the job. The potential labor force in the artisanal mining sector comprises of the number of people in a region living in extreme poverty. Also, there should be resources and reserves available for the artisanal miners to mine from. The artisanal mining capacity depends on the potential artisanal mining capacity, and metal price fluctuations The salary that an artisanal miner can make, depends on metal price fluctuations (Tsurukawa et al., 2011). The miner himself gets 6% of the final price of the commodity because the ore it delivers still needs to be processed (Faber et al., 2017). This model assumes that the artisanal mining capacity grows when the salary that could be made from artisanal mining is higher than US$ 3, and there is postponed demand, i.e., demand that cannot be fulfilled by industrial mining production alone.

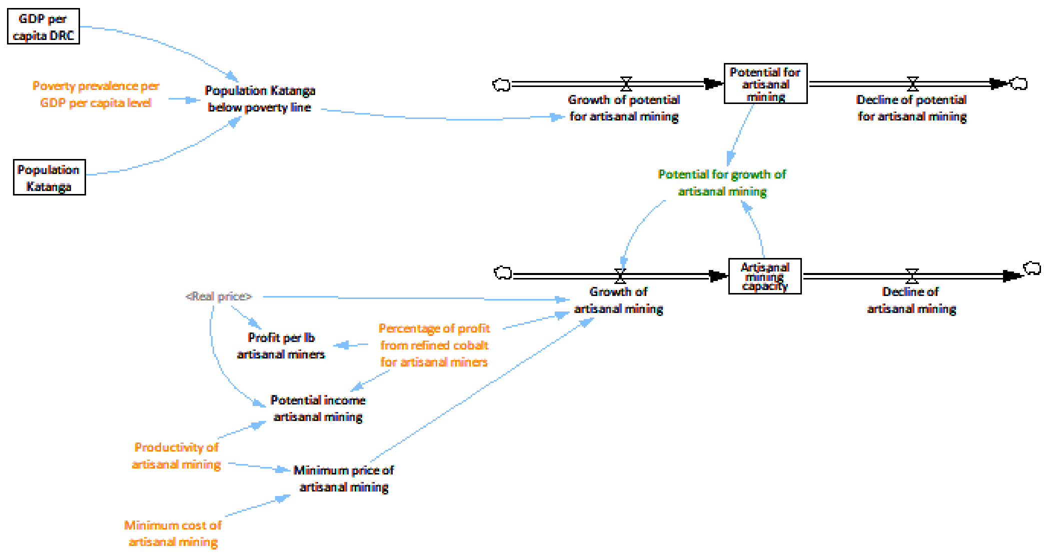

Figure 3.5: Artisanal mining capacity of copper, nickel and cobalt. Orange variables are input variables, green variables are output variables, and purple variables are switches in the system.

3.3. Demand dynamics

Demand is assumed to comprise of traditional demand, which is rather stable, and demand from new end uses like batteries. (Auping, 2011) describes two ways to model copper demand: top-down, based on GDP growth and a certain copper demand per dollar GDP, and bottom-up, based on the developments in specific end-uses of the metal. Because this paper researches the total cobalt demand, and specifically one end-use, batteries, a hybrid approach is chosen. Traditional copper, nickel, and cobalt demand is modelled in a top-down way: depending on growth in GDP (Graedel & Cao, 2010). For nickel and cobalt, the demand from the EV transition is modelled separately, in a bottom-up way. Combining these two types of demand, gives a total basic demand, which afterwards is impacted by the price of the metal through demand change due to price elasticity. The price elasticity of the demand depends on the profitability of the metal. In case of the Opportunity cost paradigm, demand is also altered by (re-)substitution. The (re-)substitution of the metal depends on the price levels of the metal and its substitution metals, and the assumed substitution threshold for the metal. It is assumed that the demand from batteries is more prone for substitution than demand from traditional end-uses (Bloomberg NEF, 2019).

3.3.1. EV transition

This subsystem describes the part of the demand for nickel and cobalt which is expected to change the most: the EV transition. Battery demand is expected to increase mainly from the automotive sector, including passenger vehicles, buses and trucks, consumer electronics and stationary storage (Bloomberg NEF, 2019). The number of cars is assumed to be dependent on both world population and GDP per capita (Auping, 2011; Sivak, 2013). A number of types of cars are modelled: convential cars, or Internal Combustion Engines (ICEs), Plug-in Hybrid Electric Vehicles (PHEVs), and Battery Electric Vehicles (BEVs). The fraction of PHEVs and BEVs is assumed to increase over time, with BEVs becoming the most common car type over time. The number of buses and consumer electronics is assumed to be dependent on world population, whereas the number of trucks is assumed to depend on global GDP (EEA, 2018), see figure 3.9. The data on battery demand from stationary storage is mainly derived from Bloomberg NEF (2019) data, as well as the data on which cathode types are used for the end uses. Combined with data from Olivetti, Ceder, Gaustad, and Fu (2017) metal content of batteries, this provides data on the metal demand from the expected rise in battery demand, see figure 3.7. See Appendix A for more information on lithium-ion batteries.

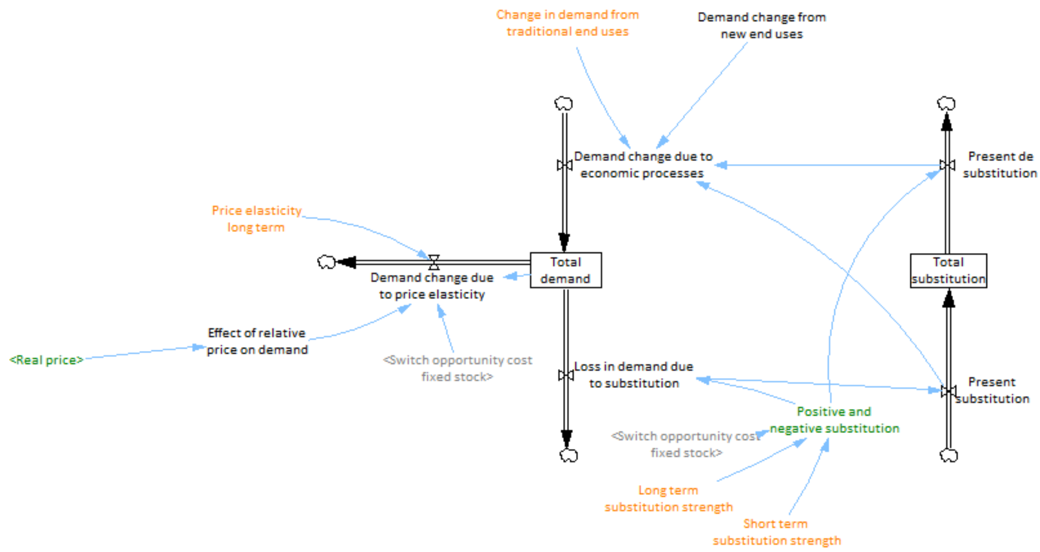

Figure 3.6: Demand for copper, nickel and cobalt. Orange variables are input variables, green variables are output variables, and purple variables are switches in the system.

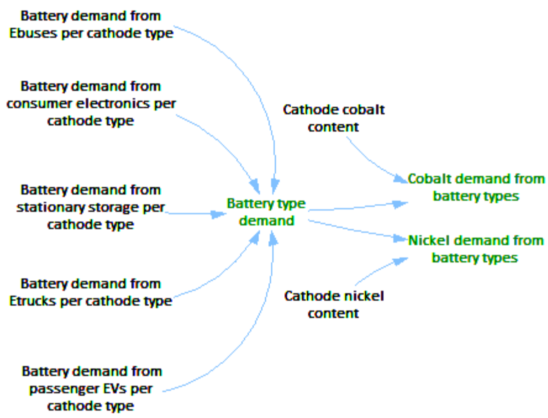

Figure 3.7: Cobalt and nickel demand from the increase in demand for battery types. Orange variables are input variables, green variables are output variables, and purple variables are switches in the system.

3.4. Economics and price dynamics

3.4.1. Price dynamics

Price dynamics are dependent on the marginal cost and the availability of metals in relation to the demand. The price can be calculated in two ways, with the baseline for both approaches being that the price is higher than the marginal cost at most moments in time. At certain points, the price can be temporarily lower than the marginal cost, if the market is over-saturated.

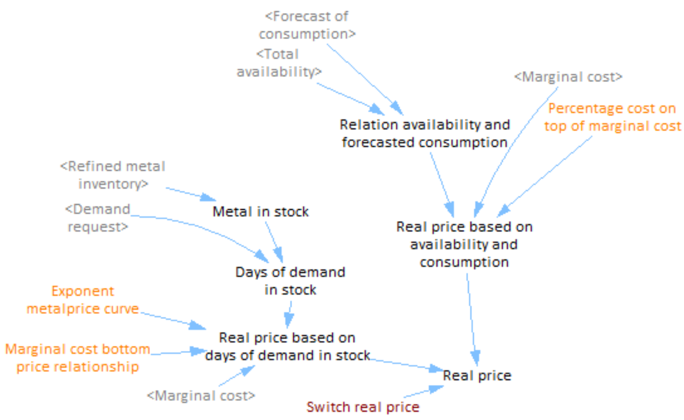

Figure 3.8: Economics and price dynamics in copper, nickel and cobalt markets. Orange variables are input variables, green variables are output variables, and purple variables are switches in the system.

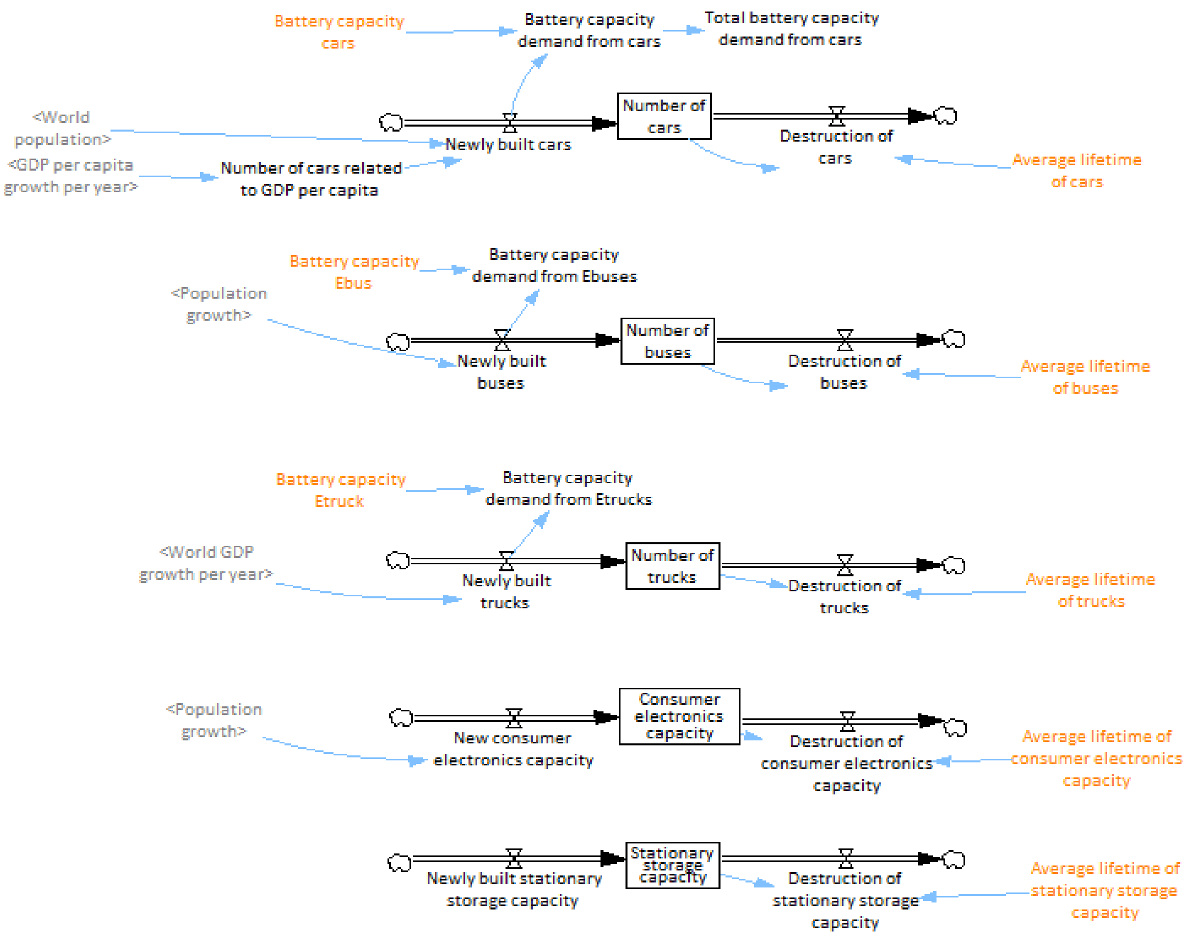

Figure 3.9: Demand from the increase in demand for battery types. Orange variables are input variables, green variables are output variables, and purple variables are switches in the system.

3.4.2. Marginal cost

The marginal cost of mining depends on its energy costs, transport costs, taxes (royalties), and possibly on a carbon price, see figure 3.11. The energy costs of smelting and refining, as well as mining, depend on the energy price. The energy usage of metal mining depends on the ore grade (Elshkaki, Reck, & Graedel, 2017; Koppelaar & Koppelaar, 2016; Sverdrup et al., 2017b), see figure 3.10. The ore grade decreases as the cumulative mined metals increases. This causes increasing marginal costs over time, unless the energy price decreases, or innovation provides a way to reduce energy usage.

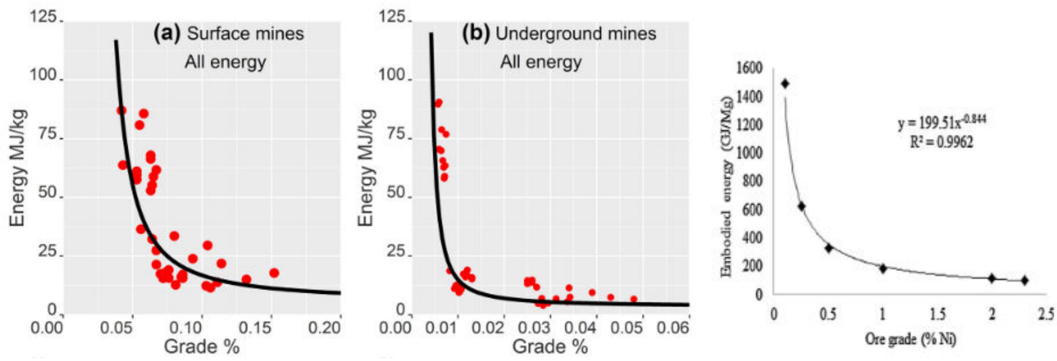

Figure 3.10: Relation between oregrade and energy usage for copper and nickel mines. Sources: Elshkaki, Reck, and Graedel (2017), Koppelaar and Koppelaar (2016)

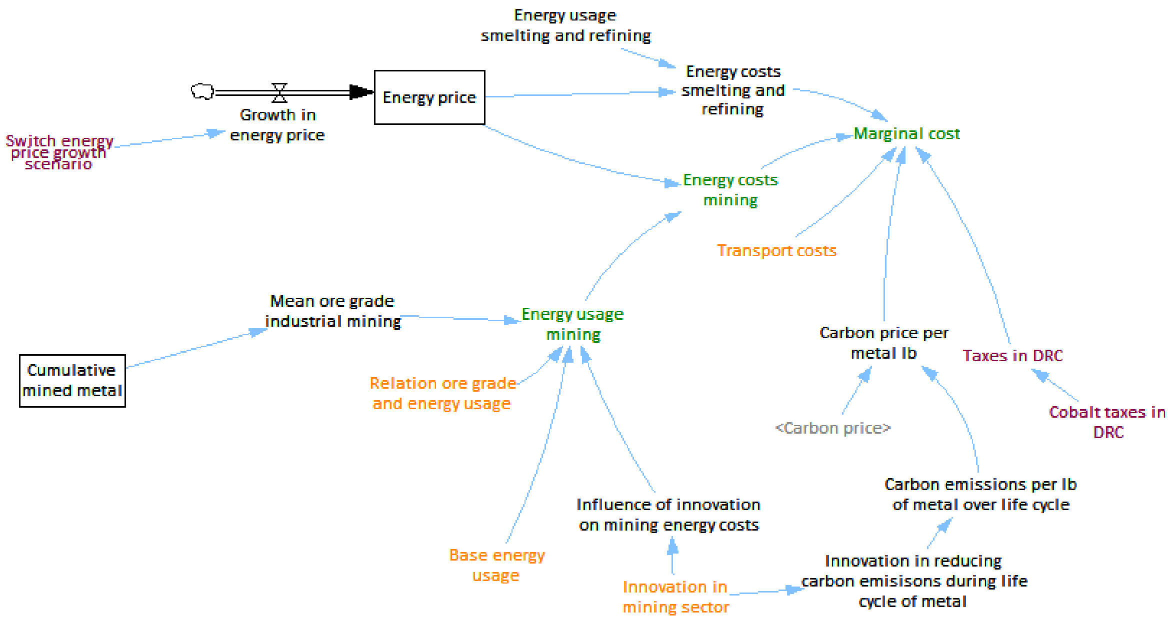

Figure 3.11: Marginal cost of copper, nickel and cobalt production. Orange variables are input variables, green variables are output variables, and purple variables are switches in the system.

3.4.3. Profitability and price elasticity

The price and the marginal cost determine the profitability of metal production capacity, which in turn determines the relative in- or decrease in the production capacity. The changes due to elasticity of supply depend on the short, and long term price elasticity. The same holds for the mining capacity, although based on the profitability of the respective deposits instead of the metals.

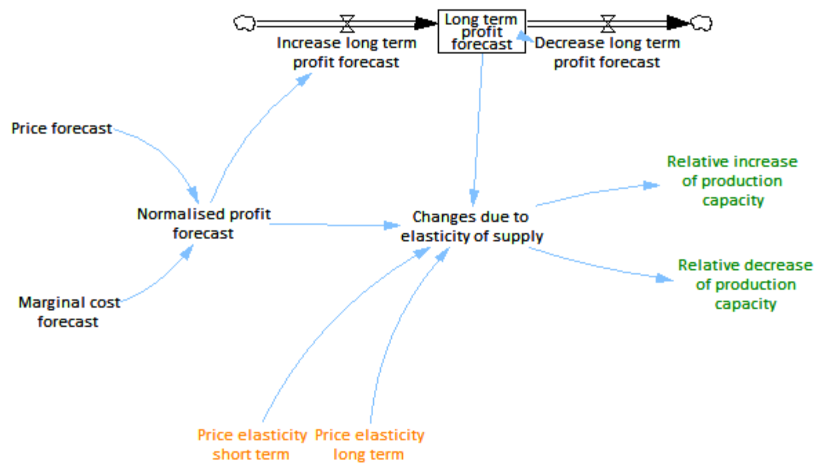

Figure 3.12: Profitability and price elasticity in copper, nickel and cobalt markets. Orange variables are input variables, green variables are output variables, and purple variables are switches in the system.

3.5. High level overview of the cobalt system

The separate sub-systems are all connected to each other in many different ways, and via many variables. Figures 3.13 and 3.14 show high level CLDs of the supply and demand dynamics in the model, with causal loops that cross the boundaries of the subsystems.

With regards to the supply dynamic, the shown loops are balancing rather than reinforcing loops. Industrial mining is balanced mainly through balancing loops that are influenced by the average oregrade, the average cobalt recovery rate, and the mining capacity per deposit. As the price increases, the cobalt recovery rate will increase, bringing more available raw cobalt to the market, decreasing the price. The same holds for the mining capacity of cobalt holding deposits: as the cobalt price increases and provided that the deposit is profitable given the prices of the other metals mined from it, the mining capacity for the deposit increases, which influences the maximum possible yearly availability of raw cobalt.

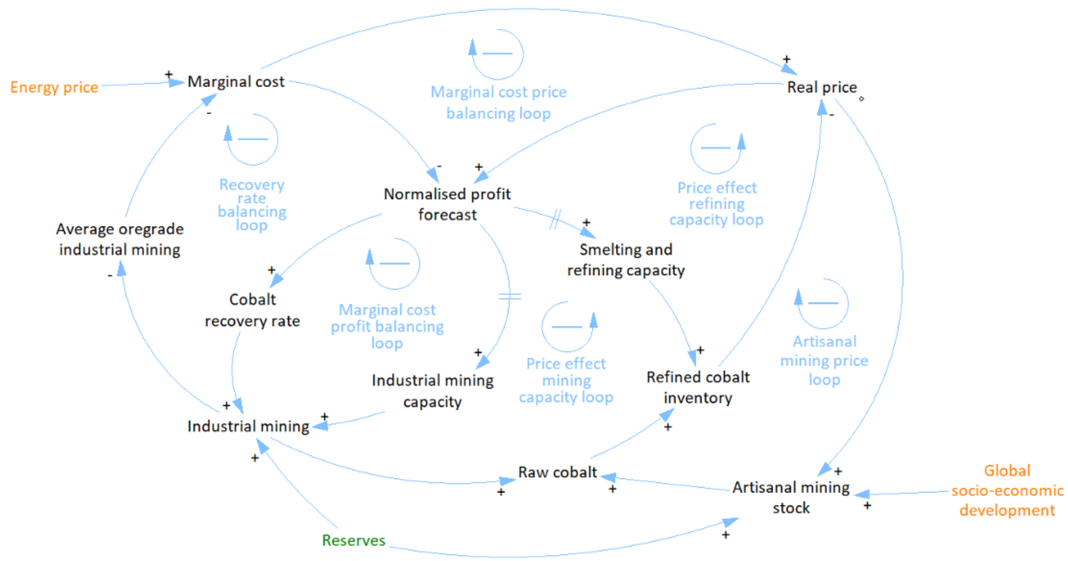

Figure 3.13: High level CLD of supply dynamics in the model in which some of the causal loops in the system have been indicated. Arrows indicate a causal influence of a variable on the variable that the arrow points to. A strike through the arrow indicates a delay in the causal influence, and the + and - signs indicate a positive or negative influence. Input variables to the model are indicated in orange, variables that are influenced by other variables in the model which are not shown in this diagram, are indicated with green.

The CLD with demand dynamics shows the balancing feedback loop that involves the average oregrade and the recycling efficiency. As the forecasted demand increases, the cobalt that is mined industrially increases, causing a decline in the average cobalt oregrade. The recycling efficiency reacts to this decline in the average oregrade, and recycling increases. As recycling increases, a larger part of the demand is fulfilled by the availability of recycled scrap, and the demand for industrially mined cobalt decreases. The balancing substitution loop is only incorporated in the Opportunity Cost paradigm.

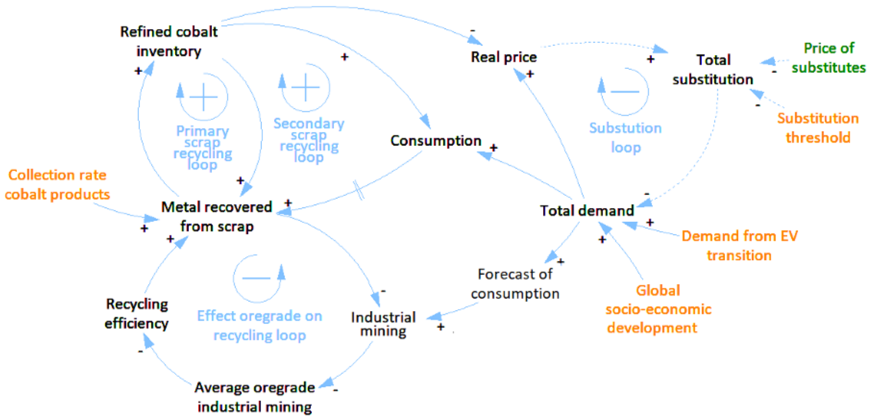

Figure 3.14: High level CLD of demand dynamics in the model in which some of the causal loops in the system have been indicated. Arrows indicate a causal influence of a variable on the variable that the arrow points to. A strike through the arrow indicates a delay in the causal influence, and the + and - signs indicate a positive or negative influence. Input variables to the model are indicated in orange, variables that are influenced by other variables in the model which are not shown in this diagram, are indicated with green. The substitution loop is indicated with dotted arrows because it is only incorporated in the Opportunity cost paradigm, and not in the Fixed stock paradigm.

3.6. Verification and Validation

Verification of the model is checking whether the model is representative of the system it simulates. The model runs from 2000 to 2050, and therefore, model results were continuously compared with historic data from 2000 to 2018 throughout the process of building the model. For example, with regards to the real price of the metals, the cobalt price between 2000 and 2018 was between 6 and 40 $ /lb, the nickel price between 2 and 6 $ / lb for most of the time, and the copper price between 1 and 4 $ / lb. As visible in figures 3.15, the model shows results between these boundaries.

Validation can be done through performing tests on the model, like an extreme conditions test. The extreme condition test is a situation in which in 2020 suddenly the cobalt mining production capacity in the DRC falls out, for example due to a civil war. As visible in figure 3.15, the price responds to this by increasing to a high level, after which it slowly decreases again. This behavior is valid, since the price should peak due to the sudden decline in demand, but also stabilize again when more production capacity is available.

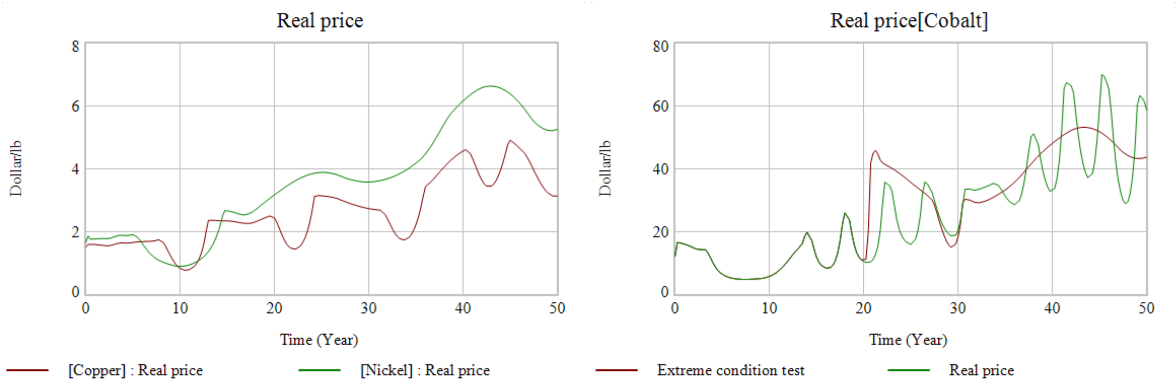

Figure 3.15: Left: Real price for copper and nickel, output from Vensim model with default values for parameters. Right: Real price for cobalt, for normal scenario and for extreme condition test. Outcome from Vensim model, with default values for parameters. N.B.: the meaning of 'Real' in this case is real as opposed to nominal. The real price does not reflect historical prices.

4 Uncertainties in the cobalt model

This chapter presents the main uncertainties considered in the implementation of the cobalt model. They are classified based on their location, and their level of uncertainty, following the framework by Kwakkel, Walker, and Marchau (2010). In terms of location, uncertainties are either structural or parametric. Structural uncertainties are uncertainties on system boundaries, the conceptual model, or how a structure is implemented in the computer model. Parametric uncertainty is on scenarios, which are sets of assumptions, or on parameters in the computer model, see table 4.1.

4.1. Boundary and conceptual uncertainty: paradigms

The main conceptual model uncertainty is which paradigm is the right one to describe the development of mining of resources: the Opportunity cost paradigm, or the Fixed stock paradigm. The paradigms differ in opinion on the cobalt system boundaries, and the appropriate model to describe the system. The Fixed Stock paradigm focuses on physical scarcity of metals, whereas the Opportunity cost paradigm focuses on economic scarcity. As visualized in figure 4.1, the Opportunity Cost paradigm argues that dynamics influencing the economic scarcity of metals should be included, such as innovation, and substitution of the metal. Also, this paradigm views all possible resources as potential future reserves, including deep-sea-bed mining, and resources in space. The Fixed Stock paradigm on the other hand focuses on the the depletion of reserves due to consumption. The Fixed Stock paradigm assumes that the physical availability of resources constitutes reserves and resources, but not the resource base. Therefore, it does allow resources to turn into reserves, but the resource base is not taken into account in the model structure. The Opportunity Cost paradigm on the other hand, does include the Resource Base. Furthermore, demand is dynamic in the Opportunity Cost paradigm, and static in the Fixed Stock paradigm. Substitution between metals is incorporated in the model structure of the Opportunity Cost paradigm, but not in the Fixed Stock paradigm. Also, in the Opportunity Cost paradigm, price elasticity of demand is considered, but in the Fixed Stock paradigm it is not, hence, a higher price does not decrease demand.

In recent years, there has been a shift in attention in the Fixed Stock paradigm, towards reasoning from a fixed stock not of resources but of carbon that is allowed to be emitted (Tilton, 2003). In order for the global temperature change to stay below 2 degree Celsius, there is a global carbon budget. This global carbon budget can be seen as a virtual stock that can be 'depleted'. In order to stay within the carbon budget, a carbon tax could be imposed. This research, however, assumes that the carbon tax is not only relevant for the Fixed Stock paradigm: its optional introduction in the cobalt system is also relevant in the case of the Opportunity Cost paradigm. Therefore, it is included as an uncertainty, which can be combined with both paradigms rather than a third paradigm.

As visualized in figure 4.1, the main metric for the Fixed Stock paradigm is the P/R ratio: the production over reserves ratio or the years to depletion, whereas the main metric for the Opportunity Cost paradigm is the price of cobalt. The main metric in this paradigm is the P/R ratio of the carbon 'stock': the number of years left to emit with current carbon emissions and carbon reserve. The actor of interest also influences the outcomes of interest.

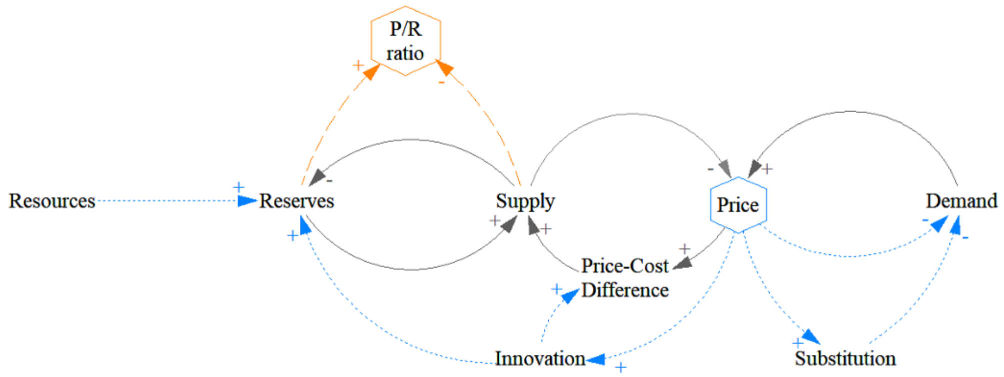

Figure 4.1: High level causal loop diagram that captures conceptual differences between the Fixed Stock (Orange, long dashed) and Opportunity Cost (blue, dotted) paradigm. The main metrics for the paradigms are shown with the hexagons.

4.2. Structural uncertainty: price dynamics

The price of metals can be modeled in two ways. While one method takes as input the number of days of demand that can be supplied with the current availability of stocks of metals, the second takes the marginal cost plus a certain percentage profit as starting point. The first way is based on Sverdrup et al. (2017b), see figure 4.2. The equation is implemented as described by equation 4.1:

$$P = MCb(\frac{S}{Y})^m \qquad (4.1)$$

with:
P = Price
MC = Marginal Cost
b = bottom of curve, expressed in terms of percentage of marginal cost
S = days of demand in stock
Y = days in a year
m = exponent of the metalprice curve.

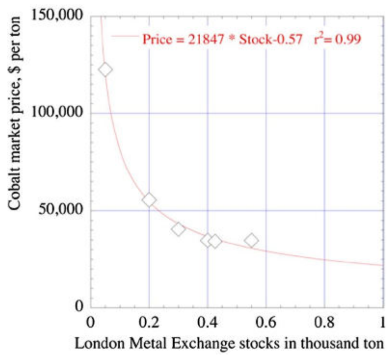

Figure 4.2: Price curve found for cobalt. Source: Sverdrup et al. (2017b)

The second method is based on (Usanov et al., 2013), and the equation is as described by equation 4.2:

$$P = MC(1+p)(\frac{A}{F}) \qquad (4.2)$$

with:
p = minimum percentage on top of marginal cost
A = available supply
F = forecasted consumption

4.3. Scenario uncertainty

4.3.1. Shared Socio-Economic Pathways

Since the demand for metals is dependent on socio-economic developments, this research includes parametric uncertainty on pathways for population and GDP. These are based on the Shared Socio-economic Pathways (SSPs), a set of scenarios that are used as a basis to explore future interactions between societal development and climate, which have been widely accepted by the climate change research community (O'Neill et al., 2017). The SSPs provide the following narratives as well as related quantitative projections on population, GDP (per capita) and urbanization, see figure 4.3 and 4.4:

- SSP1: Sustainability - Taking the Green Road. The world chooses for sustainable, inclusive development, with a focus on human well-being rather than economic growth, and respect for perceived environmental boundaries (van Vuuren et al., 2017)

- SSP2: Middle of the Road. The world broadly follows historical patterns in terms of uneven development and income growth, while there is slow progress in achieving sustainable development goals (Fricko et al., 2017)
- SSP3: Regional Rivalry - A Rocky Road. The world is divided due to resurgent nationalism and regional conflict, while inequalities worsen, consumption is material-intensive and there is low international priority for addressing environmental concerns (Fujimori et al., 2017)
- SSP4: Inequality - A Road Divided. The world faces increasing disparities in economic opportunity, with a gap between an internationally-connected, high-tech, low-carbon economy and a lower-income, labor intensive, low-tech economy, while conflict and unrest become increasingly common (Calvin et al., 2017)
- SSP 5: Fossil-fueled Development - Taking the Highway. The world has faith in competitive markets, and development of human capital to enhance sustainable development, which leads to rapid global economic growth, largely based on fossil fuel resources (Kriegler et al., 2017).

Combining the SSPs with integrated assessment models, quantitative projections can be made of energy, land use, and emissions associated with the SSPs. These combinations provide, apart from a baseline scenario, also scenarios in which projections of carbon prices have been made based on the expected global warming in the respective scenarios (Riahi et al., 2017), see figure 4.4.

Figure 4.3: Five SSPs representing different combinations of challenges to mitigation and to adaptation. Source: O'Neill et al. (2017)

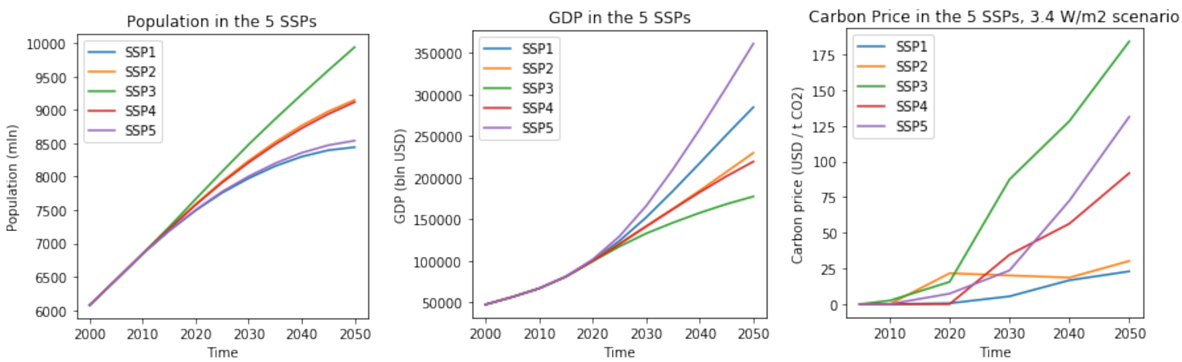

Figure 4.4: Population, GDP and carbon price for the SSPs. Following the International Institute for Applied Systems Analysis, the illustrative cases from the OECD were selected from the SSP database for the population and the GDP data, and the marker scenarios were selected for the carbon price. Source of data: Riahi et al. (2017).

4.3.2. Energy cost of metal mining

The marginal costs of metals are largely dependent on the energy costs related to mining (Koppelaar & Koppelaar, 2016). Therefore, in terms of price development, the energy costs is of large influence. The two main

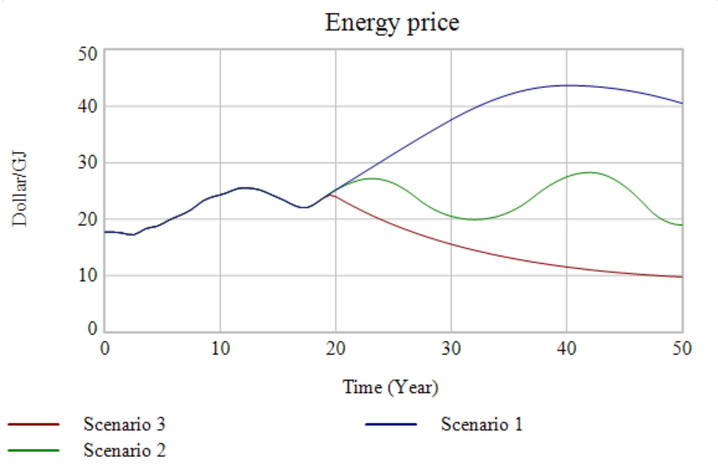

Figure 4.5: Scenarios for energy price. Still make it fancy in python Based on: (Auping, Pruyt, de Jong, & Kwakkel, 2016).

determinants of the energy costs are the energy price, and the ore grade. The lower the ore grade, the energy input needed to mine a kg of ore increases. This research bases the relationship between ore grade and energy use on assessments for metals in general by Calvo, Mudd, Valero, and Valero (2016), for copper by Koppelaar and Koppelaar (2016), for nickel by Elshkaki et al. (2017) and for cobalt on Sverdrup et al. (2017b). The energy price meanwhile, can also change over time, due to, for example, geopolitical tensions or large-scale adoption of cheap, renewable energy. In this research, a number of scenario's for the energy price have been implemented as parametric uncertainty, see figure 4.5. While it is acknowledged that the energy price varies depending on the local context, and the energy source that is used (oil, gas, electricity), this research assumes a single global average price, based on the average energy price in Europe.

4.4. Parameters uncertainty

To get an overview of the uncertainties in the model, and how uncertain they are, table 4.1 summarizes the (groups of) uncertainties in the model, categorized according to whether they are structural, or parametric in nature, their location, and their level of uncertainties, based on research by Kwakkel et al. (2010). The level of the uncertainty ranges from shallow, medium, and deep uncertainty, to recognized ignorance, see table 4.1. Structural uncertainties entail uncertainties on the system boundary, on the conceptual model, or on how the model structure is implemented in a computer model. Parametric uncertainties are in the form of scenarios, which are more elaborate combinations of parameters, or individual parameters in the model.

Table 4.2 shows an overview of the input variables in the model, their range as used as input to EMA, and the source for these values. All variables listed here were included in the first runs of the model, which were used to identify the most influential input variables to the model. To reduce computational complexity, hereafter, a dimension reduction was done, resulting in a shorter list of variables included in the model for the runs on which the graphs presented in the next chapters are based. applicable. The column Included shows whether the variable was still included as an uncertain input variable after dimension reduction.

Table 4.2: Overview of experimental set-up. The column Included shows those variables that were still included after the dimension reduction.

Variable name	Unit	Min	Max	Included	References
Ore grade energy curve parameters					
Relation ore grade energy usage copper	Dimensionless	-1.05	-0.95		Koppelaar and Koppelaar (2016)
Relation ore grade energy usage nickel	Dimensionless	-0.77	-0.67		Elshkaki et al. (2017)

Relation ore grade energy usage cobalt	Dimensionless	-3.1	-2.9		Sverdrup et al. (2017b)
Base energy usage copper	GJ/lb	0.075	0.085		Koppelaar and Koppelaar (2016)
Base energy usage nickel	GJ/lb	0.09	0.13		Elshkaki et al. (2017)
Base energy usage cobalt	GJ/lb	0.09	0.11		Sverdrup et al. (2017b)
Price curve parameters					
Marginal cost bottom price relationship copper	Dimensionless	0.065	0.08		AME (2019)
Marginal cost bottom price relationship nickel	Dimensionless	0.3	0.36		AME (2019)
Marginal cost bottom price relationship cobalt	Dimensionless	0.05	0.075		AME (2019)
Exponent copper price curve	Dimensionless	-1.2	-1		AME (2019)
Exponent nickel price curve	Dimensionless	-0.85	-0.65		AME (2019)
Exponent cobalt price curve	Dimensionless	-1.3	-1.1		AME (2019)
Percentage cost on top of marginal cost	Dimensionless	0.05	0.25		Auping (2011)
Battery transition parameters					
Battery capacity PHEV	kWh/Car	10	30		Bloomberg NEF (2019)
Battery capacity BEV	kWh/Car	20	120	x	Bloomberg NEF (2019)
Number of cars per dollar GDP	Car/Dollar	1.37E-6	2.37E-6		Sivak (2013)
Battery capacity Ebus	kWh/Bus	150	220		Bloomberg NEF (2019)
Number of buses per person	Bus/Person	0.001	0.002		EEA (2018)
Battery capacity Etruck	kWh/Truck	70	150		Englmann and Woeckener (2019)
Increase in demand stationary storage	Dimensionless	0.2	0.4		Bloomberg NEF (2019)
Slowing of increaes in demand statationary storage	Dimensionless	0.88	0.96	x	Bloomberg NEF (2019)
Parameters resources, reserves and mining					
Percentage lost during artisanal mining	Dimensionless	0.4	0.6	x	Auping and Pruyt (2013)
Part artisanal mining from classified reserves	Dimensionless	0.1	0.3		Faber et al. (2017)
Administration time	Year	10	20		Auping and Pruyt (2013)
Average time mining until refining	Year	0.09	0.11		Assumption
Parameters recycling					
Average time scrap until recycling	Year	0.38	0.42		Assumption
Maximum recycling efficiency score	Dimensionless	0.8	0.99		Glöser et al. (2013)
Yearly increase recycling efficiency score	1/Year	0.03	0.07		Glöser et al. (2013)
Percentage of primary scrap	Dimensionless	0.25	0.4	x	International Copper Association (2017)
Initial average lifetime of metal in use	Year	5	15	x	Glöser et al. (2013)

Collection rate metal products	Dimensionless	0.6	0.8	x	Glöser et al. (2013)
Minimum usage mining capacity	Dimensionless	0.7	0.9		Auping (2011)
Parameters mining, smelting and refining capacity					
Short forecasting period	Year	0.5	2		Assumption
Minimum usage smelting and refining capacity	Dimensionless	0.7	0.9	x	Auping (2011)
Percentage lost during operations	Dimensionless	0.04	0.08		Auping (2011)
Mining usage investment cap	Dimensionless	0	0.95	x	Auping (2011)
Average permit term	Year	5	20		Kindt (2019)
Smelter and refiner usage investment cap	Dimensionless	0	0.95		Auping (2011)
Maximum increase recovery rate	Dimensionless	0.05	0.25	x	Sverdrup et al. (2017b)
Sed hosted Co typical Co recovery rate	Dimensionless	0.65	0.75		Sverdrup et al. (2017b)
Ni laterite Co typical Co recovery rate	Dimensionless	0.625	0.775		Sverdrup et al. (2017b)
Magm sulfide Co typical Co recovery rate	Dimensionless	0.55	0.65		Sverdrup et al. (2017b)
Maximum increase production capacity	1/Year	0.1	0.2		Assumption
Maximum decrease production capacity	1/Year	0.02	0.05		Assumption
Parameters artisanal mining					
Percentage of profit from refined cobalt for artisanal miners	Dimensionless	0.04	0.1		Tsurukawa et al. (2011)
Productivity of artisanal mining	lb/Person/Year	800	1600	x	Tsurukawa et al. (2011)
Minimum cost of artisanal mining	Dollar/Year /Person	800	1300		Tsurukawa et al. (2011)
Parameters demand					
Ni per dollar GDP	lb/Dollar	4E-6	8E-6		INSG (2018), World Bank (2019)
Co per dollar GDP	lb/Dollar	1E-6	1.5E-6		USGS (2019), World Bank (2019)
Cu per dollar GDP	lb/Dollar	6E-5	8E-5		ICSG (2019), World Bank (2019)
Long term substitution strength	1/Year	0.01	0.05		Assumption
Short term substitution strength	1/Year	0.02	0.06		Assumption
Period for long term effect of substitution demand	Year	5	15		Auping and Pruyt (2013)
Copper substitution threshold	Dimensionless	2.5	5		Auping (2011)
Nickel substitution threshold	Dimensionless	5	10		Assumption
Cobalt substitution threshold	Dimensionless	2	4		Assumption

Substitution strength battery compared to traditional	1/Year	0.01	0.05		Assumption
Price elasticity long term	1/Year	0.1	0.25		Auping and Pruyt (2013)
Price elasticity short term	1/Year	0.02	0.08		Auping and Pruyt (2013)
Price amplifying factor	Dimensionless	0.5	0.3		Auping and Pruyt (2013)
Parameters marginal costs					
Cobalt taxes in DRC	Dollar/lb	0.3	0.8		AME (2019)
Innovation in mining sector	Dimensionless	0.7	1		Assumption
Transport costs copper	Dollar/lb	0.02	0.06		AME (2019)
Transport costs nickel	Dollar/lb	0.1	0.3		AME (2019)
Transport costs cobalt	Dollar/lb	0.1	0.3		AME (2019)
Price averaging period	Year	0.1	0.4		Assumption
Power for oregrades	Dimensionless	0.38	0.42	x	Elshkaki et al. (2017), Koppelaar and Koppelaar (2016), Sverdrup et al. (2017b)

Table 4.1: Overview of implemented uncertainties in the cobalt model, based on the framework by Kwakkel, Walker, and Marchau (2010)

Location			*Level* Level 1: Shallow uncertainty	Level 2: Medium uncertainty	Level 3: Deep uncertainty	Level 4: Recognized ignorance
Structural	System boundary				Underlying paradigms	
	Conceptual model			Price dynamics		
	Computer model	Model structure				
Parametric		Scenarios			SSPs Energy price	
		Parameters	Average permit term Collection rate Percentage primary scrap Average lifetime of metal in use Administration time Transport costs Taxes Productivity artisanal miners % profit for artisanal miners Percentage lost during artisanal mining	Substitution thresholds Investment caps Minimum usage capacity Maximum recycling efficiency Battery capacity EVs Maximum increase recovery rate Part artisanal mining from reserves Forecasting period	Price curves Ore grade energy curves Power for oregrades Price elasticity	

5

Exploration of cobalt system scenarios

The future cobalt system can show many different scenarios, and this chapter explores the scenarios that the model results show. Specifically, the relevant results of the cobalt model are analysed in light of the influence of the paradigms, the sustainability consequences of the scenarios, and the implications for investors. The sustainability of the cobalt system has many aspects: this chapter focuses on local and global externalities of cobalt mining, and recycling of cobalt to make it part of a circular economy. The most relevant changes for investors in the cobalt system are the increased volumes, which create more investment opportunities, and an increased need to balance financial, and EHS risks.

5.1. Clusters of scenarios

A first exploration of the scenarios can be done by examining the future cobalt demand. The demand influences many of the other main outcomes of the model, like how much is mined, both by industrial and artisanal miners, and the price. Future cobalt demand could follow a wide range of scenarios, ranging from increasing exponentially to decreasing as compared to current demand. Figure 5.1 presents these scenarios, grouping the results of the model for cobalt demand in 3 clusters, based on the behavior of the scenarios over time. The density plot in the right part of the graph shows the range and density of the clusters at the last point in time that was simulated, in this case 2050.

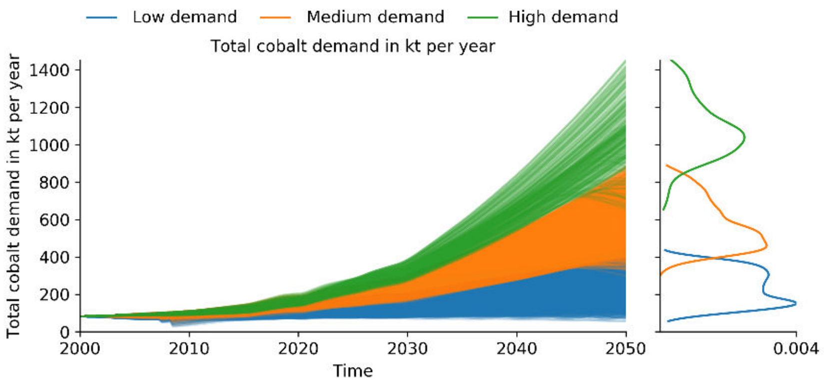

Figure 5.1: Cobalt demand, clustered based on behavior of scenarios over time

In order to understand what causes the differences between the clusters, figure 5.2 presents the results of extra trees feature scoring, which show the variables that are most influential on the cobalt demand, for each period of 2 years of simulation. The higher the extra trees feature score, the more influential the variable (Breiman, Friedman, Olshen, & Stone, 1984). At every point in time, the two most influential variables are selected, and the figure presents the influence of these selected variables over time. The most influential variables are which paradigm is used to model the cobalt system, how fast the average oregrade of deposits will decline, how much capacity the batteries in BEVs will have, and, although to a lesser extent, how fast the demand from stationary storage will increase.

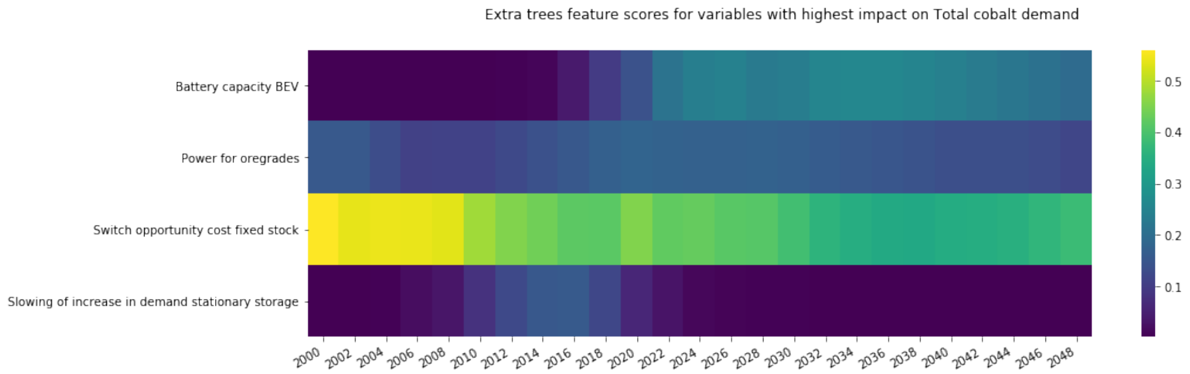

Figure 5.2: Results from Extra Trees Feature Scoring: most influential variables on cobalt demand over time

To illustrate how the decline of the average oregrade, the battery capacity of BEVs, and the choice of paradigm influence the demand of cobalt, figures 5.3 and 5.4 show violin plots for the values of these variables for the clusters as identified in figure 5.1. According to the Opportunity cost paradigm, the lower the power of the oregrade (i.e., the slower the decline of the average oregrade of deposits), the higher the demand. In both paradigms, a higher average battery capacity of BEVs causes a higher demand, although the influence of this variable is higher in case of the Fixed stock paradigm.

The consistently high influence of the choice of paradigm throughout the graphs can be explained due to its effect on substitution and price elasticity of demand in the model: these processes are only assumed to happen according to the Opportunity cost paradigm. In the Fixed Stock paradigm, demand is assumed to be continuously increasing, and not be influenced by these substitution and price elasticity. The decline of the average oregrade of deposits influences the price through the marginal cast. A deposit with a lower average oregrade requires more energy to be mined, which increases the marginal cost of mining cobalt (unless the energy price decreases correspondingly), which pushes price levels up. If the price level of cobalt becomes higher than substitutes, cobalt demand is substituted, and demand declines. Since the Fixed stock paradigm assumes that substitution of demand does not happen, no difference is visible between the clusters with regards to how fast the oregrade declines. BEVs are assumed to become the main car type over time, therefore, the average size of their battery packs is going to be influential for the size of the cobalt demand. In the Opportunity cost paradigm, the influence of the EV transition is relatively less important because other variables also influence demand, like price elasticity and substitution. Finally, the demand for stationary storage could become a major part of the cobalt demand, provided that the demand for stationary storage will continue to grow over time.

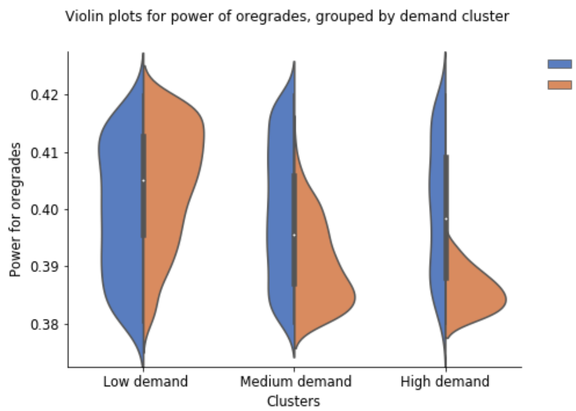

Figure 5.3: Violin plot for power of oregrades, specified for clusters of cobalt demand, and choice of the Opportunity cost or Fixed stock paradigm.

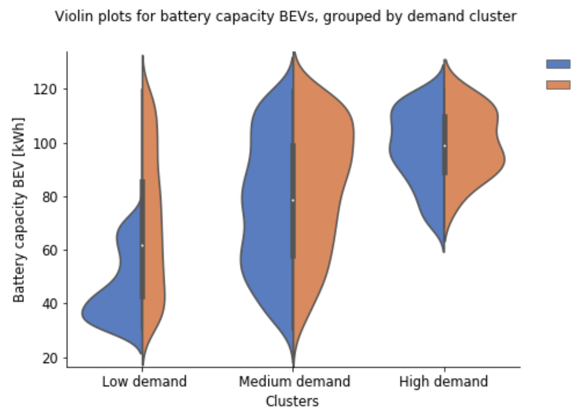

Figure 5.4: Violin plot for battery capacity of BEVs, specified for clusters of cobalt demand, and choice of the Opportunity cost or Fixed stock paradigm.

These results show that the cobalt system is most sensitive to the assumptions regarding which paradigm is the most realistic, the demand from the EV transition, and the future physical scarcity of cobalt. The choice of paradigm is the most influential on the dynamics in the model: the Fixed stock paradigm assumes a constantly exponentially growing demand, whereas the Opportunity Cost paradigm assumes a more dynamic demand, that could also decrease over time. The demand from the EV transition becomes more influential from the start of the EV transition. The speed with which cobalt becomes physically scarce, lastly, could be of high importance to determine how much of cobalt's demand will be substituted. If the average oregrade declines fast, high price levels could cause many battery producers to choose battery technologies that do not contain cobalt.

5.2. Sustainability of the cobalt system

There are many angles to the sustainability of the cobalt system. The physical scarcity of cobalt is according to some scientists an important parameter. The carbon emissions and other externalities are also important sustainability outcomes of the system, as well as how much cobalt is being recycled, and to what extent recycled cobalt can serve as input for new products, rather than newly mined cobalt.

5.2.1. Externalities of cobalt mining

Externalities are a form of market failure, which exists when one economic actor experiences an external effect due to the action of another actor, who created this effect as an unintended or incidental by-product of its activity (van den Berg, 2002). Externalities can be both positive and negative. Mining can be responsible for a variety of global and local externalities, like carbon emissions and environmental damage of the surroundings of a mine.

The energy usage of cobalt mining is expected to increase in the coming years, see figure 5.5. The main influence on the speed of this increase is the decline of the average cobalt oregrade.This can be explained by that a lower oregrade means that the mining facility needs to process higher deposit volumes in order to produce the same amount of raw cobalt. This causes the energy usage to increase. The average oregrade is modelled such that it declines across the possible scenarios, although at different speeds, depending on the power that is used in the formula for the oregrade. The cause of this difference in speed of decline is how much cobalt is industrially mined in each scenario: the more there is being mined, the more the average oregrade is assumed to decline. One could argue that the oregrade is a measure

Since most of the energy used in mines nowadays is still based on fossil fuels like diesel, the increase in energy usage also means an increase in carbon emissions from mining (Koppelaar & Koppelaar, 2016; Northey, Mohr, Mudd, Weng, & Giurco, 2014). In the future, energy used at mines could also be generated by renewable energy sources like wind and solar energy. This would contribute to lowering the carbon emissions from the production process, since it would decouple the increased energy usage from carbon emissions. Future energy usage of cobalt mining could also be influenced by the deposit type cobalt is mined from. Although the majority of current nickel production is from sulphides, it is expected that the majority of future nickel production is from Nickel laterite (Moskalyk & Alfantazi, 2002). Mineral processing involved in Nickel cobalt laterite projects is more energy intensive than processing of sulphide ores (Mudd et al., 2013).

The decline in average oregrade is also responsible for other local externalities of cobalt mining. Provided that the local oregrades of other metals in the deposit is also declining, a lower cobalt oregrade means that in order to mine the same amount of raw cobalt, the mine needs to take up a bigger area, and the size of mines increases because low grade deposits are typically larger ore deposits (Northey et al., 2014). Other environmental impacts of metal mining also increase with declining ore grade (Northey et al., 2014), like water, and explosives usage (Mudd et al., 2013). The combination of increased mine size and declining ore grade means that waste rock removal increases, as well as tailings generation, and the size of the area of local habitat that is disturbed (Northey et al., 2014).

A solution for the increased carbon emissions of mining is to introduce a global carbon tax per lb to the system. Its influence on the price and the demand is visible in figures 5.6 and 5.7. The figures show that the influence of the introduction of a carbon tax on the price of and demand for cobalt is rather small: there is hardly any difference between the density plots of the price and the demand with and without the carbon tax.

The carbon tax could be introduced differently to the cobalt system and potentially create more incentive to lower carbon emissions that way. The small influence of the introduction of a carbon tax means that this way, the cobalt producers will not be incentivized to decrease their carbon emissions. The carbon tax is now based on the assumption of a certain amount of carbon emissions per lb cobalt. The carbon tax could also globally be implemented to tax energy production instead of metal production. This way, metal producers would be incentivized to switch energy sources from fossil fuels to renewable energy sources, and/or to

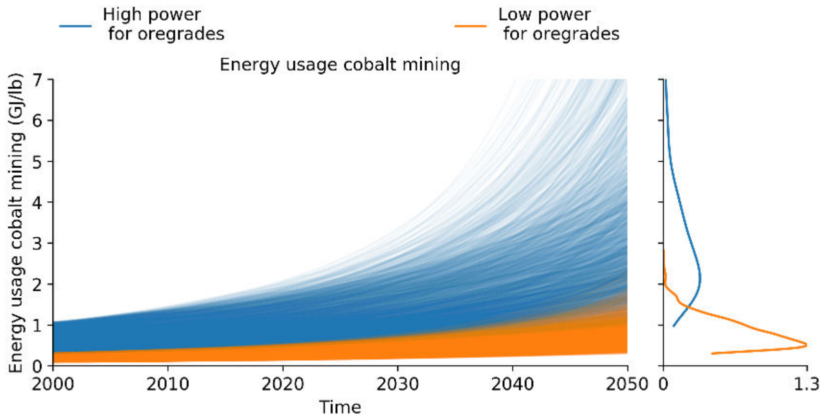

Figure 5.5: Energy usage of cobalt mining over time, grouped by fast (power >0.4), and slow decline of oregrades (power <0.4).

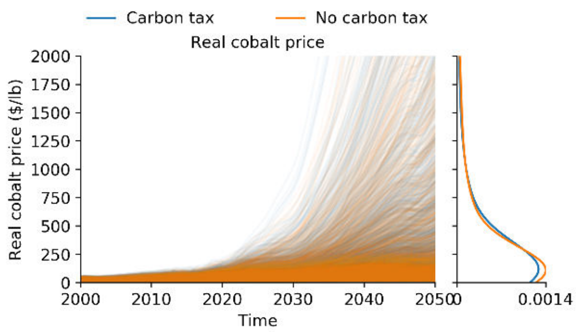

Figure 5.6: Cobalt price, with and without carbon tax.

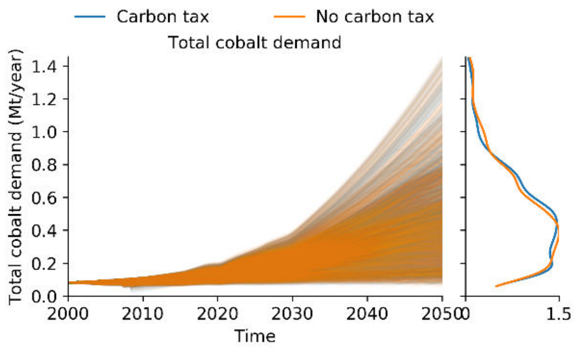

Figure 5.7: Cobalt demand, with and without carbon tax.

decrease their energy usage altogether.

Other solutions to lower the impact of negative externalities of cobalt mining are, for example, the digitization and/or the electrification of mining facilities, and increased recycling of cobalt. Digitization of vehicles used at mining facilities could decrease the EHS risks in mining. Also, it could lead to more efficient use of resources, and therefore lower the carbon footprint of mining. Electrification of vehicles and machinery at mining facilities could make it easier to make use of renewable energy sources. Increased recycling would decrease the demand for newly mined metals, and hence mitigate negative externalities from mining.

5.2.2. Recycling of cobalt

A variable of interest is the percentage of input metal to the smelting and refining process that is derived from recycled scrap, instead of newly mined cobalt. This variable is called the recycling input rate (Glöser et al., 2013). The higher the value of this variable, the higher the part of the cobalt demand that recycling can fulfill. Figure 5.8 shows the variables with the highest influence on the recycling input rate: the percentage of primary scarp, the average lifetime in use, the collection rate of metal products and the power for oregrades (which represents how fast the oregrade is expected to decline).

The reason for the high influence of the collection rate of metal products and the percentage of primary scrap is simply that the higher these variables, the more cobalt there is to recycle. The percentage of primary scrap is the percentage of metal that is turned into scrap during the smelting and refining process, instead of ending up in the end product. This material usually stays within the smelting and refining facilities and is immediately reused as input for the smelting and refining process. The influence of this variable is therefore rather straightforward, but does not necessarily contribute to the circularity of the cobalt system: if the primary scrap was not recycled, it would have ended up in the end product in the first place. The influence of the collection rate, on the other hand, is of high relevance for the circularity of the cobalt system. This variable represents the part of the discarded cobalt-containing products that are collected. These collected products can be recycled, and used as an input for new products as secondary scrap. The higher influence of

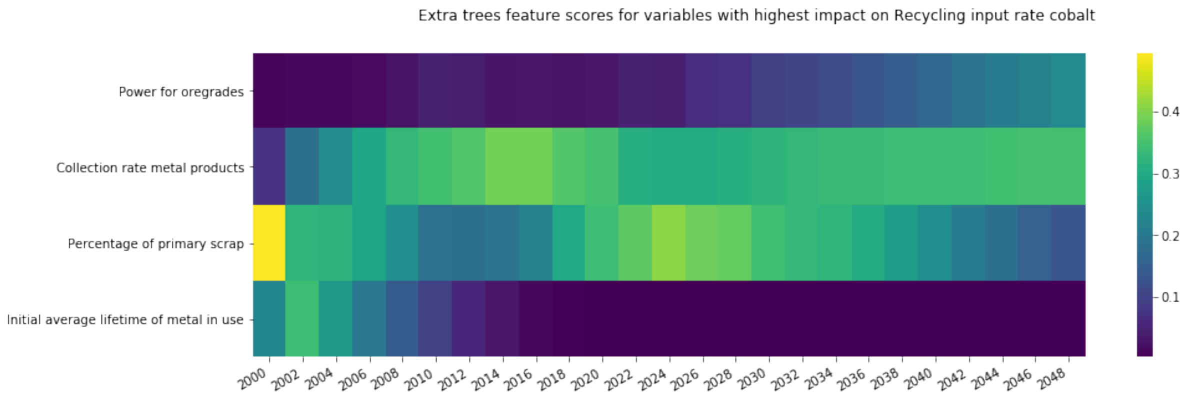

Figure 5.8: Extra trees feature scores for variables with highest influence on Recycling input rate, the percentage of production from recycled cobalt

the average lifetime of metal in use at the start of the simulation runs, can be explained by the influence that the variable has on how much secondary scrap becomes available at the start of the simulation. If the average lifetime is shorter, the stock of metal in use becomes available sooner than if the average lifetime is longer. This causes a difference in the availability of secondary scrap between simulation runs during the first years, because a higher availability of secondary scrap means that the recycling input rate can be higher. Finally, the influence of the power of oregrades on the recycling input rate is due to the influence the oregrade has on the recycling efficiency. The recycling efficiency is a variable that represents the percentage of available (primary and secondary) scrap that is ultimately reused as input for the smelting and refining process. It is assumed in the model that the lower the oregrade, the more attractive recycling of scraps, and the higher the recycling efficiency.

The relationship between the collection rate and recycling of cobalt is explored in more detail in figures 5.9 and 5.10. The collection rate of cobalt is the percentage of the cobalt products that are discarded, that is collected in order to be recycled into secondary scrap. The recycling input rate is the percentage of input metal to the smelting and refining process, that comes from recycled scrap. Figure 5.9 shows that the higher the collection rate, the higher the recycling input rate, on average. This relationship holds, regardless of the recycling volumes, as visible in figure 5.10, although the influence of the collection rate on the volumes is less pronounced.

The relationship between the collection rate and cobalt recycling can be explained by the fact that if more used cobalt products are collected, there is more collected material to recycle cobalt from. The recycling input rate is also influenced by the recycling efficiency, which in turn is influenced by the average oregrade as part of a balancing feedback loop. If the availability of recycled scrap becomes higher, there is less demand for newly mined cobalt, which means that the average oregrade will decline slower. The increase in recycling efficiency is dependent on the decline of the average oregrade, because recycling is assumed to become more attractive as the average oregrade declines.

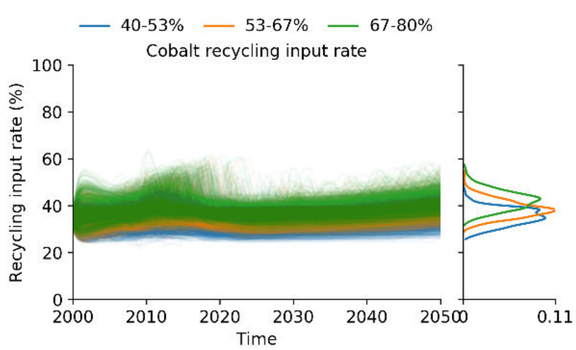

Figure 5.9: Recycling input rate, grouped by collection rate. The recycling input rate is the percentage of cobalt that is used as input to the smelting and refining process that comes from recycled scrap.

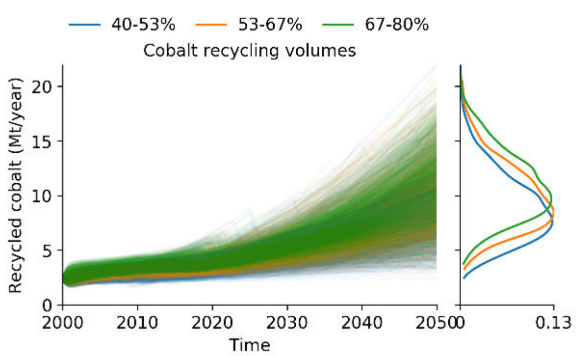

Figure 5.10: Recycling volumes in the cobalt system, as influenced by the collection rate.

Using more recycled metals instead of newly mined metals can make the supply chain of metals more circular, and decrease externalities. The results show that improving the collection rate of cobalt products should be encouraged, if the objective is to increase recycling of cobalt. Scrap is a relatively high-value material, and using this instead of newly mined metal reduces the energy demand of metal production (Alonso et al., 2007). For example, copper recycling requires 80-90% less energy than primary production (International Copper Association, 2017). Since energy usage is the driver of carbon emissions of metal production, recycling also reduces carbon emissions (Alonso et al., 2007). Recycling of complex scraps containing multiple metals, increases the recovery rates of multiple metals from discarded products at once (International Copper Association, 2017). Nickel and copper are highly recyclable metals (INSG, 2018), with copper even being 100% recyclable (Glöser et al., 2013). On the other hand, little cobalt is currently recycled, and with most being discarded to landfills, improvements in recycling could increase the sustainability of the cobalt supply chain substantially (Mudd et al., 2013). Improving the collection rate of cobalt products could contribute both to the circularity of the cobalt system, and to decreasing the externalities from cobalt mining. The battery transition provides an opportunity here, because the batteries are a rather homogeneous group of cobalt end products. A collection scheme could therefore be easier to set up for batteries than for other cobalt containing products. However, there are also dangers involved with battery recycling. There is a risk at battery explosion during the transportation and processing of batteries. When implementing a battery recycling scheme, these risks should be taken into account and it is advised to also implement relevant safety policies.

5.3. Investors in the cobalt system

The most important changes for investors in the cobalt system are the increased volumes of cobalt in the system, which create more investment opportunities, the importance of cobalt for profit of mines, and an increased need to balance financial and EHS risks.

5.3.1. Volumes in the cobalt system

The volumes of cobalt in the system are of interest to investors because higher volumes create more investment opportunities. More industrial mining, for example, means that it is likely that there will be more industrial mining facilities to invest in. Figure 5.11 shows the variables with the biggest influence on how much there is industrially mined in the simulations over time: the choice of paradigm, the mining usage investment cap, the maximum increase in the cobalt recovery rate per year, and the formula that is used for the price. The influence of the paradigm especially increases over time.

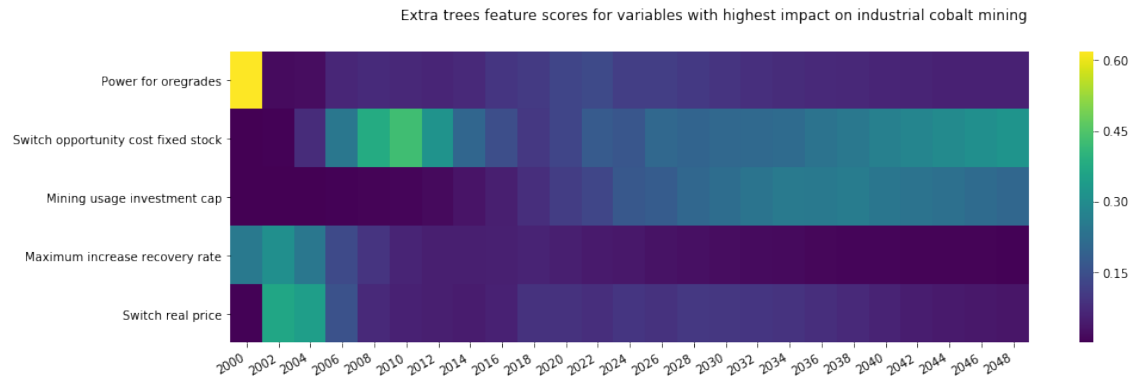

Figure 5.11: Results from Extra Trees Feature Scoring: most influential variables on industrial cobalt mining over time.

The influence of the switch for the paradigms is due to the big influence of this parameter on the demand. In the Fixed stock paradigm, the demand increases over time, whereas in the Opportunity cost paradigm, the (growth in) demand can also decrease over time. The forecasted demand, in turn, is one of the main drivers of how much cobalt is industrially mined. The mining usage investment cap influences how fast mining capacity can ramp up and down, and therefore how much of a change in demand can be met with an increase in industrial mining. Alternative 'swing factors' in the system to meet a change in the demand are the cobalt recovery rate, and artisanal mining. A demand increase could be met by an increase in the recovery rate of cobalt. The maximum increase recovery rate indicates how much the increase rate can increase as compared to the typical cobalt recovery rate of a deposit. If the demand increase cannot be met by an increase in recovery rate because it is already close to its maximum, and price levels are high, artisanal mining could fill the gap between the demand and the availability. The power for oregrades influences the attractiveness of recycled scrap, as well as the marginal cost of industrial mining. As the oregrade declines, recycling of scrap is assumed to become more attractive. Via the marginal cost of industrial mining, and its influence on cobalt's price level, the power of the oregrade influences the favourability of industrially mined cobalt as compared to artisanal mining, as well as the favourability of cobalt compared to substitutes. The same holds for the influence of the switch for the formula of the real price.

The higher volumes mined, traded, and used in the cobalt system increases the number of investment opportunities for investors. The increased demand for batteries and the increased price of cobalt offers opportunities for miners and traders. Owners of mines can produce more cobalt, see figure **??** through the increase in the cobalt recovery rate. Increased demand offers opportunities for new mining capacity, although this also depends on the development of recycling. The recycling input rate is expected to increase, see figure 5.9. More recycling means a higher availability of recycled scraps, and thus, less industrial mining is necessary.

New battery technologies contain less cobalt, but for now most industrially used batteries for EVs use at least some cobalt (Bloomberg NEF, 2019). Even if a big part of the battery demand in the future will use less cobalt than before, or even no cobalt, the cobalt demand is still likely to increase, because of the relative size of the current cobalt market compared to the demand from batteries. If the demand increases and the supply cannot keep up, margins for miners will increase. This decreases the risk for investors that the miners will not pay their loans back. However, as prices get higher, substitution is likely to be higher as well, because battery manufacturers are more likely to substitute cobalt for a cheaper metal, provided the substitutes do not increase substantially in price as well. Therefore, increased volumes in the cobalt system offer investment opportunities, but there is also a demand risk involved.

5.3.2. Risks in the cobalt system: Financial risk

There is a trade-off between financial risk and reputation risk. High margins on cobalt price scenarios are attractive for investors because of the increased likeliness of miners to repay investments, but they also make artisanal mining more interesting for the local population, and because of low traceability in the supply chain, this creates a higher risk for investing in cobalt from artisanal mining.

The ING has established a number of types of financial risks, as visualized in figure 5.12. The main financial risks in the cobalt market are country risk and demand risk. Demand risk is high because of the possibility of high price fluctuations. High price fluctuations impact the extent to which cobalt becomes an important by- or co-product of a mine, and the fluctuations of margins per lb.

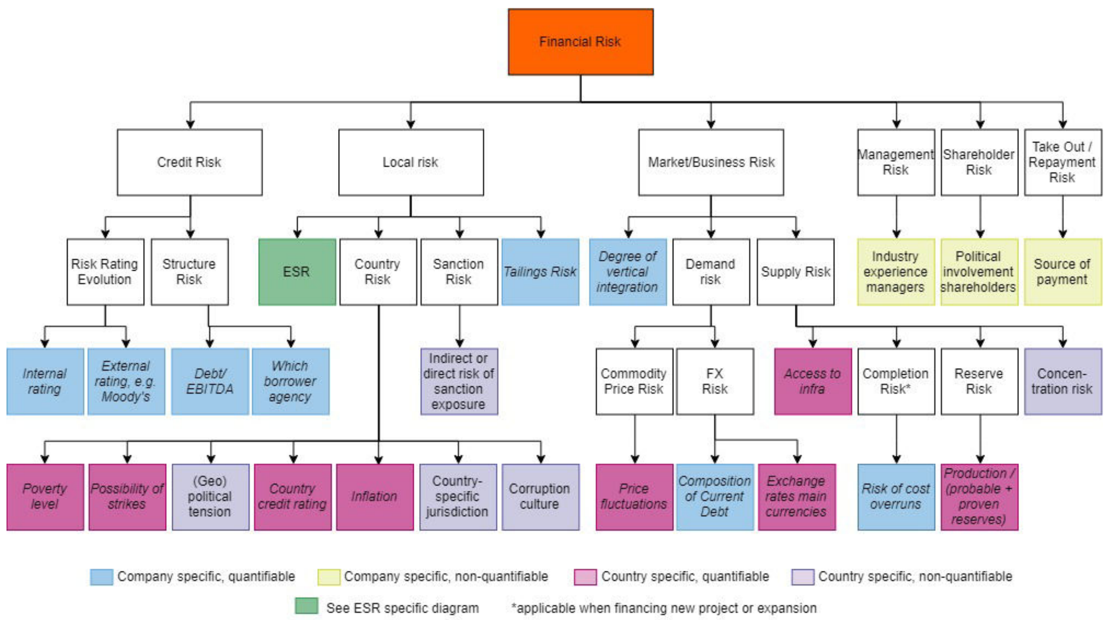

Figure 5.12: An overview of financial risks involved when financing metals. Risks are grouped and split out until they reach a level at which they are (semi-) quantifiable. Risks in italics are quantifiable.

Country risk is especially influenced by the part of the supply that comes from sediment-hosted sediments containing cobalt. Figure **??** shows that although the percentage of industrial cobalt mining from this deposit type could decrease, it is likely to remain the main source of cobalt over time.

The average cobalt recovery rate varies significantly across simulation runs, see figure **??**. The higher the demand, the higher the recovery rate.

The recovery rate competes with the increase in smelting and refining capacity and the increase in artisanal mining as swing factors in the cobalt system. The recovery rate is the more immediate response of the three, being delayed less than the other two.If the loop in which the recovery balances the marginal cost of a mining capacity is dominant compared to the other balancing loops, the recovery rate could fluctuate greatly.

These are mainly from the DRC, which has a high poverty level (World Bank, 2019), high possibility of strikes (Shedd et al., 2017), and high presence of artisanal mining. This creates social risks for the mining facilities (Kindt, 2019). In the future, it is likely that a large part of cobalt supply is still from sediment hosted deposits, see figure **??**. Most of the sediment hosted deposits containing cobalt are located in the DRC. Supply risk for supplies from the DRC has been high in the past (Shedd et al., 2017). Therefore, battery factories that are supplied from the DRC face a higher supply risk. Sanction risk is higher for sediments from Russia, like Nickel laterite (Kindt, 2019). Reserve risk is in general low for global cobalt supply, see figure 5.24, but should be monitored for individual projects.

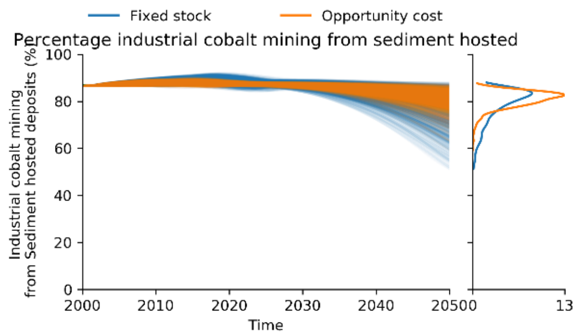

Figure 5.13: Percentage of cobalt mining capacity from sediment hosted deposits over time, specified for paradigm.

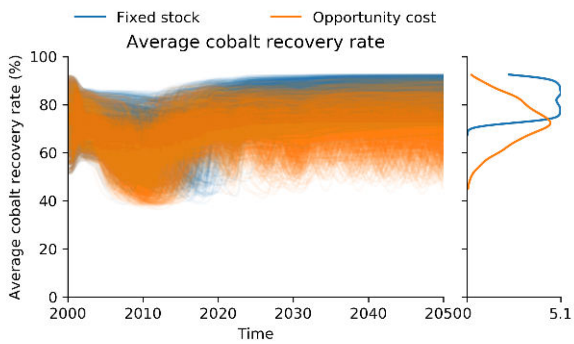

Figure 5.14: Percentage of cobalt recovered from deposits over time, specified for paradigm.

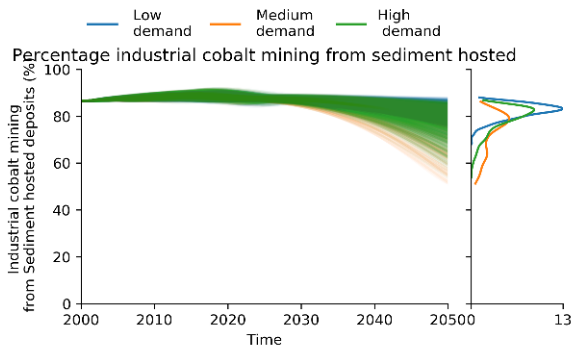

Figure 5.15: Percentage of cobalt mining capacity from sediment hosted deposits over time, specified for demand cluster.

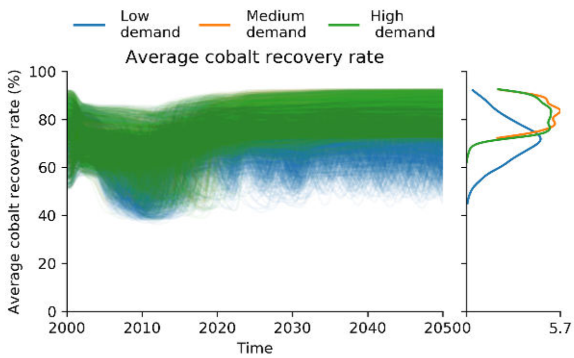

Figure 5.16: Percentage of cobalt recovered from deposits over time, specified for demand cluster.

As industrial mining of cobalt and the average cobalt recovery rate increase, and if price levels of cobalt go up, cobalt could become more important to mines. Figure 5.17 shows the average percentage of profit of mines across deposits that comes from cobalt profits, while figure 5.18 shows the same, specified for sediment hosted deposits. The plots are density plots, over time, visualized as heatmaps over time. The brighter the color, the more prevalent the value is at a specific point in time. This type of plots was chosen because of the high volatility of the behavior of this variable over time, which made normal lineplots unclear. The density plots over time show that cobalt is likely to contribute significantly to the profit of mines, although the range of the contribution is quite large. There seems to be a bifurcation between scenarios in which cobalt's contribution to the profit of mines increases, and scenarios in which the contribution stabilizes. For Sediment hosted deposits, the percentage of mining profits from cobalt profits, increases more than for the other deposits.

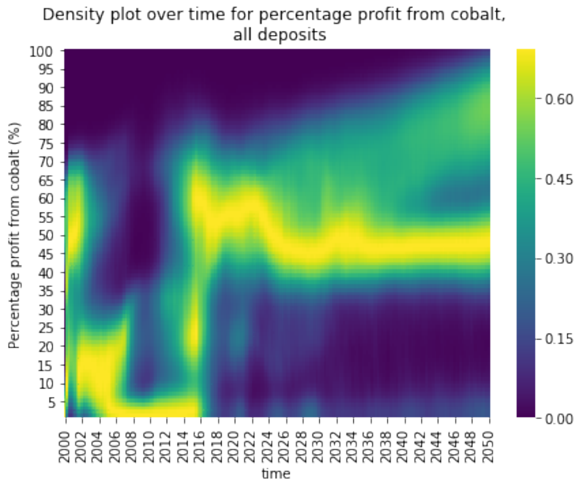

Figure 5.17: Percentage of the profit that is from cobalt profits, for all deposits.

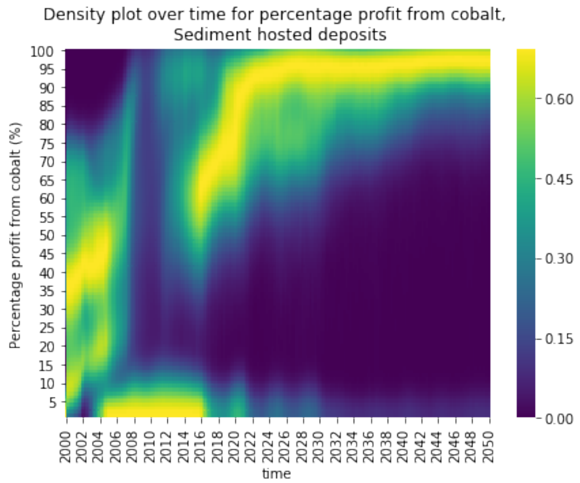

Figure 5.18: Percentage of the profit that is from cobalt profits, for Sediment hosted deposits.

The wide range of possibilities for the contribution of cobalt to the profit of mines can be explained by the volatility of the nickel, copper, and especially the cobalt prices. In all the markets, there is the possibility that the price of the metal is temporarily lower than the marginal cost of the metal. This causes the contribution of each metal to vary over the full range of 0 and 100% contribution to the profit of a mine. The contribution of cobalt to profit out of sediment hosted deposits increases more than for the other deposits. This is due to the higher cobalt content of this deposit, and due to the lower average price (and thus margins and profits) of copper. Important to note again here is that the profit, being a function of the price and the marginal cost, is influenced by how marginal cost is defined. The marginal cost of mining a metal can be defined in many different ways. The costs of a mine are normally calculated on a mine level, so when the marginal cost per metal needs to be calculated, the total mining costs for the mine need to be distributed over the individual metals in a way. In the model, a specific energy usage of mining is assumed per metal. This influences the results of contribution of cobalt to the profit of the mine: with a different calculation of the marginal cost, the results on the profit could be very different from the figures presented here.

The results point out that cobalt could become a more important by-product of mines, and even a co-product or the main product from a mine if demand and price levels stay high. Which metal is a mine's primary product, depends on which metal brings most profit to the mine. Mines mining from Sediment hosted deposits are currently primary copper mines. If the EV transition increases demand sufficiently, and pushes price levels up sufficiently, it is likely that these mines become primary cobalt mines. For nickel mines with cobalt as by-product, the EV transition influences nickel demand as much as it influences cobalt demand, whereas copper is effected to a lesser extent.

Another angle to the market risk are the margins per lb of mined cobalt. The margins per lb are the difference between the price and the marginal costs. To explore the influence of input variables on margins per lb for different input variables, the variables are chosen with the highest impact on the price, see figure 5.26: the choice of paradigm, the energy price scenario, the choice of formula for the price, and the power for the average oregrade. Figure 5.19 shows the influence of the variables. The price of cobalt in the Fixed stock paradigm increases more than in the Opportunity cost paradigm. In order to explore the more dynamic cobalt price in the Opportunity cost paradigm, the graphs on the other variables zoom in on results from the Opportunity cost paradigm. The margins per lb increase with a higher energy price, and with a higher power for oregrades. The formula for the price based on the amount of cobalt in stock allows for bigger fluctuations in the margin per lb.

The difference in price dynamics between the paradigms can be explained by the fact that the Opportunity cost paradigm includes a substitution loop in its assumed demand dynamics. This balancing loop balances both the price and the demand in the cobalt system more directly than the other balancing loops included in both paradigms. The higher margin fluctuations for higher energy price scenarios and the higher power of oregrades are influenced by higher marginal costs of cobalt mining. As the average marginal cost becomes higher, the price levels are likely also higher, and the fluctuations between the two can grow bigger. With regards to the price formula, the formula for the price that is based on days of demand in stock is more prone to show very high and very low prices, because of its shape, see figure 4.2. This fluctuating behavior of the price causes the margins to fluctuate more as well.

The results show that the higher the energy price and the power for oregrades, the higher the fluctuations of the margins per lb over time. This means that it is important for investors in cobalt projects to assess the local energy price: if this is relatively low, or the project generates its own energy, the risk on high fluctuation in margins is lower. Also, the average oregrade in the reserves of the project could give an indication of the margins per mined lb in the future.

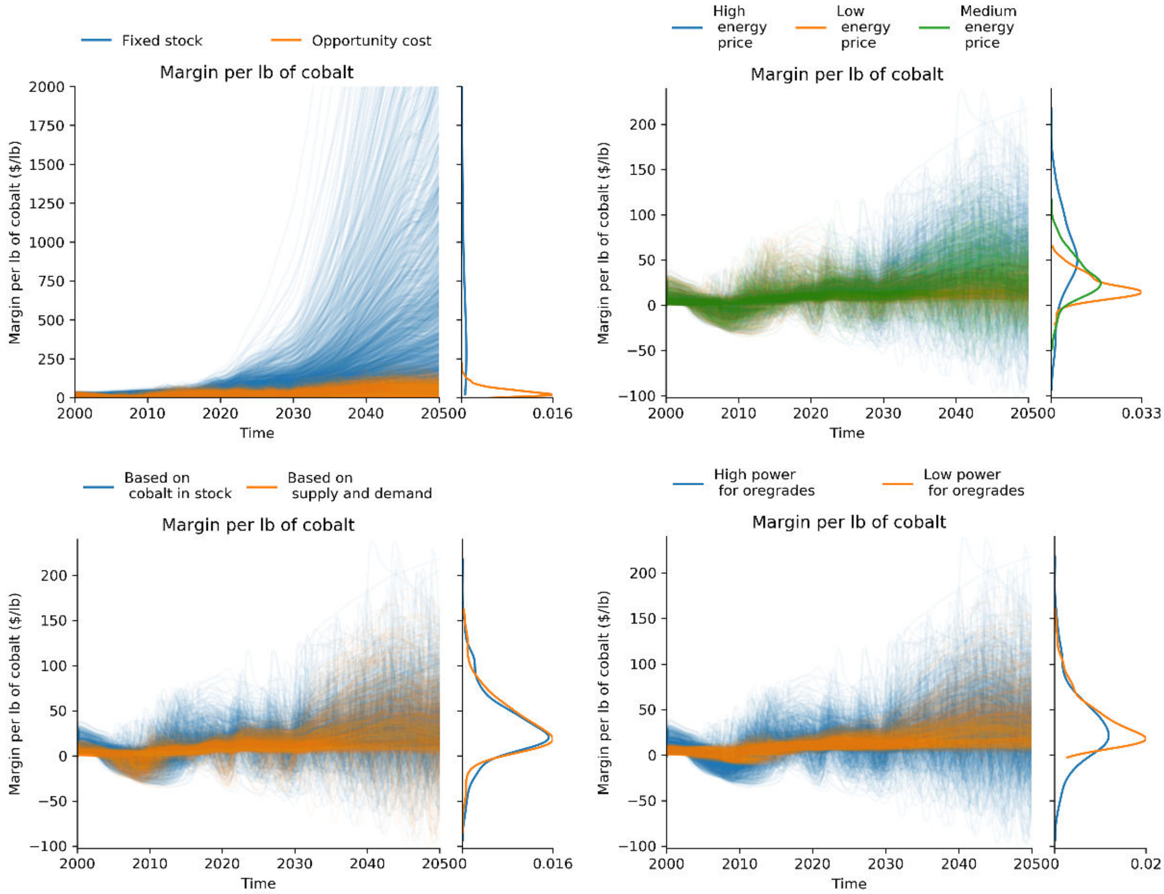

Figure 5.19: Dynamics of margin per lb over time, given different input parameters. Upper-left: grouped by paradigm. Upper-right: zoomed in on opportunity cost paradigm, grouped by energy price scenario. Lower-left: zoomed in on opportunity cost paradigm, grouped by price formula. Lower-right: zoomed in on opportunity cost paradigm, grouped by how fast the average oregrade declines: with a high power for oregrade, the oregrade declines faster.

5.3.3. Risks in the cobalt sytsem: EHS risk

ING Bank, like many other banks, supports the global EHS risk management framework called the Equator Principles (Equator Principles Association, 2013). This framework applies a number of performance standards, including those of the International Finance Corporation (IFC) (International Finance Corporation, 2012), a sister organization of the World Bank. The implementation of these risks in ING Bank's risk framework is visualized in figure 5.20.

The main EHS risks involved in the cobalt system for investors are due to artisanal mining. The most influential variables for artisanal mining over time are visualized in figure 5.21. The productivity of artisanal mining is the most influential variable, especially at the start of the simulations, as well as the percentage lost during artisanal mining. Later in time, the influence of the power for oregrades and the choice of paradigm

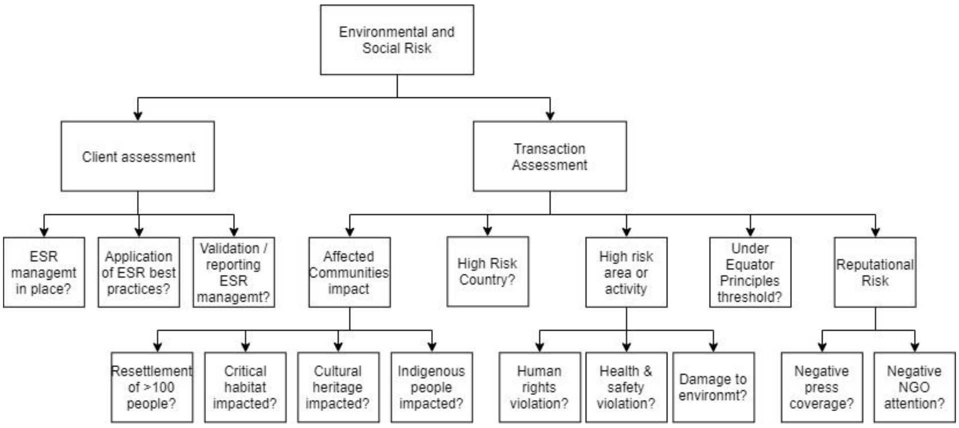

Figure 5.20: EHS risk framework of ING, on client-level and on transaction-level. EHS risk is called Environmental and Social Risk (ESR) within ING. Based on ING (2019a)

gain in influence. Finally, the percentage of the profit that goes to artisanal miners, and the maximum increase in the cobalt recovery rate are influential factors.

The influence of the productivity of artisanal mining and the percentage of profit from cobalt that ends up with the artisanal miners influence the profitability of artisanal mining as a job for people in the region. The higher their productivity and the percentage of the profit they get, the higher their potential wage. Therefore, these variables influence the potential artisanal mining capacity: the number of people willing to do the job. Furthermore, the productivity of artisanal mining and the percentage lost during artisanal mining influence the volumes that artisanal miners can actually produce. The influence of the maximum increase in recovery rate can be explained by the fact that the cobalt recovery rate and artisanal miners are in way competing swing factors in the cobalt system. If industrial miners are capable of increasing their recovery rate, less demand is postponed. This means there is both less need for artisanal miners to jump in to fill the demand gap, and price levels are less likely to increase because of this gap, which would also otherwise spur artisanal mining. The decline of the power for oregrades and the choice of paradigm, lastly, influence the favourability of artisanal mining compared to industrial mining. As the average oregrade declines, the price of industrial mining increases, making artisanal mining more attractive as a job. The choice of paradigm influences

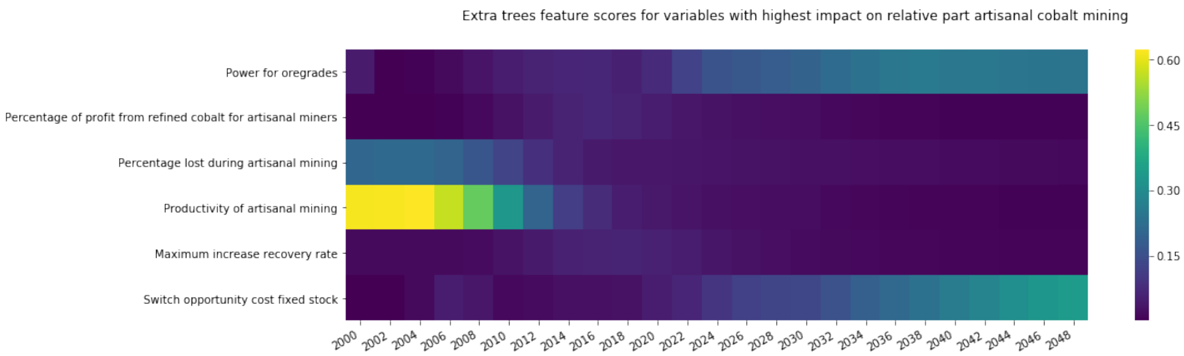

Figure 5.21: Results from Extra Trees Feature Scoring: most influential variables on relative part artisanal mining over time

Artisanal mining is expected to remain an important source of cobalt in the next decades, see figures 5.22 and 5.23. The dynamics in artisanal mining can be explained by the poverty levels in the DRC and by price levels of cobalt. Poverty levels in the DRC start out at 99%, and even though poverty in the country decreases over time, it remains high enough for sufficient people to be interested in artisanal mining, provided price levels of cobalt are high enough. Cobalt price levels vary over time, but in most simulations, they are sufficiently high to keep artisanal mining economically attractive. In the fixed stock paradigm, the price levels are more likely to increase exponentially due to the ever increasing demand, so artisanal mining is more likely to be prevalent.

Surprising is that no input variables that are related to the demand side of the model seems to have a big influence on artisanal mining. Figure 5.23 shows that also the size of the demand does not have a too high influence on the percentage of the demand that comes from artisanal mining. This means that the speed with which industrial mining can respond to demand changes, is more influential on artisanal mining than the size of the demand.

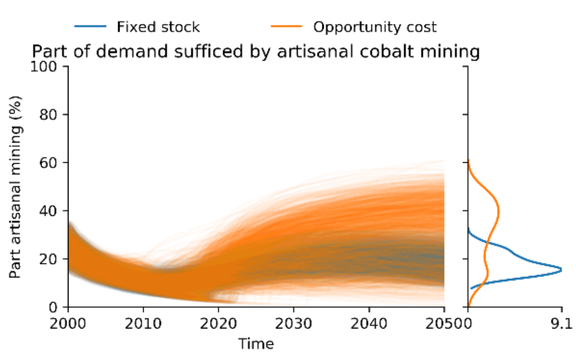

Figure 5.22: Artisanal ore trade over time. The results are grouped by the paradigms.

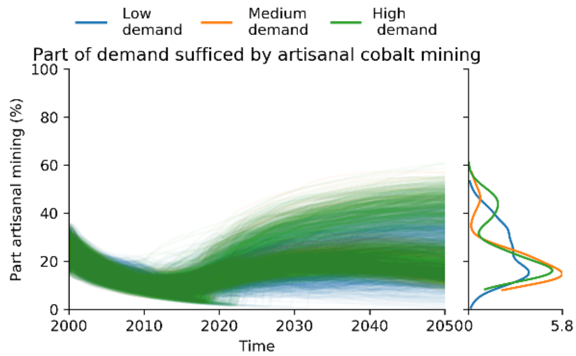

Figure 5.23: Artisanal ore trade over time. The results are grouped by the clusters of demand.

Due to lack of transparency of the supply chain, it can be uncertain whether artisanal cobalt mining is involved with mining projects of customers of ING Bank. Artisanal mining has been associated with human rights violations (Amnesty International, 2016), health and safety violations (Amnesty International, 2016; Banza Lubaba Nkulu et al., 2018), and damage to the environment (Banza Lubaba Nkulu et al., 2018). Since artisanal miners are no workers of miners and in no other way directly involved in the supply chain, the EHS risk framework does not necessarily cover artisanal mining. When it does, it is through indirect influence of artisanal mining on the mining facilities: their presence does cause social risk for the miners. In ING's EHS framework, artisanal mining is mentioned as a restricted activity: an activity "whose controversial nature and impact makes them incompatible with ING's Values and our concern for safeguarding human rights and promoting sustainable development" ((ING, 2019a, p.9). It is stated that for the metals and mining sector specifically, it is important to assess contextual circumstances like the presence of artisanal and small-scale mining in and around the client's operations, but no specific guidelines are provided on how to cope with them, or whether there are critical thresholds (ING, 2019a). If artisanal mining would take place on mines, and the mining company would be responsible, this would create a reputational risk, because in that case the mining company would be responsible for their working conditions, and their health. But in most cases, the mining company cannot help the artisanal mining taking place, because the artisanal miners mine without permission. On top of that, in most cases artisanal miners work on their own land from resources rather than from industrial reserves, so it is out of the reach of influence of mining companies, as well as of investors. The observation that artisanal mining is likely to stay around in the future due to the high poverty levels in the DRC, means that the problematique surrounding artisanal mining will remain relevant in the coming years.

5.4. The influence of the two paradigms

The assumptions underlying the two paradigms are very influential on the results throughout the model. Future supply and demand projections are very much influenced by the underlying paradigm, see figure 5.24. Demand increases more in the Fixed stock paradigm than in the Opportunity cost paradigm. Industrial cobalt mining shows greater volumes in the Fixed stock paradigm than in the Opportunity cost paradigm. The cobalt reserves stabilize over time in the Fixed stock paradigm, and the resources decline towards zero, causing the R over P ratio to stabilize and decline. Meanwhile, in the Opportunity cost paradigm, the reserves as well as the resources keep growing, leading to an increasing R over P ratio.

Demand in the Fixed stock paradigm depends on the chosen SSP, and the influence of the SSPs is still visible in other output variables as well. Demand in the opportunity cost paradigm does not depend to this extent on the SSPs. In the Fixed Stock paradigm, the reserve base can first increase due to sufficient available resources, but after some time the resources are starting to be depleted and therefore the reserve base starts to stabilize.

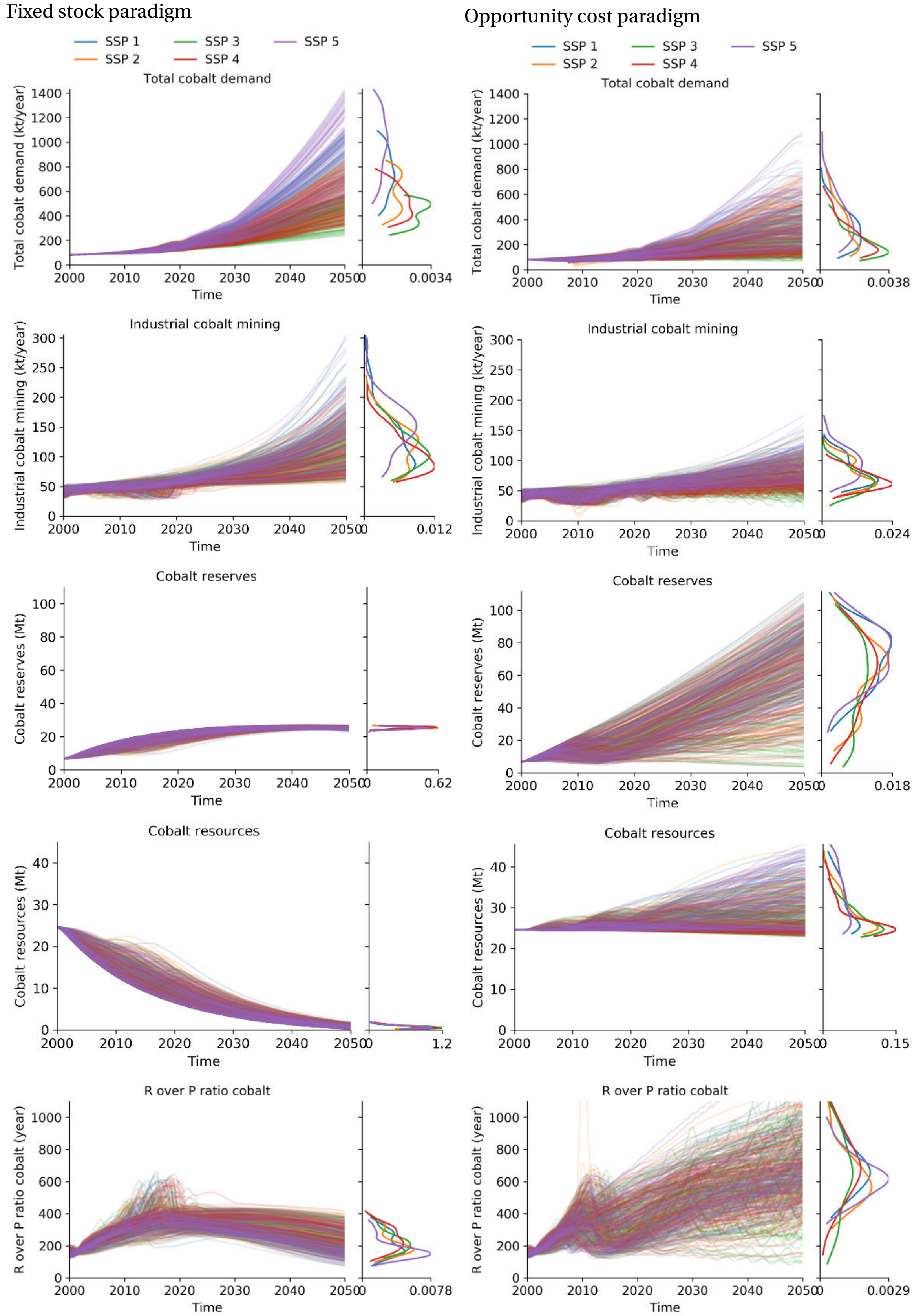

Figure 5.24: Total cobalt demand, industrial cobalt mining, cobalt reserve base, resources, and R over P ratio, for Fixed Stock paradigm model (left) and Opportunity Cost model (right). The results are grouped by the SSP scenarios.

This is also visible in the R over P ratio: it stabilizes and declines over time. In theory, resources could restrict the size of reserves and thus the amount of industrial mining taking place, but within the timeframe of this model, the size of the resources and reserves does not restrict industrial mining from happening yet. In the opportunity cost paradigm on the other hand, resources and the reserve base can still grow over time, and therefore, the R over P ratio is higher in the opportunity cost paradigm.

The figures in 5.24 show the differences between the general behavior of simulations in each paradigm, but the figures hide in a certain way the dynamics within each run. Therefore, the figures in 5.25 show the dynamics of individual runs, in both paradigms. The runs have been chosen as follows: one from the high demand scenario for the Fixed stock paradigm, with a high power for oregrades and battery capacity of the BEV, and a high energy price growth scenario. Another run was chosen for the low demand scenario, with a low power for oregrades, low battery capacity, and low energy price growth scenario. Since the runs for both paradigms are exactly the same, the same runs are chosen in the Opportunity Cost paradigm.

The figures show that the dynamics in the Fixed Stock paradigm are rather stable over time: the demand and price increase in a rather stable manner. The reserves grow at first and then decline, with the same pattern being visible in the R over P ratio. In the Opportunity cost paradigm, the demand shows stabilization over time, instead of continued growth. The real price fluctuates in a more dynamic matter, as does the R over P ratio. The reserves on the other hand, grow more steadily in the Opportunity cost paradigm. These results show that not only the ranges for the outputs differ between the paradigms, also the behavior over time is different.

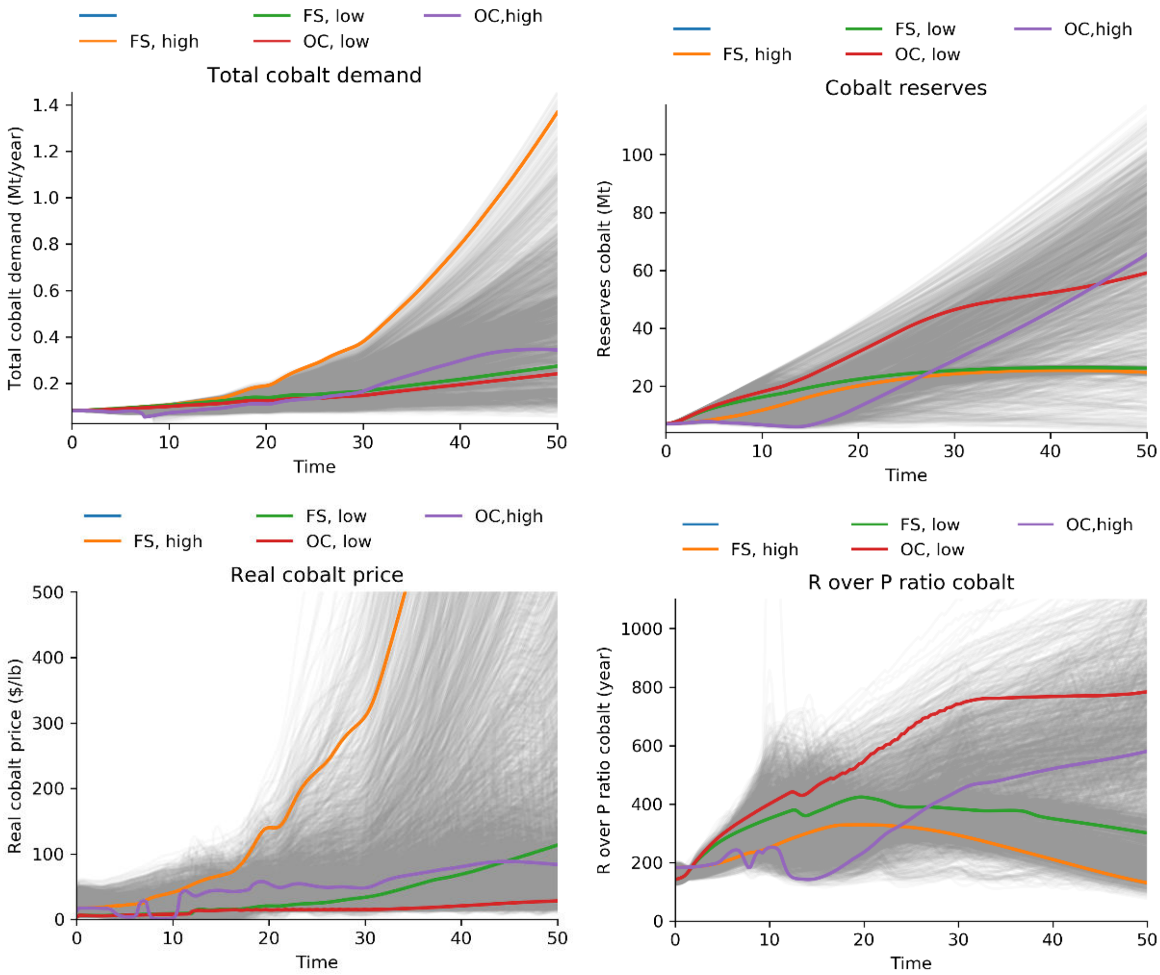

Figure 5.25: Difference in dynamics per run between the different paradigms, for demand (upper-left), reserves (upper-right), price (bottom-left), R over P (bottom-right). FS = Fixed stock paradigm, OC = Opportunity cost paradigm, low = values for the input variables are chosen that influence the price to be low, high = values for the input variables that influence the price to be high

5.4.1. The main Opportunity cost metric: price

The Opportunity cost paradigm focuses on one main metric: the price. This variable is influenced most by the choice of paradigm, the formula to calculate the price, the speed of decline of the average oregrade, and the development of the energy price, as visualized in figure 5.26. The influence of the energy price and the choice of paradigm grow over time.

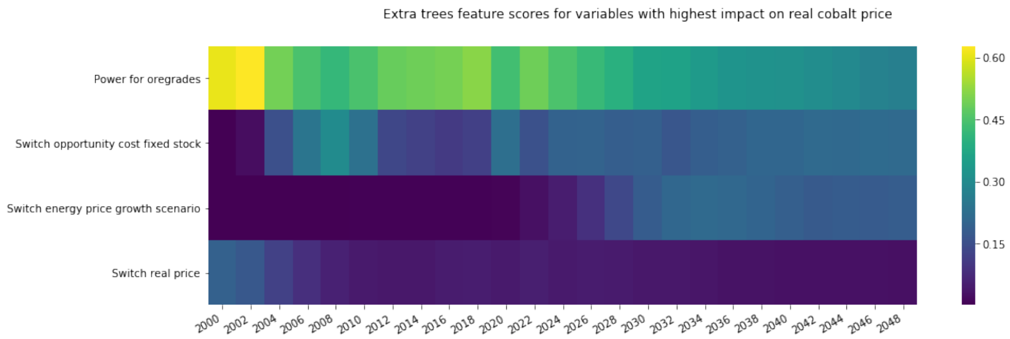

Figure 5.26: Results from Extra Trees Feature Scoring: most influential variables on the real cobalt price over time

The influence of these variables is explored more in depth in figure 5.27. The paradigm influences the range of the price as well as the price dynamics. In the Fixed stock paradigm, there are less balancing loops that influence price and demand, and therefore the price increases exponentially in this paradigm. Concerning the influence of the formula: calculating the price based on how many days of demand there are available in stock keeps the price more rigidly around a middle value, but as soon as the available supply is too high or too low, the response in price is stronger than in the formula based on supply and demand. The lower the energy price, the lower the price of cobalt, on average. Lastly, the slower the decline of the oregrades, the lower the cobalt price.

Important to note here is that even though the cobalt price is regarded as the most important Opportunity cost paradigm metric, it does not have too much influence on its own in the cobalt system. It only drives demand only provided the prices of substitutes. It only drives (investments in) industrial mining and smelting and refining as long as the price is higher than the marginal cost. The very notion of a 'high cobalt price' is relative: a price that was considered high 10 years ago, might not be regarded as high nowadays. In other words: the value of a price does not mean too much unless it is put into context.

5.4.2. The main Fixed stock metric: R over P ratio

The main metric usedin the Fixed stock paradigm is the R over P ratio. This variable shows how many years of production of a metal are left in the reserves of the metal: it is regarded as a measure of physical scarcity. Figure 5.28 shows the most influential variables over time for the R over P ratio. The most influential variables are the choice of paradigm, the choice of price formula, the speed with which the average oregrade declines, and how fast the recovery rate of cobalt increases.

The influence of the paradigm is due to the differences in assumptions on the resources and reserves. According to the Opportunity cost paradigm, the currently known resources can still grow due to discoveries of metal that up till now is still in the resource base. In the Fixed stock paradigm, the resources are fixed, and therefore, it is depleted, which creates a maximum for how much the reserves can still grow. As the production grows due to ever growing demand, and the reserves stabilize or even decline, see figure 5.24, the R over P ratio stabilizes and declines. The power for oregrades determines how fast the average oregrade of cobalt deposits declines. As the oregrade declines faster, the

The fact that the paradigm is one of the most influential variables for this metric of the Fixed stock paradigm, shows that the promised physical scarcity in this paradigm is partially a self-fulfilling prophecy: the assumptions made by the Fixed stock paradigm influence the dynamics of the model in such a way that they result in physical scarcity. The validity of the R over P ratio as a metric is widely discussed, see Chapman and Roberts (1983, e.g.). In practice, the reserves are those deposits that miners have identified as their source for mining in the coming years, and thus there is an incentive for miners to keep these around a certain number of years of future production. However, the resources of their mines are also likely to be mined at a certain point. This causes the R over P ratio to be able to increase over time rather than decrease. Also this metric needs to be put into context before it can be interpreted properly.

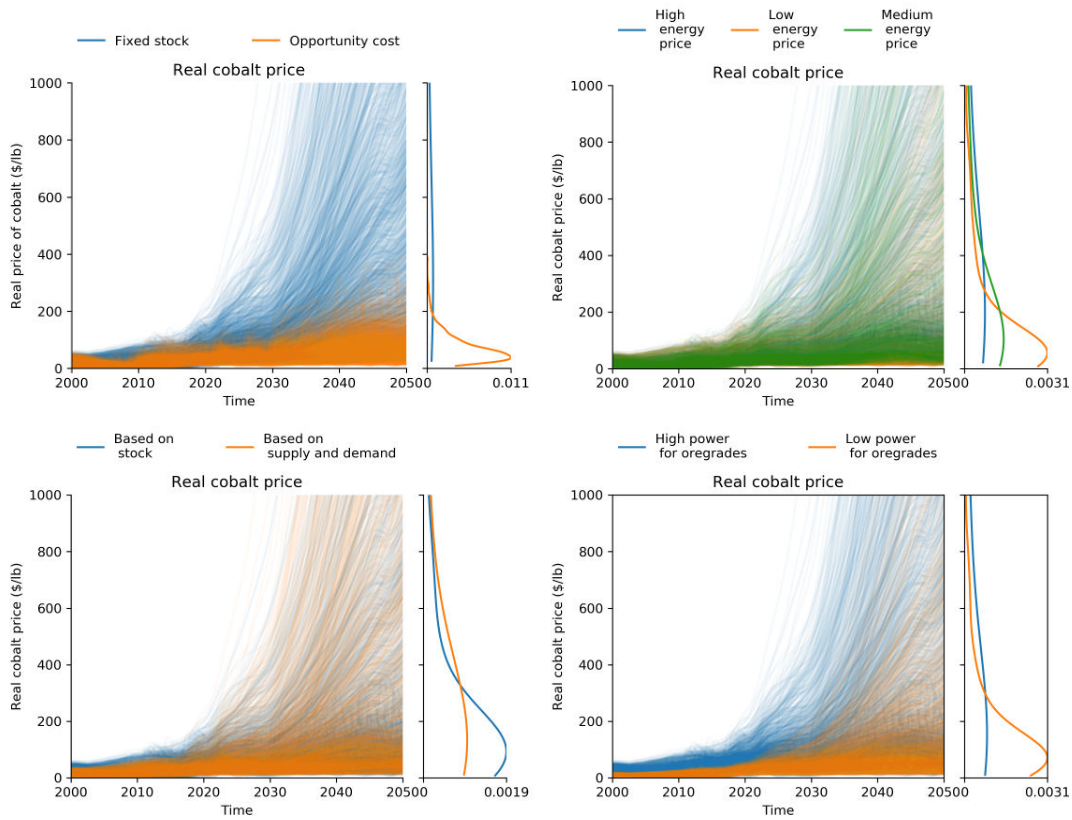

Figure 5.27: Real cobalt price, grouped by scenario for energy price, and a low or high power for oregrades, which means a slow or fast decline of the oregrades.

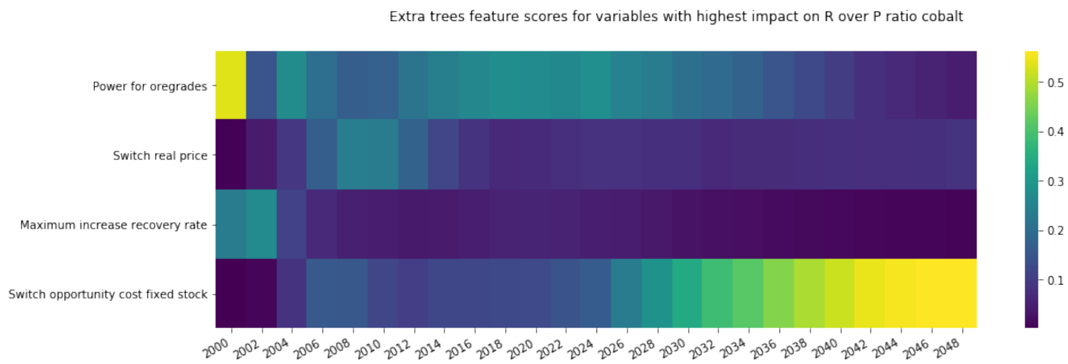

Figure 5.28: Results from Extra Trees Feature Scoring: most influential variables on the R over P ratio over time

6 Discussion

This chapter puts the results from the cobalt model in the context of relevant literature, reflects on the limitations of the results, and proposes research recommendations.

6.1. Cobalt extraction in the wider sustainable transition debate

The results show that the cobalt system has many sustainability angles to it. The sustainability angles can even be conflicting, when improving one angle might just mean damaging another sustainability angle. This also shows that sustainability can be interpreted in many different ways. Improved understanding of the different meanings of sustainability could contribute to increased understanding of potential trade-offs between sustainability angles in the low-carbon transition.

First of all, cobalt contributes to the low-carbon transition because of its role as a critical material in the EV transition. Cobalt is used in many of the current battery technologies that are in use for EVs. Even if in the future, more batteries with low or even no cobalt might become used, the demand for cobalt is still likely to increase because of the current small cobalt market. The currently planned battery facilities in Europe produce batteries containing cobalt. If this remains the case in the coming years, it could be that the EV system becomes path dependent, and cobalt will remain a critical material for EVs. Not only the passenger car market is relevant here. Cobalt could also contribute to the electrification of Ebuses and Etrucks through the batteries in these vehicles, and to the increased use of stationary storage and consumer electronics. Due to mitigated carbon emissions from the transport industry when adopting EVs, cobalt contributes to this angle of sustainability.

Cobalt mining contributes to the EV transition, but also potentially contributes to climate injustice. The discussion on the desirability of cobalt extraction can be seen as part of a wider debate on the climate justice of the energy transition in developed countries (Sovacool et al., 2019). Historically speaking, developed countries have contributed the lion's share of the current cumulative carbon emissions (Matthews, 2016). The impact of climate change, however, is going to be the largest in developing countries, because they do not have the same financial capacities to work on their climate adaptation measures, as developed countries do (Hardoon, Ayele, & Fuentes-Nieva, 2016). This is seen by some as unfair, and therefore, it is called climate injustice.

With regards to cobalt mining, another dimension is added to this discussion. To mitigate the consequences of their past, current, and future carbon emissions, developed countries aim to transition to low-carbon economies. Because low-carbon energy systems are more metal-intensive than traditional systems, the transition towards them requires an increase in the mining of metals like cobalt. On the one hand, increased cobalt mining can contribute to (possibly sustainable) economic development of countries. On the other hand, increased mining can have adverse effects on the local environments of mines in developing countries. This paper showed that sustained increase of mining contributes to a faster decline of average ore-grades, increasing the environmental consequences of mining even more (Swart & Dewulf, 2013). As such, one could see increased extraction of metals for the energy transition as another way of 'exploiting' developing countries by developed countries for their own needs.

By some, artisanal mining is seen as the prime example of increased local climate injustice, and point as the responsible to the 'exploiting behavior' of developed countries. The many health and environmental hazards artisanal mining creates, are seen as human rights abuses (Amnesty International, 2016). Recently, a court case has established more attention on this topic (Kelly, 2019). Major Western technology companies like Google and Apple are sued for buying cobalt that was mined through forced labor by artisanal miners. This raises the question of responsibility for the health dangers for the artisanal miners. The consumers of EVs in developed countries could be held responsible because they create the demand for cobalt. On the other hand, one could argue that artisanal miners choose their profession themselves, and therefore any hazards are the risk they are allowed to take for themselves. It could also be argued that because artisanal mining is poverty related, it is the fault of the government in their country that artisanal miners do not have another job. In that sense, artisanal mining could be seen as an economic opportunity for people who would otherwise have a hard time finding a job. Others could argue that it does not matter whose responsibility the hazardous circumstances of artisanal mining are, but that there should be something done about it.

These complexities show the trade-off between sustainability angles: on the one hand, the goal of the EV transition is to decrease climate injustice because of its global carbon reduction effects, however, on the other hand, it could potentially increase climate injustice because of its local adverse effects on people and nature in developing countries. A complicating factor in this is that it is often hard to pinpoint exactly who's responsibility these global and local climate injustices are, and there is not always an answer on what is 'right' and 'wrong'. There are trade-offs between values involved, and only (subjective) human appreciation of these values could possibly determine how these trade-offs should be decided upon.

Adverse effects of cobalt mining could be mitigated by increased recycling, a good tax regime, and global taxation of negative externalities. Increased recycling, especially in developed countries, could lower the demand for newly mined metals, as well as the related negative externalities. A good battery recycling scheme should therefore be put in place as soon as the EV transition starts in a country. Furthermore, a good tax regime in developing countries should support mitigating negative externalities of mining, and increase positive externalities of mining. Especially in countries like the DRC, royalty flows and economic benefit sharing should be discussed extensively (Mudd et al., 2013). Lastly, global taxation of negative externalities, like carbon emissions, could contribute to mitigating them, and mitigating global climate injustices.

6.2. Scarcity and sustainability: A tale of two paradigms

The two main paradigms in literature on the structure of resource systems, could improve themselves through building upon the other. The assumption of the Fixed Stock paradigm that physical scarcity is bound to occur, is rather unrealistic. Historical patterns of physical scarcity have shown that warnings for upcoming physical scarcity, like often flagged by fixed stock paradigm scholars, were disproved more often than not Tilton, 2003. The scholars supportive of this paradigm, have done research on when - rather than whether - physical scarcity will become a problem. The assumptions made in this paradigm regarding demand substitution and availability of reserves create in this regard a self-fulfilling prophecy. The fixed stock paradigm assumes that the resource base will not be turned into resources. Due to this assumed restriction on the size of resources, the resources will deplete faster. Demand is assumed to be stable or growing, with no substitution as feedback on higher price levels. With a limited supply and a stable demand, physical scarcity is bound to occur at some point. Historical patterns, however, show that resources do grow over time due to new discoveries, when the price level creates incentive for exploration. Also, demand is substituted, in case the price level is too high relative to potential substitutes (Auping, 2011). Therefore, it can be concluded that disregarding these demand and price stabilizing feedback loops and focusing on physical scarcity is rather normative than descriptive of nature.

The assumption of the opportunity cost paradigm that economic scarcity is pushing supply and demand in metal systems is, therefore, more realistic. However, the trust that the paradigm places in the all-regulating capability of price mechanisms, is misplaced. Even though prices give a good account of the scarcity of metals, not all relevant information is considered in the cost of production, which lowers the extent to which a price is representative of its actual cost, and its scarcity. Arguments for the price not being accurate are:

1. Externalities, like carbon emissions, and local adverse effects of mining, are not internalized in prices.
2. Price setters could be ignorant of the actual scarcity of a metal, and the externalities related to production of the metal.
3. Not all relevant stakeholders in a resource system are included in the price setting process, for example, future generations, other species and nature, and poorer parts of the world population are not consulted in the price setting mechanism.

Tilton (2003) defends the opportunity cost paradigm against these allegations with the following arguments:

1. A failure of governance on such a scale is not possible, especially in countries where the government is held accountable by the people in the country: if the negative externalities are not mitigated by the governments, apparently, the people in these countries do not value the impact of the externalities that much that they vote for parties that will mitigate them.
2. Price setters are incentivized through the economic system to make predictions of the price that are as accurate as possible, so they will educate themselves if their account of scarcity is not correct
3. Who should be included in the price setting process is a philosophical debate, and is, although interesting, not relevant for the question of how much metal will be extracted in the coming years.

These arguments can be summarized as *"It is the way it is, and therefore this is the way it is."*. This paper argues that Tilton did not read his Economics Nobel laureates, and the arguments that Tilton brings forward, are refuted for the following reasons:

1. Elaborate literature on negative externalities, amongst others by Nobel laureate in Economics Ostrom (2002), shows that actually, negative externalities do exist, and it is hard for governments to properly cope with them. Furthermore, although Tilton is right about that citizens should hold governments accountable for bad decisions, research from another Nobel laureate in Economics, Kahneman (2011), shows that humans value short term benefits over long term benefits, even if long term drawbacks are known. Therefore, citizens are more likely to vote for parties that promise short term benefits than parties that promise mitigation of long term negative externalities, and failure of governance on a grand scale with regards to (especially long term negative externalities) is in fact very plausible.
2. Price setters, just like any other economic actors, suffer from imperfect information, is what research by another Nobel laureate in Economics, Phelps (1968), showed. Economic actors react more irrational to economic incentives than often assumed in classical economics, for example, information on the short term is valued over information on the long term (Kahneman, 2011). Prices depend the short term availability of metals is Furthermore, spot prices are based on short term availability of metals, which is not necessarily reflective of longer term scarcity.
3. Assuming that because something is they way it is, it is right the way, hardly spurs progress. Even though future generations, nature and poorer parts of the human population are not included in the price setting process right now, does not mean they should not, nor that they will not be included in the future.

The opportunity cost paradigm could, therefore, take into consideration the main message from the Fixed Stock paradigm: that even if something is economically viable, it does not mean that it is preferable. Externalities may not be included - and due to their underlying problematique it might not even be possible to include all externalities in prices within the current economic system - but governments could aim to make the the prices of products reflect at least some externalities. For example, the carbon emissions that are inherent to metal production, are not reflected in the metal prices at the moment.

Recent research has pointed out that mining of resources might not be threatened by physical scarcity of ores, but by changing ore characteristics, e.g., the ore grade, mineral type and location (Swart & Dewulf, 2013), which cause increasingly more externalities, like increased water and energy usage, and carbon emissions. They point to the scarcity of those goods that the negative externalities impact, rather than to the physical scarcity of metals per se (Swart & Dewulf, 2013). These scholars, acknowledging that the mineral reserves could increase in size over time, instead focus on the depletion of social goods. For example, carbon emissions deplete the so-called carbon reserve, which is the artificial reserve of carbon in case the global community acts upon the intention to keep global warming underneath 2 degrees. Although the exact size of this carbon reserve is still uncertain, this abstract reserve does help to show the urgency of externalities in case they effect a finite source of something of value. Of course, the same could be done for other negative externalities, for example, biodiversity loss, clean air, or adverse effects on the health of people surrounding a mine.

Another type of externality is the possibly undesirable distribution of metals over countries. This research assumes that equal distribution of metals should be desired, and since the energy transition will cause for a higher consumption of metals such as cobalt, nickel and copper in developed countries, this causes the distribution of metals to become unequal (Bosch, van Exter, Sprecher, de Vries, & Bonenkamp, 2019). The researchers argue that every country should be assigned a certain percentage of the global metal availability for the energy transition. Although this artificial account of physical scarcity is not likely to become reality any time soon, it is an interesting new approach to scarcity.

The opportunity cost paradigm could learn from these alternative approaches to scarcity. Even if they could now still be seen as rather normative, they could well become descriptive in nature if relevant policy would be adopted. This paper follows Chapman and Roberts (1983) in their conclusion that the relevant question to ask in the discussion surrounding resource scarcity is not 'shall we run out of metals?', but a question like 'how long is a piece of string?' and 'how long are we willing to stretch it?'. The continued discussion on the paradigms in the literature, as well as the continuous emphasis environmentalists place on physical scarcity divert the attention from the externalities of mining. This (and other) research has shown that cobalt resources are not likely to soon be depleted, but externalities of mining could continue to increase. More cooperation between scientists of both paradigms could actually help to increase understanding of metal systems, and produce better advice on policies for decision makers to cope with the externalities.

6.3. Limitations

6.3.1. Method limitations

The main method limitations are that the model is not region-specific, that the model is quite sensitive for the formulas for the real price and the energy usage, and that system boundaries for metal systems are hard to draw. First of all, the model is not region-specific, except for the implicitly region-specific deposits. The geopolitical aspect of cobalt trade, however, is of importance throughout its supply chain. Especially the dominance of China and the DRC in the cobalt supply chain, and the vulnerability of the supply chain to these countries is possibly highly influential for future dynamics in the cobalt system, but is not reflected in the model. Secondly, the outcomes of the model are sensitive to the formulas used to model the energy usage of metal mining, and the real price. The parametric uncertainty of the input parameters of the formulas, influences how fast the prices fluctuates. Although these formulas are based on literature and past data, the relationships they describe could change over time. Even if it is researched that in the past, these formulas hold, this does not guarantee that they will still hold in the future, especially 30 years from now. Another limitation of the method is that system boundaries are hard to draw for a model of metal extraction, especially when by-products are involved. By-products contribute to the profitability of a deposit, but their contribution can change over time since their recovery rates depend on their price regime over time. Because of this, it can be hard to draw a line whether a metal is a by-product, a co-product, or a main product. Modelling the extraction of deposits rather than separate metals partially solves this problem. Modelling extraction in terms of deposits on the one hand gives a good account of the dependence of by-products on the extraction of main products, but on the other hand makes it more difficult to draw the boundary of what to include in the model. Every ore from a deposit could contribute to its profitability, even ores that seem worthless nowadays could contribute in the future, depending on their price dynamics over time. However, due to computation limitations, not every possible product could be included for every deposit type. Another method limitation is that the development of cobalt demand over time is now assumed to be rather static, even for the model according to the opportunity cost paradigm, which accounts for substitution and price elasticity. The model does not take into account scenarios where for example the whole world suddenly switches to hydrogen. Lastly, the carbon tax could also be made more dynamic: if more carbon is emitted per lb of metal produced, more taxes could be imposed.

6.3.2. Limitations of exploratory modelling

Even though this research is based on exploratory modelling rather than predictive modelling, caution is needed when it comes to interpreting the results. Use of predictive models for systems that are characterized by deep uncertainty is debated, since it could be argued that modelling a structure of which is hardly known how it works is useless (Kwakkel & Pruyt, 2015). Although this research uses EMA instead of predictive modelling, it should still be kept in mind that the results of this research should not be seen as predictions of the future. Also, SD results should be interpreted with a focus on the qualitative modes of behavior rather than with a focus on the exact numerical results. The results of the model depend on the assumptions, which could be wrong. Although the combination of SD and EMA makes it possible to take all kinds of uncertainties into account, it is still possible that the true values of parameters or the true structure of the system have not been considered in the model. This ties into the issue of unknown unknowns: uncertainties of which it was not known these are uncertain, or should be considered in the system. This research mainly focuses on exploring possible futures of the cobalt system, rather than searching for ways to get to a certain desirable future. Still, the model output space with the explored possible futures may not reflect the actual space of possible futures, as, although this research has taken uncertainty as central, it is still possible that something fell out of the scope of this research, which should have been included

6.3.3. Data limitations

The data limitations of this research are mainly due to limited availability of data on artisanal mining and metal prices. With regards to artisanal mining, data is hardly available. The data that is available, is often biased on the preferability of artisanal mining. Specifically, data on artisanal mining in the DRC, as well as data on the DRC in general, is limited. The price curves for cobalt, nickel and copper are very influential for the rest of the system, but long term historical data on metal prices is not freely available. The price curves are now based on limited available data on the metal prices, they could be improved upon by organizations which do have access to data on long term historical data. Energy prices are now assumed to be the same around the world, due to limited data availability on energy prices in different countries. Finally, the data and insights derived from the ING Bank Metals, Mining & Fertilizers team are assumed to be representative for Western investors. However, other banks could make other considerations on investment decisions regarding cobalt.

6.4. Research recommendations

Further research could elaborate on finding a middle ground between the two paradigms, on the model, and on the sustainability of the energy transition. This paper found that the two paradigms could learn from each other. Further research could be done on how taking externalities into account would influence outcomes of the opportunity cost paradigm, and explore the price dynamics in this hybrid paradigm. The model could be elaborated in many ways. First of all, the various recycling indicators could be internalized even more in the model. It would be interesting to see how this would effect the demand for newly mined metals. Secondly, demand and/or supply could be modelled region-specific. The cobalt supply chain is geopolitically sensitive. Cobalt mining is mainly done in the DRC, cobalt smelting and refining is mainly done in China, and currently the major part of the demand is from China. Regionalizing part of the model could factor in these global trade dynamics. Furthermore, the modelling of the oregrades could be more elaborate. For example, deposits could be specified for being low-, medium-, or high-grade. This would also make it possible to build in the model that mining operations could decide to do high-grading in low price regimes and low-grading in high price regimes to improve their profits. Fourthly, more by-products and co-products could be included in the modelling of the deposits, to increase accuracy of the profits from deposits. Finally, this model could be used for other (by-product) metals as well. Another research recommendation is to do more research on what formula is the right one for prices in metal markets. This paper includes two possible formulas, but the author does not have enough data to test their historical accuracy. Further research could also focus on increasing the accuracy of the data by addressing the data limitations described in the previous paragraph. However, the main objective of this research proposal is to gain better insight, and better data does not necessarily mean better insight (Crawford, Miltner, & Gray, 2014). Finally, further research should be done on how the energy transition can be done in a sustainable way - taking into account all aspects of sustainability.

7 Conclusions

This chapter presents the answers that were found to the research questions that were posed in the introduction and the problem formulation, and derives the main conclusions from this research. This research explores various scenarios in the cobalt system, in light of the low-carbon transition. To do so, the structure of the cobalt system is examined, as well as the key uncertainties that drive change in the system. This research also explores the influence of the assumptions of two paradigms on resource extraction on the behavior of the system, and the implications of system scenarios for investors and for the sustainability of the cobalt system.

The structure of the cobalt system is characterized by a by-product nature of copper and nickel mining. Its supply chain is dominated by cobalt from Sediment hosted deposits, which are mainly situated in the DRC. Here, artisanal mining occurs, depending on poverty levels in the region and cobalt price levels. Industrial mining output is controlled by the average oregrade, which declines over time, the recovery rate of cobalt that varies with price levels, and industrial mining capacity. The demand for batteries is influenced by the EV transition and global socio-economic developments. Primary and secondary cobalt scrap contribute to the recycling of cobalt, and the bigger the amount of available scrap, the lower the demand for newly mined cobalt.

The key uncertainties in the model with regards to supply dynamics are the development of the energy price, the speed of the decline of the average oregrade of cobalt, and the collection rate of cobalt products influences the extent to which recycled cobalt contributes on the supply side. With regards to demand, the global socio-economic development and how much demand the EV transition will contribute. Finally, the choice of paradigm and formula for the price are influential throughout the model.

Scenarios for cobalt are pushed by demand in cobalt, which could vary between a demand about as high as today, and exponentially increased demand. These demand scenarios influence the size of volumes of cobalt throughout the model. Cobalt could become more like a co-product of copper and nickel, if price levels of cobalt and margins on cobalt production are high. Depending on the collection and recycling of cobalt-containing products, such as batteries, recycling can suffice for a significant part of the demand. As the average oregrade declines, recycling of cobalt scrap becomes more attractive, and recycling could suffice for an even bigger part of the demand. However, industrial mining of cobalt is likely to remain necessary in the coming decades to meet global demand.

With regards to sustainability, there is a trade-off between local and global sustainability aspects. Using cobalt in batteries supports the transition to a low-carbon economy. However, locally, there are EHS risks, possible involvement in artisanal and/or child labor, and local negative externalities such as local environmental damage. Globally, an increase in mining contributes to an increase in carbon emissions carbon emissions from producing more metals contributes to even faster global warming. Supply chain management to manage responsible cobalt sourcing is detrimental to track all aspects of sustainability, as well as innovation in the sector, or introducing a carbon tax, which contribute to lower carbon emissions. Lastly, recycling also contributes to mitigating carbon emissions.

For investors, the increase in traded cobalt volume brings more investment opportunities, but financial risks and EHS risks need to be balanced when investing in cobalt, especially with regards to artisanal mining. The main financial risks are country risk and demand risk. Demand risk is high because of potential fluctuations in the margins per pound of cobalt. The marginal cost depends on the development of the average oregrades, and energy costs. Country risk is high specifically for cobalt from the DRC, since this country has high poverty levels, and governance in the region has been unstable in the past. EHS risk is high because of the presence of artisanal mining and child labor in the DRC. Supply chain management and transparency is necessary to make sure that any cobalt mines, trade, or batteries, are not involved with artisanal mining, or child labor.

With regards to the two main paradigms in literature on the structure of metal systems, the Opportunity cost paradigm and the Fixed stock paradigm, these result in very different results, especially on supply and demand dynamics. This paper argues that the Opportunity cost paradigm gives a more realistic description of metal systems because of its assumptions that substitution and price elasticity can decrease demand, and that continued exploration can increase future reserves. The assumptions of the Fixed stock paradigm result in scenarios in which the demand rises unrestrained due to the EV transition, whereas Opportunity cost scenarios show demand to be dynamic, and price-dependent, which is more realistic. However, the Opportunity cost paradigm could learn from the Fixed stock paradigm that even if it is economically viable, it does not necessarily mean that it should be mined. The price can very well be a signal of economic scarcity, it does not include all relevant information on externalities, and therefore, it should not be taken as the only relevant variable in a system. Instead of continued emphasis on the differences between the paradigms, the scientists of both paradigms could learn from each other, and come to increased understanding of the behavior of metal systems over time. Thus, they could provide better advice on relevant policies to mitigate externalities of mining for decision makers.

To conclude, cobalt is a critical material for the low-carbon transition, and is likely to remain critical in the future. Industrial and artisanal mining, and recycling in the system could vary greatly for different demand scenarios, depending on the EV transition. There are many sustainability angles to the cobalt system, both on a global and on a local scale. In order for the cobalt system to contribute to the low-carbon transition a better understanding of the meaning of scarcity and sustainability, and possible trade-offs between different angles to sustainability is necessary. Although physical scarcity itself is not an imminent threat to cobalt supply, increased material demand does increase the strain on aspects like water availability, undamaged natural habitats, clean atmosphere, and a climate that is habitable for humans, to name only a few. Increased research into understanding how these externalities could be mitigated is therefore recommended.

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A | Lithium-ion Batteries

Lithium-ion batteries consist of three key components: a negative electrode called the anode, a positive electrode called the cathode, and the electrolyte which promotes the movement of ions from the cathode to the anode. Cobalt can be included in the cathode, see figure A.1.

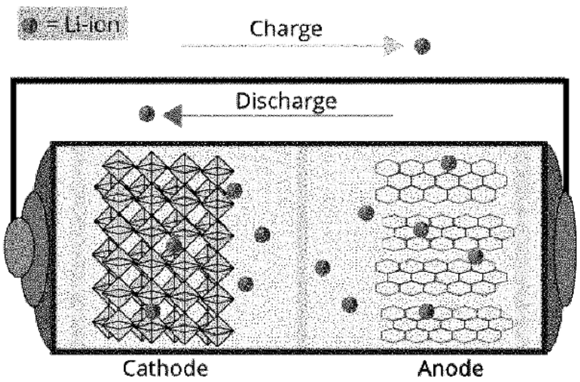


Figure A.1: Lithium-ion battery representative diagram. Source: DeCarlo and Matthews (2019). *Als ik nog een beter overzicht vind, dit gebruiken.*

There are many types of Lithium-ion batteries, each with a different metal content, which allows for different characteristics of the battery. The first battery developed for large scale manufacturing was the LCO battery: the Lithium-Cobalt-Oxide battery. After the development of this first battery, various other types of batteries have been developed. Most notably, the LFP battery: its cathode consists of Lithium, Iron and Phosphate and is used mostly in Ebuses; and the NCA battery, of which the cathode consists of nickel, cobalt and aluminium. Lastly, the NMC battery has been developed, with a nickel manganese cobalt cathode. For the latter, the amount of cobalt has slowly decreased for batteries with newer types of cathode. The first NMC batteries had a 1:1:1 ratio for nickel, manganese and cobalt, whereas later the cobalt and manganese content was decreased and the nickel content increased. Nowadays, most NMC batteries have a 8:1:1 ratio. The increased nickel content increases the specific energy of a battery. The lowered cobalt content however makes the battery less stable and more prone to explosions. The percentages of metals per cathode type are visualized in figure A.2

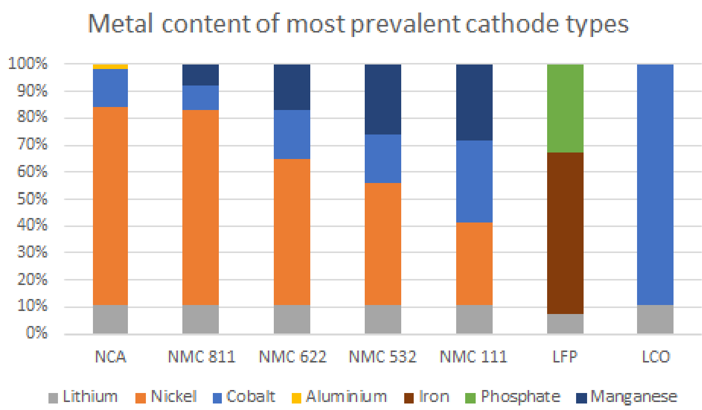


Figure A.2: Metal content per cathode type. CO = Lithium Cobalt Oxide, NCA = Nickel Cobalt Aluminium, NMC = Nickel Manganese Cobalt, LFP = Lithium Iron Phosphate. Based on Bloomberg NEF (2019).

Since each battery has different characteristics, the end uses for which they are suitable are different as well. Figure A.3 shows per end use which types of batteries are currently used.

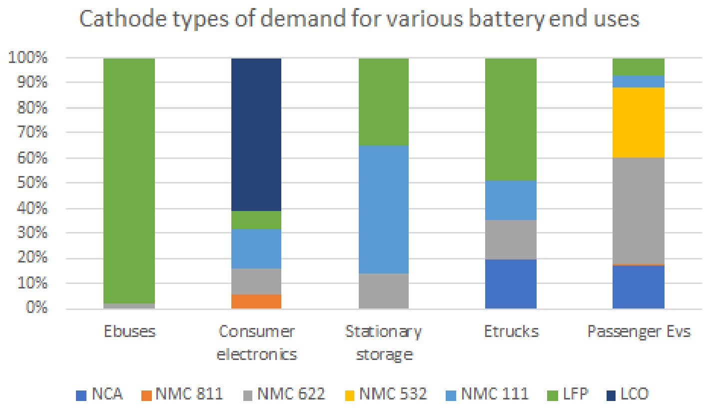
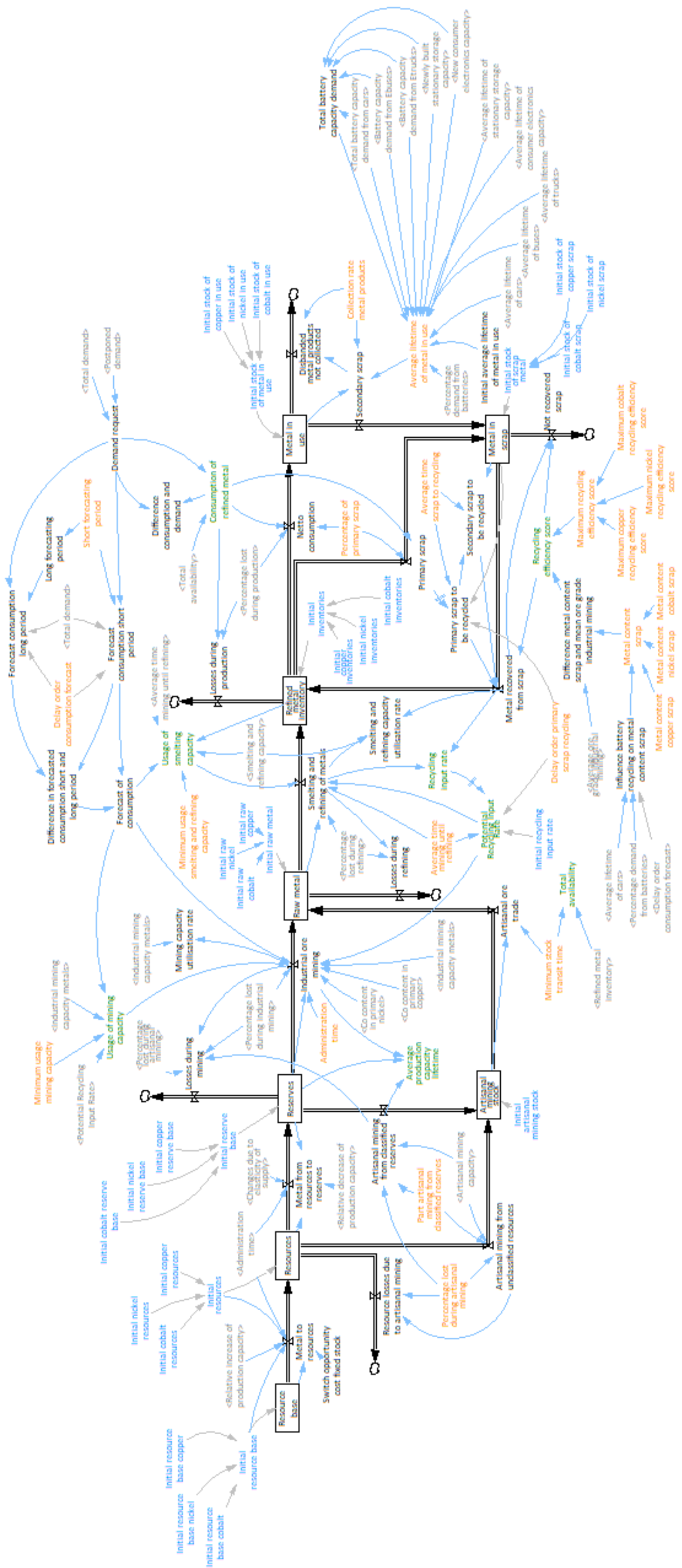


Figure A.3: Cathode type battery demand in percentage per end use (2019). LCO = Lithium Cobalt Oxide, NCA = Nickel Cobalt Aluminium, NMC = Nickel Manganese Cobalt, LFP = Lithium Iron Phosphate. Based on Bloomberg NEF (2019)

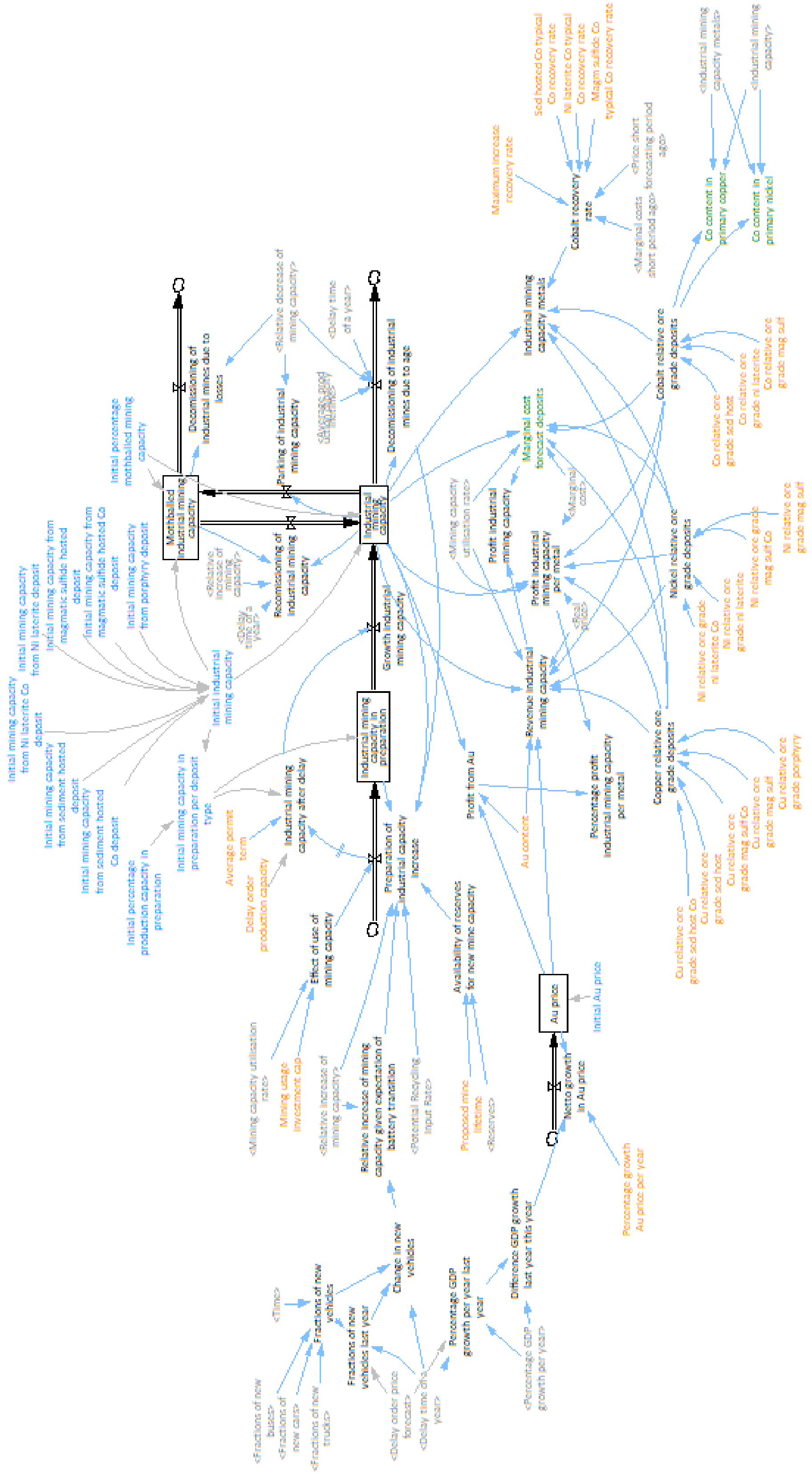
B | Implementation of SD model in Vensim

This appendix contains screenshots of the implementation of the SD model in Vensim. Blue are initital variables, orange are input variables.

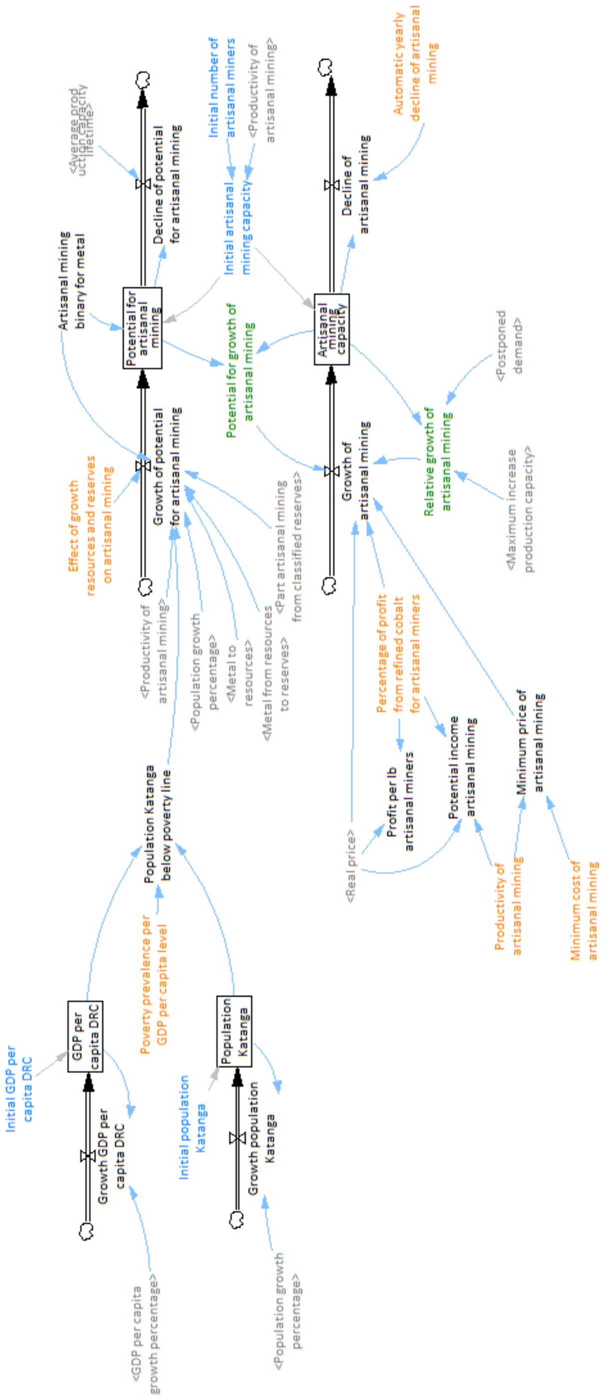
B.1. Metal stocks



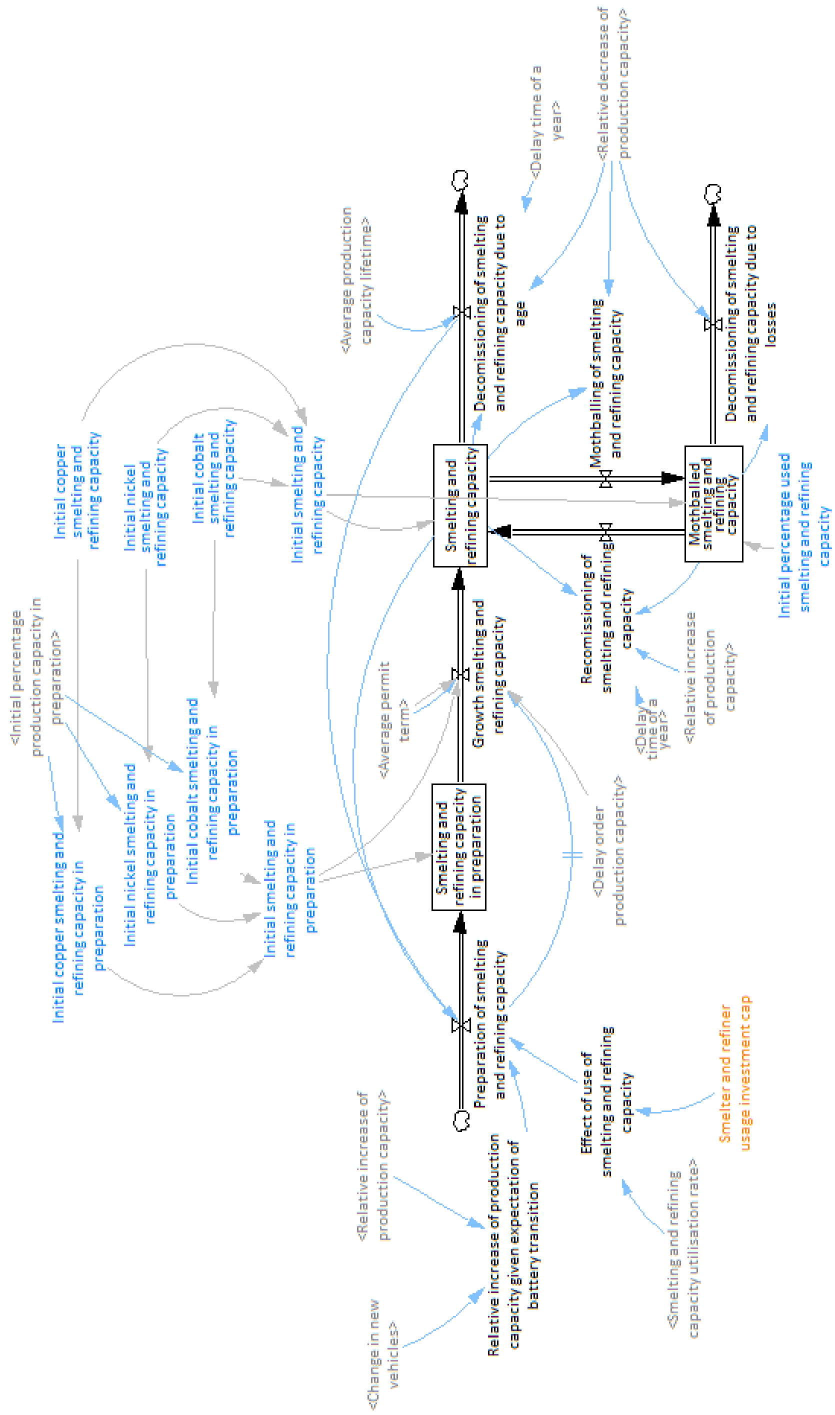
B.2. Industrial mining capacity



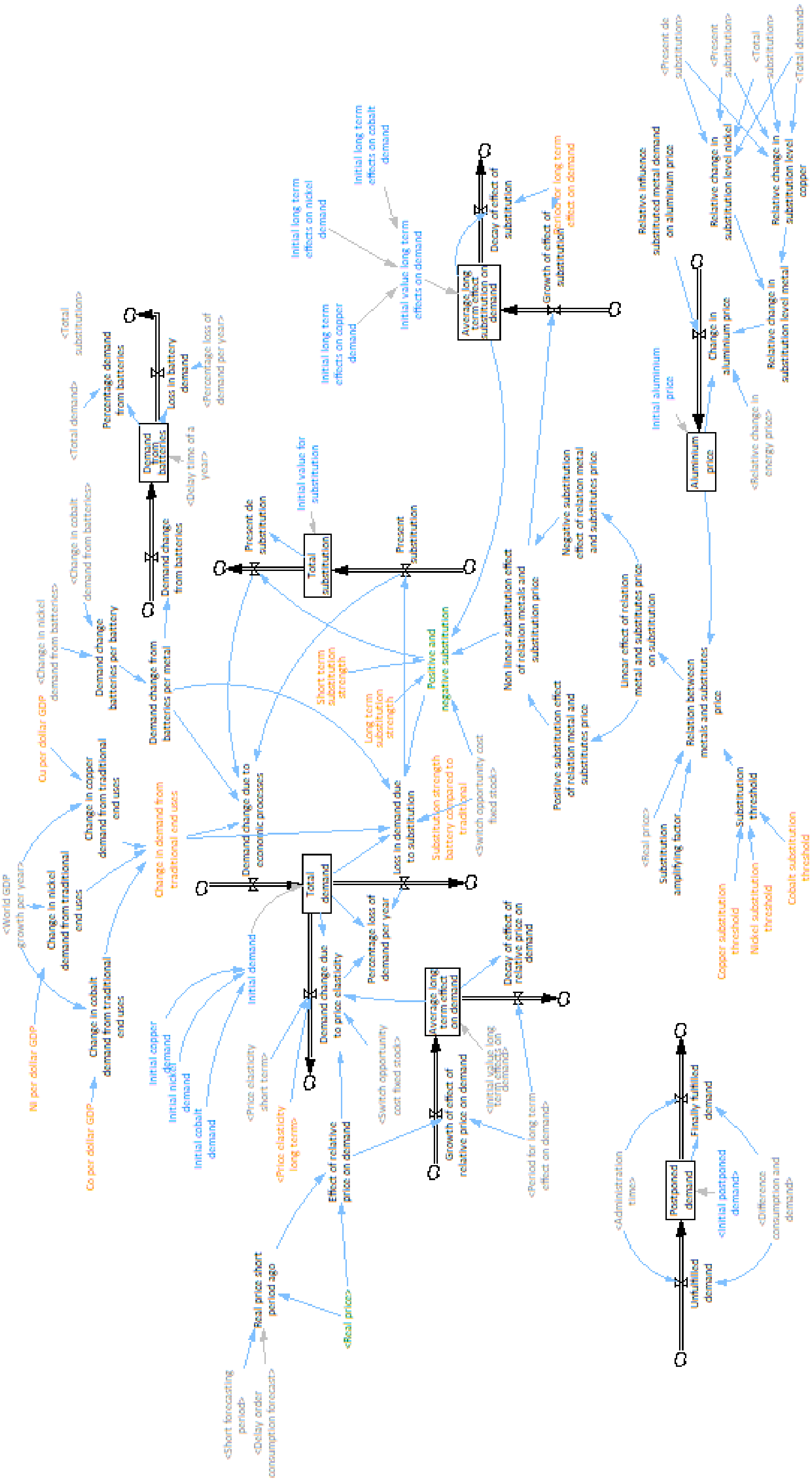
B.3. Artisanal mining capacity



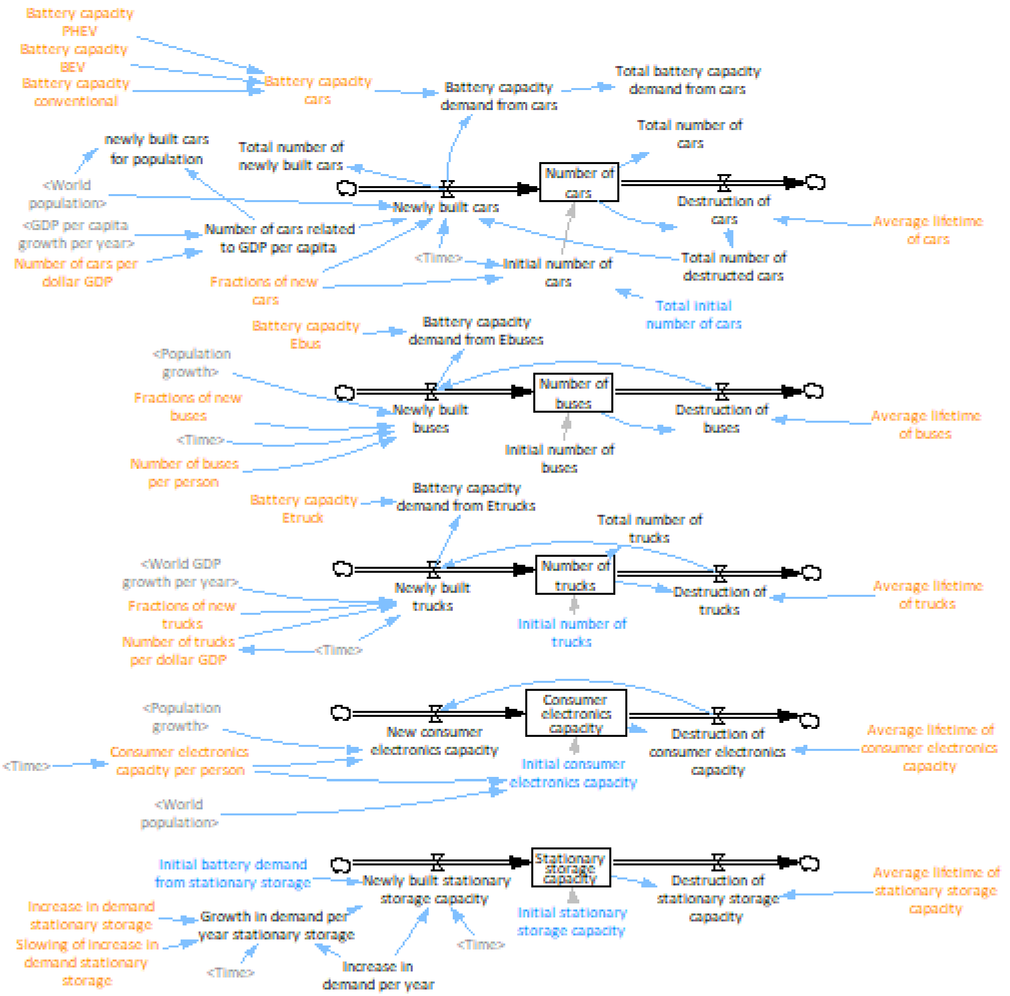
B.4. Smelting and refining capacity

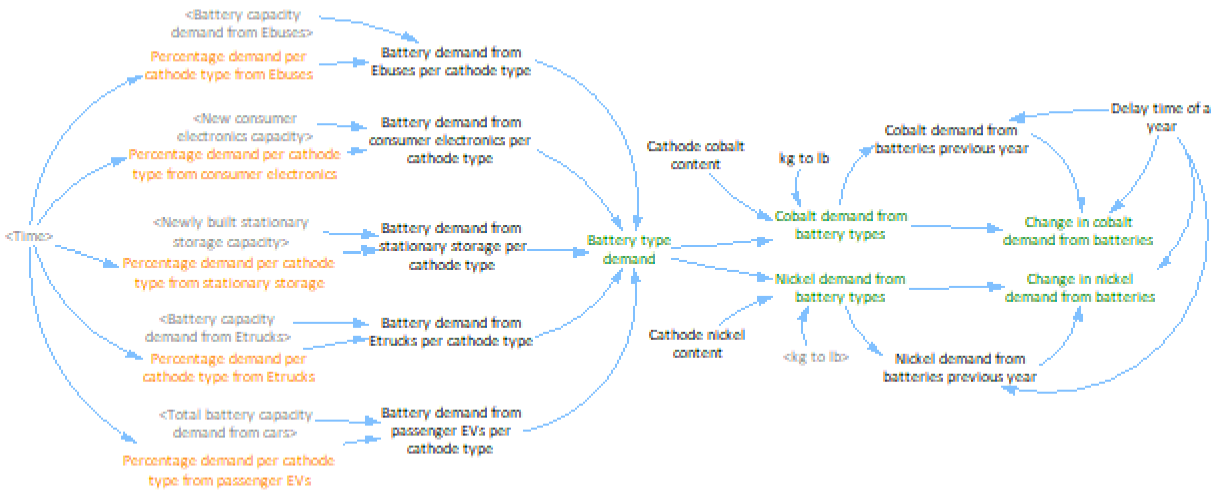


B.5. Demand

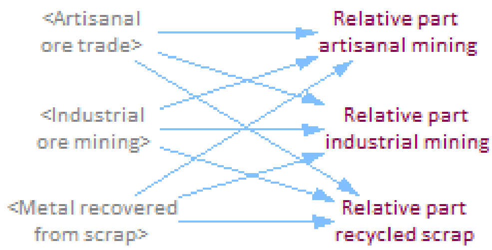


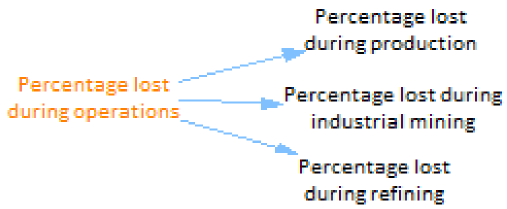
B.6. EV transition

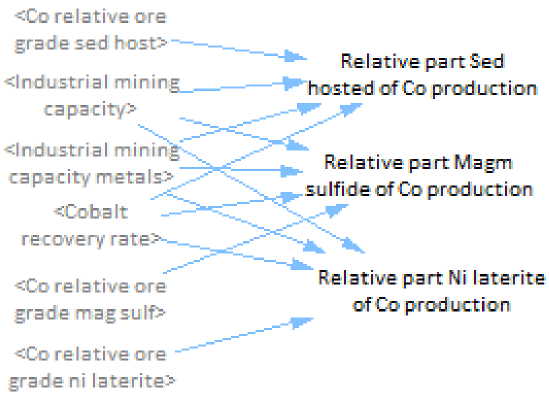


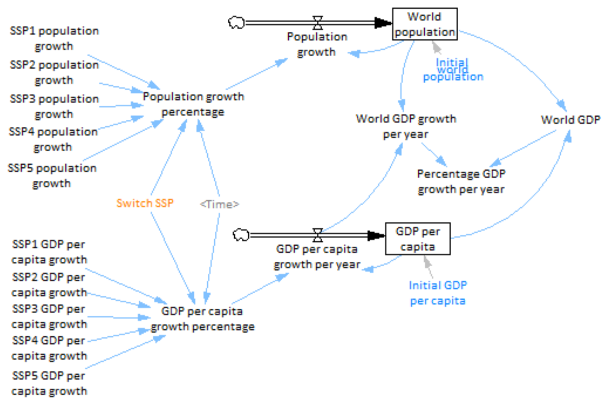


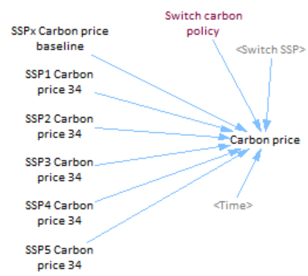
B.7. Output parameters and SSPs











C | Implementation of ESDMA in EMA workbench

ESDMA implementatation of Cobalt model in EMA workbench

January 9, 2020

1 Exploratory Modelling and Analysis of Vensim Cobalt Model

1.0.1 First, import packages

[409]:
```
from __future__ import (absolute_import, print_function, division, ␣
 ↪unicode_literals)
from ema_workbench import (Model, RealParameter, ScalarOutcome, Constant,␣
 ↪Policy, perform_experiments, ema_logging,
                           TimeSeriesOutcome, perform_experiments,␣
 ↪save_results, load_results)
from ema_workbench.analysis import (feature_scoring)
from ema_workbench.analysis.pairs_plotting import (pairs_lines, pairs_scatter,␣
 ↪pairs_density)
from ema_workbench.connectors.vensim import (VensimModel) #LookupUncertainty,␣
 ↪VensimModel, VensimModelStructureInterface)
from ema_workbench.em_framework import CategoricalParameter
from ema_workbench.em_framework.evaluators import LHS, SOBOL, MORRIS
from ema_workbench.analysis.plotting import lines, envelopes, kde_over_time,␣
 ↪multiple_densities
from ema_workbench.analysis import clusterer, plotting, Density
from ema_workbench.analysis import scenario_discovery_util as sdutil

import numpy as np
import seaborn as sns #; sns.set(style="ticks", color_codes=True)
import pandas as pd
import matplotlib.pyplot as plt

from Figures import plot_lines_with_envelopes
from plotting_util import group_results, filter_scalar_outcomes,make_grid,␣
 ↪make_legend
TIME_LABEL = 'Time'
from ema_workbench.analysis.plotting_util import prepare_data, COLOR_LIST,␣
 ↪simple_kde, group_density,\
                                                plot_envelope, simple_density,␣
 ↪do_titles,\
```

```
                                                         do_ylabels, TIME
import ema_workbench.analysis.plotting_util as plt_util
from ema_workbench.analysis.plotting import group_by_envelopes,␣
 ↪single_envelope, plot_lines_with_envelopes
from ema_workbench.analysis.pairs_plotting import pairs_scatter, pairs_density
from ema_workbench.analysis import pairs_plotting
from ema_workbench.analysis import (get_ex_feature_scores,
                                    RuleInductionType)
import ema_workbench.analysis.cart as cart
```

[619]:
```
import importlib
importlib.reload(sdutil)
importlib.reload(cart)
```

[619]:
```
<module 'ema_workbench.analysis.cart' from
'C:\\ProgramData\\Anaconda3_32bits\\lib\\site-
packages\\ema_workbench\\analysis\\cart.py'>
```

[3]:
```
import itertools
import copy
from copy import deepcopy

import numpy as np
import datetime
import math
import matplotlib.gridspec as gridspec

import scipy.stats.kde as kde
from matplotlib.colors import ColorConverter
from matplotlib.collections import PolyCollection, PathCollection
import matplotlib.pyplot as plt
from matplotlib.pyplot import pie
from matplotlib.ticker import FormatStrFormatter, FuncFormatter
from matplotlib.patches import ConnectionPatch
import matplotlib.font_manager as fm
import matplotlib as mpl
```

1.0.2 Set WD

[4]:
```
# wd = 'C:/Users/erika/Google Drive/EPA/Thesis/Model/'
wd = 'C:/Users/erika/Desktop/EMA_runs/'
ema_logging.log_to_stderr(ema_logging.INFO)
```

[4]:
```
<Logger EMA (DEBUG)>
```

1.0.3 Define model

[7]:
```
Cobalt_model = VensimModel('Vensim', wd = wd,␣
↪model_file=wd+'ExplorationCobaltSystem_EvanderLinden.vpm')
```

1.0.4 Define uncertainties and outcomes

[8]:
```
Cobalt_model.uncertainties = [
#     Switches
        CategoricalParameter('Switch opportunity cost fixed stock',(1,2),pff =␣
↪True ),
        CategoricalParameter('Switch SSP', (1,2,3,4,5) ),
        CategoricalParameter('Switch carbon policy',(0,1) ),
        CategoricalParameter('Switch energy price growth scenario', (1,2,3) ),
        CategoricalParameter('Switch real price', (1,2)),
#     Assumptions metal stocks
        RealParameter('Percentage lost during artisanal mining',0.4 ,0.6 ),
#         RealParameter('Part artisanal mining from classified reserves',0.1 ,0.
↪3 ),
#         RealParameter('Administration time',10 ,20 ),
#         RealParameter('Average time mining until refining',0.09 ,0.11 ),
#         RealParameter('Average time scrap to recycling',0.38 ,0.42 ),
#         RealParameter('Maximum cobalt recycling efficiency score',0.7 ,0.9 ),
#         RealParameter('Maximum nickel recycling efficiency score',0.9 ,0.99␣
↪),
#         RealParameter('Maximum copper recycling efficiency score',0.95 ,0.999␣
↪),
#         RealParameter('Metal content cobalt scrap',0.003 ,0.006 ),
#         RealParameter('Metal content nickel scrap',0.01 ,0.02 ),
#         RealParameter('Metal content copper scrap',0.01 ,0.02 ),
        RealParameter('Percentage of primary scrap',0.25 ,0.4 ),
        RealParameter('Initial average lifetime of metal in use',5 ,15 ),
        RealParameter('Collection rate metal products',0.4 ,0.8 ),
#         RealParameter('Short forecasting period', 0.5,2 ),
#         CategoricalParameter('Delay order consumption forecast',(1,3,5) ),
#         RealParameter('Minimum usage mining capacity', 0.7,0.9),
        RealParameter('Minimum usage smelting and refining capacity', 0.7,0.9),
#         RealParameter('Percentage lost during operations', 0.04, 0.08),
# #     Assumptions industrial and artisanal mining capacity
        RealParameter('Mining usage investment cap',0 ,0.95 ),
#         CategoricalParameter('Delay order production capacity',(1,3,5) ),
#         RealParameter('Average permit term', 5 , 15 ),
#         RealParameter('Smelter and refiner usage investment cap', 0, 0.95),
#         RealParameter('Percentage of profit from refined cobalt for artisanal␣
↪miners', 0.04, 0.1),
        RealParameter('Productivity of artisanal mining', 800, 1600),
#         RealParameter('Minimum cost of artisanal mining', 800, 1300),
```

```
        RealParameter('Maximum increase recovery rate', 0.05, 0.25),
# #     Assumptions Demand
#         RealParameter('Ni per dollar GDP', 0.000004, 0.000008 ),
#         RealParameter('Co per dollar GDP', 0.0000001, 0.0000005 ),
#         RealParameter('Cu per dollar GDP', 0.000025, 0.000035 ),
#         RealParameter('Period for long term effect on demand', 5,15),
#         RealParameter('Copper substitution threshold', 3,5),
#         RealParameter('Nickel substitution threshold', 5,9),
#         RealParameter('Cobalt substitution threshold', 5,7),
#         RealParameter('Long term substitution strength',0.1, 0.15),
#         RealParameter('Short term substitution strength', 0.02, 0.06),
#         RealParameter('Substitution strength battery compared to␣
↪traditional', 0.01,0.05),
# #     Assumptions Battery transition
#         RealParameter('Increase in demand stationary storage', 0.2 , 0.4),
        RealParameter('Slowing of increase in demand stationary storage', 0.88␣
↪, 0.96),
#         RealParameter('Battery capacity PHEV', 10 , 30),
        RealParameter('Battery capacity BEV', 30 , 120),
#         RealParameter('Number of cars per dollar GDP', 5e-007, 3e-006),
#         RealParameter('Battery capacity Ebus',150, 220 ),
#         RealParameter('Number of buses per person',0.001, 0.002),
#         RealParameter('Battery capacity Etruck', 70, 150),
# #     Assumptions Economics
#         RealParameter('Percentage cost on top of marginal cost', 0.05 , 0.25␣
↪),
#         RealParameter('Price elasticity long term', 0.1 , 0.25),
#         RealParameter('Price elasticity short term', 0.02, 0.08),
#         RealParameter('Price amplifying factor', 0.5 , 3),
#         RealParameter('Cobalt taxes', 0.4, 2),
#         RealParameter('Nickel taxes', 0.1, 0.5),
#         RealParameter('Copper taxes', 0.05, 0.3),
#         RealParameter('Marginal cost bottom price relationship copper', 0.01,␣
↪0.015),
#         RealParameter('Marginal cost bottom price relationship nickel', 0.08,␣
↪0.12),
#         RealParameter('Marginal cost bottom price relationship cobalt', 0.
↪05,0.075),
#         RealParameter('Exponent copper price curve',-1.6, -1.4),
#         RealParameter('Exponent nickel price curve',-0.95, -0.85),
#         RealParameter('Exponent cobalt price curve',-1.3, -1.1),
#         RealParameter('Innovation in mining sector', 0.8 ,1 ),
#         RealParameter('Relation ore grade energy usage copper',-1.05,-0.95 ),
#         RealParameter('Relation ore grade energy usage nickel',-0.77, -0.67␣
↪),
#         RealParameter('Relation ore grade energy usage cobalt',-3.1, -2.9 ),
```

```
#         RealParameter('Base energy usage copper', 0.075,0.085),
#         RealParameter('Base energy usage nickel', 0.09, 0.13),
#         RealParameter('Base energy usage cobalt', 0.09, 0.11),
#         RealParameter('Transport costs copper', 0.02, 0.06),
#         RealParameter('Transport costs nickel', 0.1, 0.3),
#         RealParameter('Transport costs cobalt', 0.1, 0.3),
#         RealParameter('Price averaging period', 0.1, 0.4),
        RealParameter('Power for oregrades', 0.38, 0.42 ),
#         RealParameter('Maximum increase production capacity', 0.1, 0.2),
#         RealParameter('Maximum decrease production capacity', 0.02, 0.05),
]

Cobalt_model.outcomes =  [
#     General
        TimeSeriesOutcome('TIME'),
#         TimeSeriesOutcome('Total demand[Copper]'),
#         TimeSeriesOutcome('Total demand[Nickel]'),
        TimeSeriesOutcome('Total demand[Cobalt]'),
#         TimeSeriesOutcome('Marginal cost[Copper]'),
#         TimeSeriesOutcome('Marginal cost[Nickel]'),
#         TimeSeriesOutcome('Marginal cost[Cobalt]'),
#     Fixed Stock metrics
#         TimeSeriesOutcome('R over P ratio[Copper]'),
#         TimeSeriesOutcome('R over P ratio[Nickel]'),
        TimeSeriesOutcome('R over P ratio[Cobalt]'),
#         TimeSeriesOutcome('Exponential index of depletion[Copper]'),
#         TimeSeriesOutcome('Exponential index of depletion[Nickel]'),
        TimeSeriesOutcome('Exponential index of depletion[Cobalt]'),
#     Opportunity Cost metrics
#         TimeSeriesOutcome('Real price[Copper]'),
#         TimeSeriesOutcome('Real price[Nickel]'),
        TimeSeriesOutcome('Real price[Cobalt]'),
#     Relative parts types of mining
        TimeSeriesOutcome('Relative part artisanal mining[Cobalt]'),
        TimeSeriesOutcome('Artisanal ore trade[Cobalt]'),
#         TimeSeriesOutcome('Industrial Ore mining[Copper]'),
#         TimeSeriesOutcome('Industrial Ore mining[Nickel]'),
        TimeSeriesOutcome('Industrial Ore mining[Cobalt]'),
#         TimeSeriesOutcome('Relative part industrial mining[Copper]'),
#         TimeSeriesOutcome('Relative part industrial mining[Nickel]'),
#         TimeSeriesOutcome('Relative part industrial mining[Cobalt]'),
#         TimeSeriesOutcome('Relative part recycled scrap[Copper]'),
#         TimeSeriesOutcome('Relative part recycled scrap[Nickel]'),
        TimeSeriesOutcome('Relative part recycled scrap[Cobalt]'),
#     Metal stocks
#         TimeSeriesOutcome('Resources[Copper]'),
#         TimeSeriesOutcome('Resources[Nickel]'),
```

```
        TimeSeriesOutcome('Resources[Cobalt]'),
#         TimeSeriesOutcome('Reserve base[Copper]'),
#         TimeSeriesOutcome('Reserve base[Nickel]'),
        TimeSeriesOutcome('Reserves[Cobalt]'),
#         TimeSeriesOutcome('Recycling input rate[Copper]'),
#         TimeSeriesOutcome('Recycling input rate[Nickel]'),
        TimeSeriesOutcome('Recycling input rate[Cobalt]'),
#         TimeSeriesOutcome('Recycling efficiency score[Copper]'),
#         TimeSeriesOutcome('Recycling efficiency score[Nickel]'),
        TimeSeriesOutcome('Recycling efficiency score[Cobalt]'),
#         TimeSeriesOutcome('Smelting and refining capacity utilisation␣
↪rate[Copper]'),
#         TimeSeriesOutcome('Smelting and refining capacity utilisation␣
↪rate[Nickel]'),
#         TimeSeriesOutcome('Smelting and refining capacity utilisation␣
↪rate[Cobalt]'),
        TimeSeriesOutcome('Metal recovered from scrap[Cobalt]'),
# #     Industrial and artisanal mining capacity
        TimeSeriesOutcome('Industrial mining capacity[Sed hosted Co]'),
#         TimeSeriesOutcome('Industrial mining capacity[Sed hosted]'),
        TimeSeriesOutcome('Industrial mining capacity[Ni laterite Co]'),
#         TimeSeriesOutcome('Industrial mining capacity[Ni laterite]'),
#         TimeSeriesOutcome('Industrial mining capacity[Porphyry Cu]'),
        TimeSeriesOutcome('Industrial mining capacity[Magm sulfide Co]'),
#         TimeSeriesOutcome('Industrial mining capacity[Magm sulfide]'),
#         TimeSeriesOutcome('Industrial mining capacity metals[Copper]'),
#         TimeSeriesOutcome('Industrial mining capacity metals[Nickel]'),
        TimeSeriesOutcome('Industrial mining capacity metals[Cobalt]'),
        TimeSeriesOutcome('Cobalt recovery rate[Sed hosted Co]'),
        TimeSeriesOutcome('Cobalt recovery rate[Ni laterite Co]'),
        TimeSeriesOutcome('Cobalt recovery rate[Magm sulfide Co]'),
#         TimeSeriesOutcome('Smelting and refining capacity[Copper]'),
#         TimeSeriesOutcome('Smelting and refining capacity[Nickel]'),
#         TimeSeriesOutcome('Smelting and refining capacity[Cobalt]'),
#         TimeSeriesOutcome('Population Katanga below poverty line'),
        TimeSeriesOutcome('Percentage profit industrial mining capacity per␣
↪metal[Cobalt,Sed hosted Co]'),
#         TimeSeriesOutcome('Percentage profit industrial mining capacity per␣
↪metal[Copper,Sed hosted Co]'),
#         TimeSeriesOutcome('Percentage profit industrial mining capacity per␣
↪metal[Nickel,Ni laterite Co]'),
        TimeSeriesOutcome('Percentage profit industrial mining capacity per␣
↪metal[Cobalt,Ni laterite Co]'),
#         TimeSeriesOutcome('Percentage profit industrial mining capacity per␣
↪metal[Copper,Magm sulfide Co]'),
```

```
#         TimeSeriesOutcome('Percentage profit industrial mining capacity per␣
↪metal[Nickel,Magm sulfide Co]'),
        TimeSeriesOutcome('Percentage profit industrial mining capacity per␣
↪metal[Cobalt,Magm sulfide Co]'),
    #     Demand
#         TimeSeriesOutcome('Total substitution[Copper]'),
#         TimeSeriesOutcome('Total substitution[Nickel]'),
#         TimeSeriesOutcome('Total substitution[Cobalt]'),
#         TimeSeriesOutcome('Postponed demand[Copper]'),
#         TimeSeriesOutcome('Postponed demand[Nickel]'),
#         TimeSeriesOutcome('Postponed demand[Cobalt]'),
# #     Battery transition
#         TimeSeriesOutcome('Total battery capacity demand from cars'),
#         TimeSeriesOutcome('Battery capacity demand from Ebuses'),
#         TimeSeriesOutcome('Battery capacity demand from Etrucks'),
#         TimeSeriesOutcome('New consumer electronics capacity'),
#         TimeSeriesOutcome('Newly built stationary storage capacity'),
# #     Economics
#         TimeSeriesOutcome('Energy price'),
#         TimeSeriesOutcome('Energy costs mining[Copper]'),
#         TimeSeriesOutcome('Energy costs mining[Nickel]'),
#         TimeSeriesOutcome('Energy costs mining[Cobalt]'),
        TimeSeriesOutcome('Energy usage mining[Cobalt]'),
#         TimeSeriesOutcome('Normalised profit forecast[Copper]'),
#         TimeSeriesOutcome('Normalised profit forecast[Nickel]'),
#         TimeSeriesOutcome('Normalised profit forecast[Cobalt]'),
        TimeSeriesOutcome('Marge per lb[Cobalt]'),
# #     SSPs
#         TimeSeriesOutcome('World population'),
#         TimeSeriesOutcome('Population growth'),
#         TimeSeriesOutcome('GDP per capita growth per year'),
#         TimeSeriesOutcome('World GDP growth per year'),
]
```

1.1 Create, or load results

[9]:
```
nr_experiments =1500
results_both_alloutcomes = perform_experiments([Cobalt_model],
                                  nr_experiments, uncertainty_sampling='pff')
```

```
[MainProcess/INFO] performing 3000 scenarios * 1 policies * 1 model(s) = 3000
experiments
[MainProcess/INFO] performing experiments sequentially
[MainProcess/INFO] 300 cases completed
[MainProcess/INFO] 600 cases completed
[MainProcess/INFO] 900 cases completed
[MainProcess/INFO] 1200 cases completed
```

```
[MainProcess/INFO] 1500 cases completed
[MainProcess/INFO] 1800 cases completed
[MainProcess/INFO] 2100 cases completed
[MainProcess/INFO] 2400 cases completed
[MainProcess/INFO] 2700 cases completed
[MainProcess/INFO] 3000 cases completed
[MainProcess/INFO] experiments finished
```

[11]:
```
save_results(results_both_alloutcomes, r'C:/Users/erika/Desktop/EMA_runs/
↪4000runs_pff3_moreoutcomes.tar.gz')
```

```
[MainProcess/INFO] results saved successfully to
C:\Users\erika\Desktop\EMA_runs\4000runs_pff3_moreoutcomes.tar.gz
```

[10]:
```
# results_both_alloutcomes = load_results(r'C:/Users/erika/Desktop/EMA_runs/
↪4000runs_pff3_moreoutcomes.tar.gz')
```

1.2 Data preparation

[12]:
```
exp_b, out_b= results_both_alloutcomes
```

[13]:
```
exp_b['Paradigm switch'] = None
```

[14]:
```
exp_b['Paradigm switch'][exp_b['Switch opportunity cost fixed stock'] == 1] =␣
↪'Fixed stock'
exp_b['Paradigm switch'][exp_b['Switch opportunity cost fixed stock'] == 2] =␣
↪'Opportunity cost'
```

```
C:\ProgramData\Anaconda3_32bits\lib\site-packages\ipykernel_launcher.py:1:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/indexing.html#indexing-view-versus-copy
  """Entry point for launching an IPython kernel.
C:\ProgramData\Anaconda3_32bits\lib\site-packages\ipykernel_launcher.py:2:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/indexing.html#indexing-view-versus-copy
```

[15]:
```
exp_fs = None
exp_oc = None
```

[16]:
```
out_fs = {}
out_oc = {}
for i in out_b:
    out_fs[i] = out_b[i][:1500]
    out_oc[i] = out_b[i][1500:]
exp_fs = exp_b[:1500]
exp_oc = exp_b[1500:]
results_fs = exp_fs, out_fs
results_oc = exp_oc, out_oc
```

[80]:
```
out_b['Average cobalt recovery rate'] = sum([ out_b['Cobalt recovery rate[Sed␣
↪hosted Co]'],out_b['Cobalt recovery rate[Ni laterite Co]'],out_b['Cobalt␣
↪recovery rate[Magm sulfide Co]'] ])/3
out_fs['Average cobalt recovery rate'] = sum([ out_fs['Cobalt recovery rate[Sed␣
↪hosted Co]'],out_fs['Cobalt recovery rate[Ni laterite Co]'],out_fs['Cobalt␣
↪recovery rate[Magm sulfide Co]'] ])/3
out_oc['Average cobalt recovery rate'] = sum([ out_oc['Cobalt recovery rate[Sed␣
↪hosted Co]'],out_oc['Cobalt recovery rate[Ni laterite Co]'],out_oc['Cobalt␣
↪recovery rate[Magm sulfide Co]'] ])/3
```

[18]:
```
out_b['Percentage profit industrial mining from Cobalt']  =␣
↪sum([out_b['Percentage profit industrial mining capacity per␣
↪metal[Cobalt,Sed hosted Co]'],
                                                                        ␣
↪out_b['Percentage profit industrial mining capacity per metal[Cobalt,Ni␣
↪laterite Co]'],
                                                                        ␣
↪out_b['Percentage profit industrial mining capacity per metal[Cobalt,Magm␣
↪sulfide Co]']])/3
```

1.3 Defining some functions

[19]:
```
def clustering (paradigm, column, nr_of_clusters):
    if paradigm == 'fs':
        dataset=out_fs
        expdata=exp_fs
    elif paradigm == 'oc':
        dataset=out_oc
        expdata=exp_oc
    else:
        dataset = out_b
        expdata = exp_b
    data = dataset[column]
    distances = clusterer.calculate_cid(data)

    # calcuate distances
    distances = clusterer.calculate_cid(data)
```

```
    # do agglomerative clustering on the distances
    clusters = clusterer.apply_agglomerative_clustering(distances,
                                                          n_clusters=nr_of_clusters)

    # show the clusters in the output space
    x = expdata.copy()
    x['clusters'] = clusters.astype('object')
    return (x)
```

[20]:
```
def plot_clusters (paradigm,column,x, zero = False,ylabel = False):
    if paradigm == 'fs':
        dataset=out_fs
        expdata=exp_fs
    elif paradigm == 'oc':
        dataset=out_oc
        expdata=exp_oc
    else:
        dataset = out_b#smaller_out_b
        expdata = exp_b#smaller_exp_b
    #plot the clusters
    lines(x, dataset,group_by = 'Clusters',outcomes_to_show = column,
                   density=Density.KDE)
    fig = plt.gcf()
    ax = fig.get_axes()
    ax[0].set_xticklabels(labels_time)
    fig.set_size_inches(7,5)
#     plt.yscale('log')

    #layout
    plt.margins(0)
    sns.despine()

    if zero == True:
        ax[0].set_ylim([0,None])
    ax[0].set_xticklabels(labels_time)
    if ylabel:
        ax[0].set(ylabel=ylabel)
    change_fontsize(fig)
    sns.despine()
#     save_fig(fig,wd,'clustering'+paradigm+column)
    return fig,ax
```

[21]:
```
def plot_one_cluster(paradigm, column, clusternr, x, zero=False):
    if paradigm == 'fs':
        dataset=out_fs
        expdata=exp_fs
    elif paradigm == 'oc':
```

```
        dataset=out_oc
        expdata=exp_oc
    else:
        dataset = out_b
        expdata = exp_b

    data2 = prepare_data(x,out_oc, outcomes_to_show = column,group_by =␣
↪'clusters')
    #plot the clusters
    lines(x, data2[0][clusternr], outcomes_to_show = column,
                density=Density.KDE)
    fig = plt.gcf()
    ax = fig.get_axes()
    ax[0].set_xticklabels(labels_time)

    fig.set_size_inches(13,7)
    if zero == True:
        ax[0].set_ylim([0,None])
    plt.show()
```

[22]:
```
def clusters_boxplot (paradigm, column_for_boxplot,x):
    fig, ax = plt.subplots(figsize=(15,8))
    plt.suptitle('')
    x.boxplot(column=[column_for_boxplot],by='clusters', ax=ax)
```

[23]:
```
def clusters_pairplotting (x, listwithvariables ):
    # show the input space
    sns.pairplot(x, hue='clusters',
                 vars=listwithvariables)
    fig = plt.gcf()
    fig.set_size_inches(16,16)
    plt.show()
```

[24]:
```
def find_colors(ax):
    color_converter = ColorConverter()
    all_colors = []
    for line in ax.get_lines():
        orig_color = line.get_color()
        if orig_color not in all_colors:
            all_colors.append(orig_color)
    return all_colors
```

[25]:
```
def save_fig(fig, dir, name,
             dpi=300):
    '''save a high res and a low res version of the figure in the specified
    directory, using the label i.

    Parameters
    ----------
```

```
    fig : a Figure instance
    dir : str
          the directory where figures are to be saved
    name : str
    dpi : int, optional
    '''
    fig.savefig('{}/fig_{}_{}dpi.png'.format(dir, name, dpi), dpi=dpi,
                bbox_inches='tight', format='png')
```

[26]:
```
def change_fontsize(fig, fs=11.5):
    '''Change fontsize of figure items to specified size'''
    for ax in fig.axes:
        for item in ([ax.title, ax.xaxis.label, ax.yaxis.label] +
                     ax.get_xticklabels() + ax.get_yticklabels()):
            item.set_fontsize(fs)
        try:
            parasites = ax.parasites
        except AttributeError:
            pass
        else:
            for parisite in parasites:
                for axis in parisite.axis.values():
                    axis.major_ticklabels.set_fontsize(fs)
                    axis.label.set_fontsize(fs)
            for axis in ax.axis.values():
                axis.major_ticklabels.set_fontsize(fs)
                axis.label.set_fontsize(fs)
        if ax.legend_ != None:
            for entry in ax.legend_.get_texts():
                entry.set_fontsize(fs)
        for entry in ax.texts:
            entry.set_fontsize(fs)
        for entry in ax.tables:
            entry.set_fontsize(fs)
```

[27]:
```
def nice_lines (exp,out,out_to_show,
                group_by= None,
                density=None,title=None,
                exp_to_show = None,
                grouping_specifiers = None,
                legend = False,
                paradigm = '',
                convert_to_t = False,
                convert_to_kt = False,
                convert_to_Mt = False,
                zero = False ,
                yupperlim = None,
                ylabel = False,
```

```
                alpha = None,
                sizex = None,
                sizey = None):
    if convert_to_t == True:
        out[title] = out[out_to_show]/2204.622620
        lines(experiments = exp, outcomes = out,
               experiments_to_show = exp_to_show,
               outcomes_to_show  =  title, legend = legend,
               group_by = group_by, density = density,
               grouping_specifiers = grouping_specifiers)
    elif convert_to_kt == True:
        out[title] = out[out_to_show]/2204622.620
        lines(experiments = exp, outcomes = out,
              experiments_to_show = exp_to_show,
               outcomes_to_show  =  title,legend = legend,
               group_by = group_by, density = density,
               grouping_specifiers = grouping_specifiers)
    elif convert_to_Mt == True:
        out[title] = out[out_to_show]/2204622620
        lines(experiments = exp, outcomes = out,
              experiments_to_show = exp_to_show,
               outcomes_to_show  =  title,legend = legend,
               group_by = group_by, density = density,
               grouping_specifiers = grouping_specifiers)
    else:
        out[title] = out[out_to_show]
        lines(experiments = exp, outcomes = out,
              experiments_to_show = exp_to_show,
               outcomes_to_show  =  title,legend = legend,
               group_by = group_by, density = density,
               grouping_specifiers = grouping_specifiers)
    fig = plt.gcf()
    fig.set_size_inches(6,3)
    if sizex:
        fig.set_size_inches(sizex,sizey)
    ax = fig.get_axes()
    if zero == True:
        ax[0].set_ylim([0,yupperlim])
    ax[0].set_xticklabels(labels_time)
    if ylabel:
        ax[0].set(ylabel=ylabel)
    if alpha:
        for line in ax[0].get_lines():
            line.set_alpha(alpha)
    short_title = title.replace(" ","")
    change_fontsize(fig)
    sns.despine()
```

```
    save_fig(fig,wd,paradigm+short_title)
#     fig.savefig(wd+paradigm+short_title+'.jpg')
    plt.show()
```

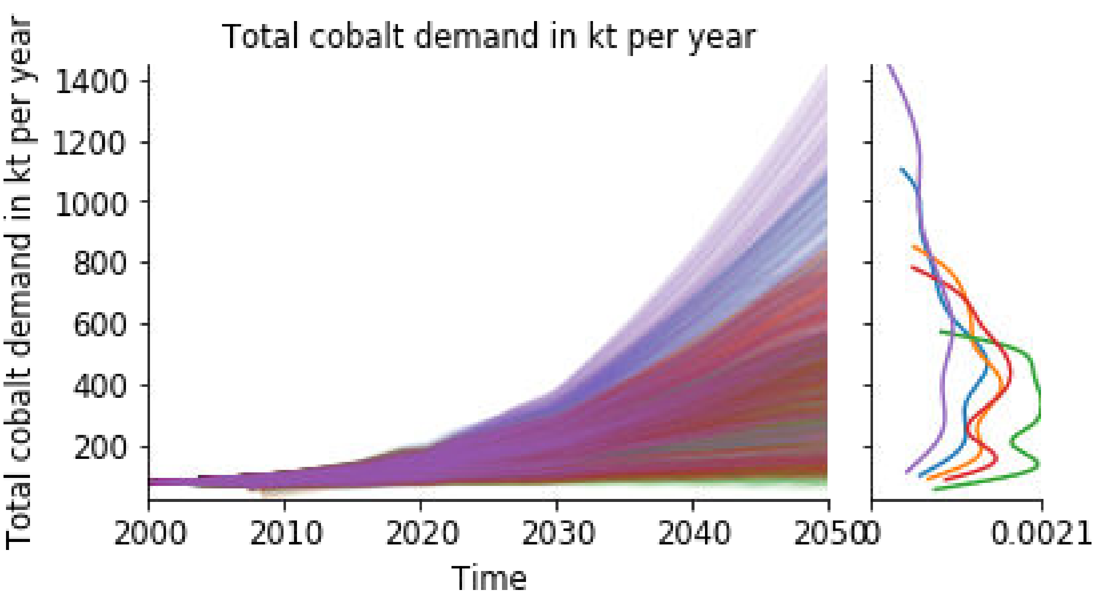
[51]:
```
labels_time = [2000, 2010, 2020, 2030, 2040, 2050]
plt.rcParams['axes.xmargin'] = 0
plt.rcParams['axes.ymargin'] = 0
plt.rcParams['legend.frameon'] = False
# Call each time:
# sns.despine()
```

```
<Figure size 432x288 with 0 Axes>
```

2 Visualisation

2.1 Clustering of demand

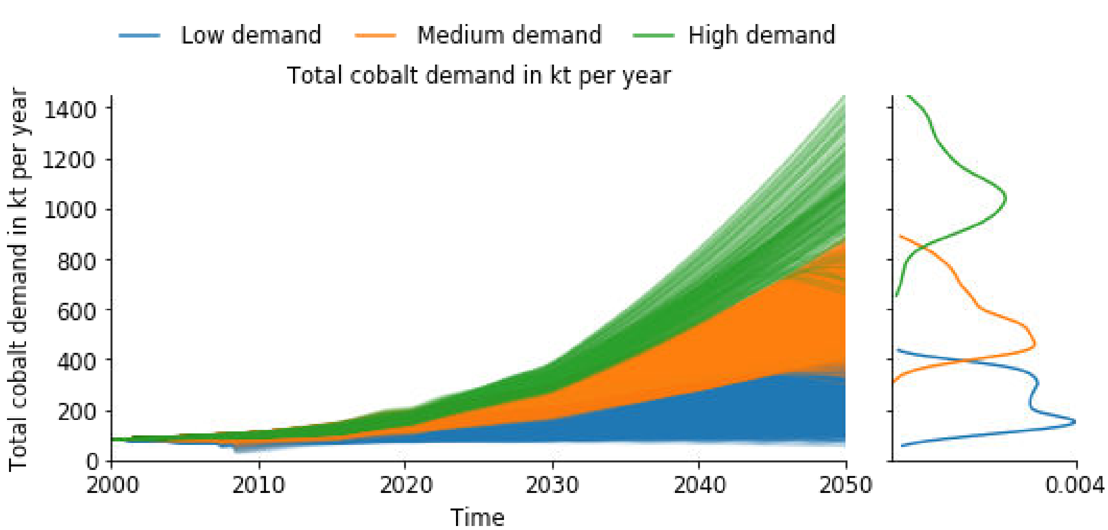
[29]:
```
nice_lines(exp_b,out_b,out_to_show = 'Total demand[Cobalt]',
           group_by = 'Switch SSP', density = Density.KDE,
          title = 'Total cobalt demand in kt per year',
           convert_to_kt = True, alpha = 0.05)
```



[31]:
```
# clustered_demand = clustering('both', 'Total cobalt demand in kt per year',3)
clustered_demand['Clusters']=None
clustered_demand['Clusters'][clustered_demand['clusters'] == 0] = ' Medium␣
 ↪demand'
```

```
clustered_demand['Clusters'][clustered_demand['clusters'] == 1] = 'High demand'
clustered_demand['Clusters'][clustered_demand['clusters'] == 2] = ' Low demand'
plot_clusters ('both','Total cobalt demand in kt per year',clustered_demand,␣
 ↪zero = True)
fig = plt.gcf()
fig.set_size_inches(9,3.5)
save_fig(fig,wd,'demandclustered')
# plt.savefig(wd+'demandclustered')
```

```
C:\ProgramData\Anaconda3_32bits\lib\site-packages\ipykernel_launcher.py:3:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/indexing.html#indexing-view-versus-copy
  This is separate from the ipykernel package so we can avoid doing imports
until
C:\ProgramData\Anaconda3_32bits\lib\site-packages\ipykernel_launcher.py:4:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/indexing.html#indexing-view-versus-copy
  after removing the cwd from sys.path.
C:\ProgramData\Anaconda3_32bits\lib\site-packages\ipykernel_launcher.py:5:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/indexing.html#indexing-view-versus-copy
  """
```



2.1.1 Explore most influential variables

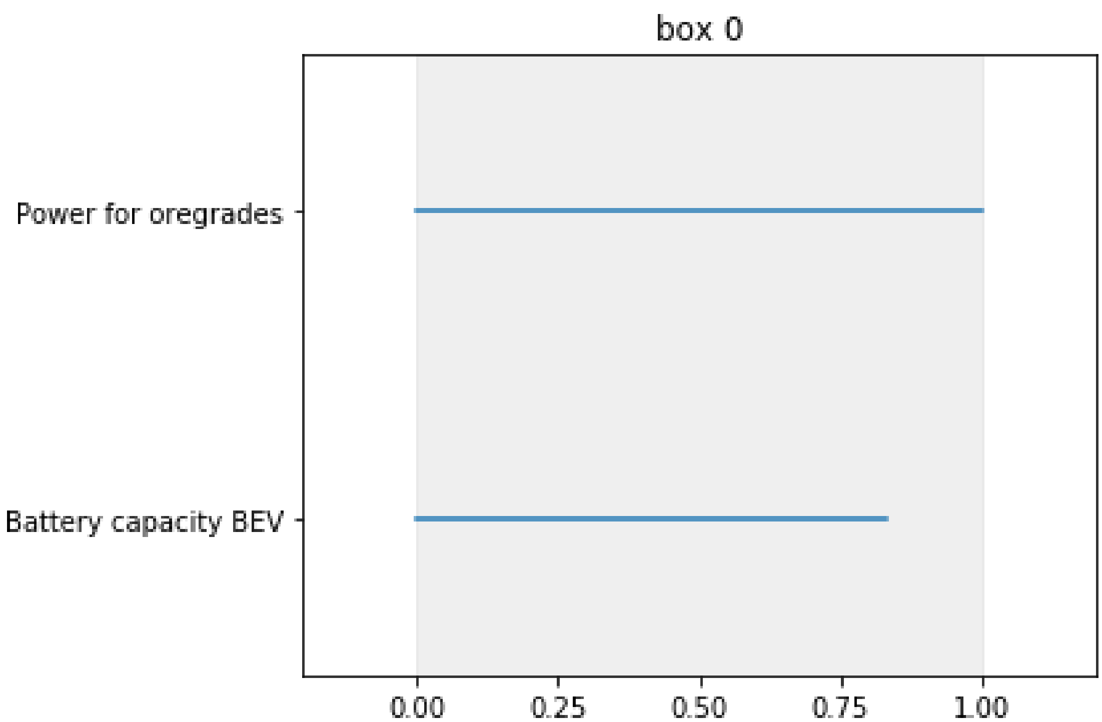
[610]:
```
def classify(data):
    result = data['Total cobalt demand in kt per year']
    classes = result[:, -1] < 800
    return classes
```

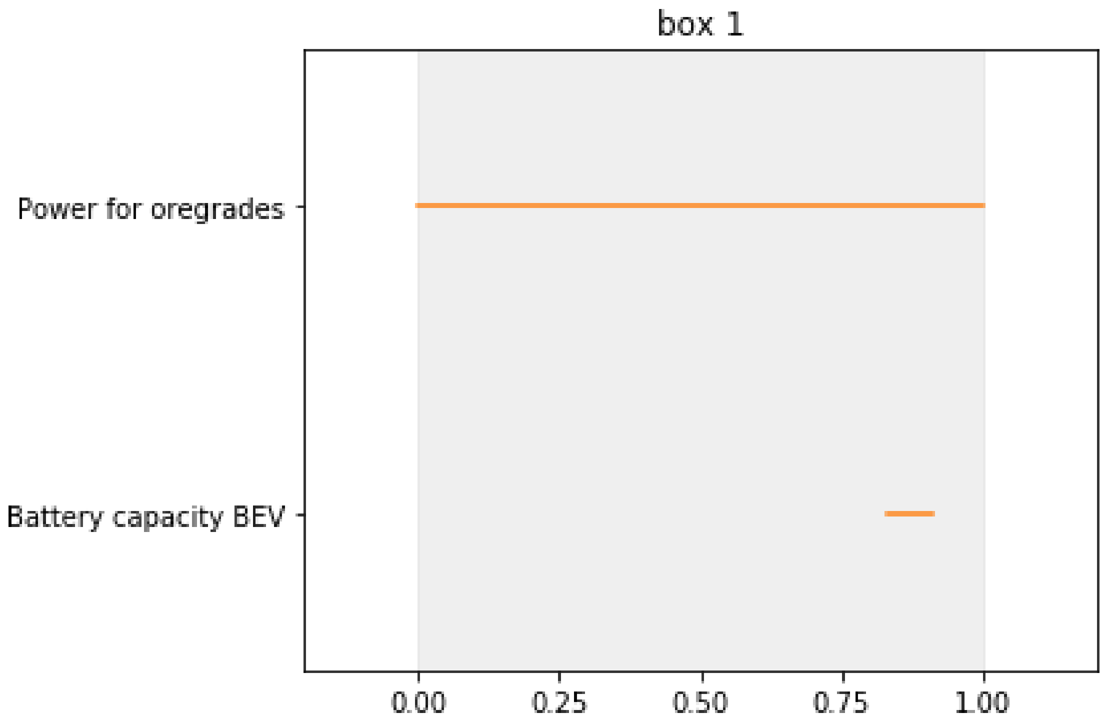
[611]:
```
cart_alg = cart.setup_cart((exp_b, out_b), classify, mass_min = 0.05)
```

[612]:
```
cart_alg.build_tree()
```

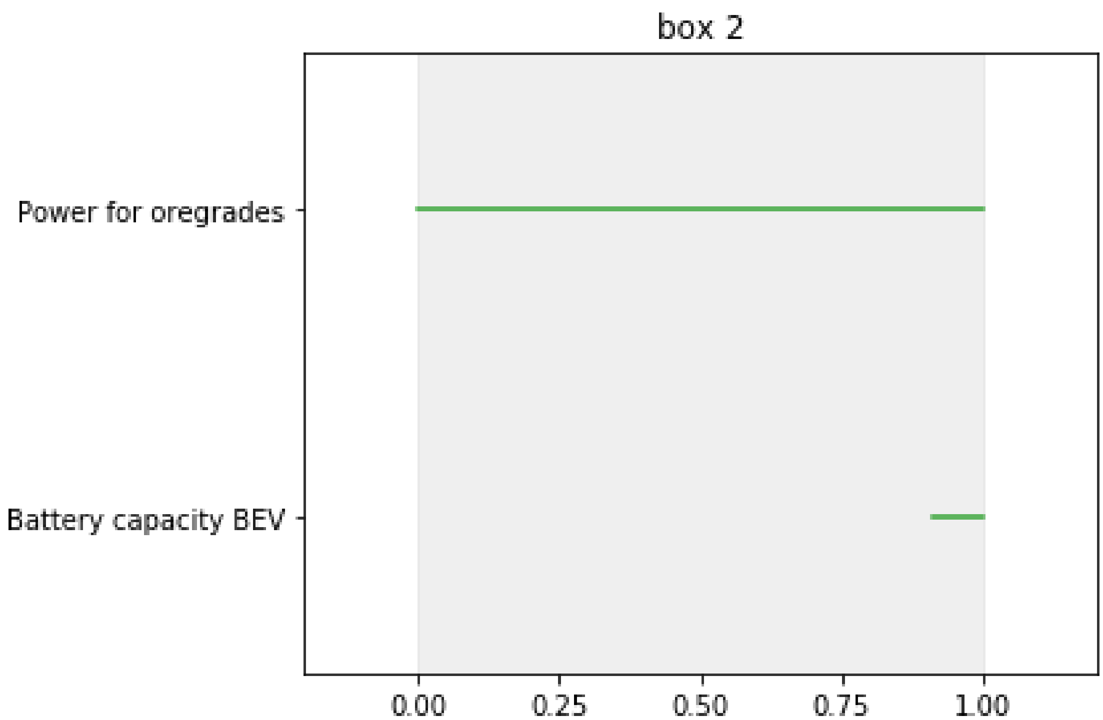
[617]:
```
for i in range(len(cart_alg.boxes)):
    cart_alg.boxes[i] = cart_alg.boxes[i].dropna(axis=1)
```

[576]:
```
cart_alg.show_boxes(together = False)
```

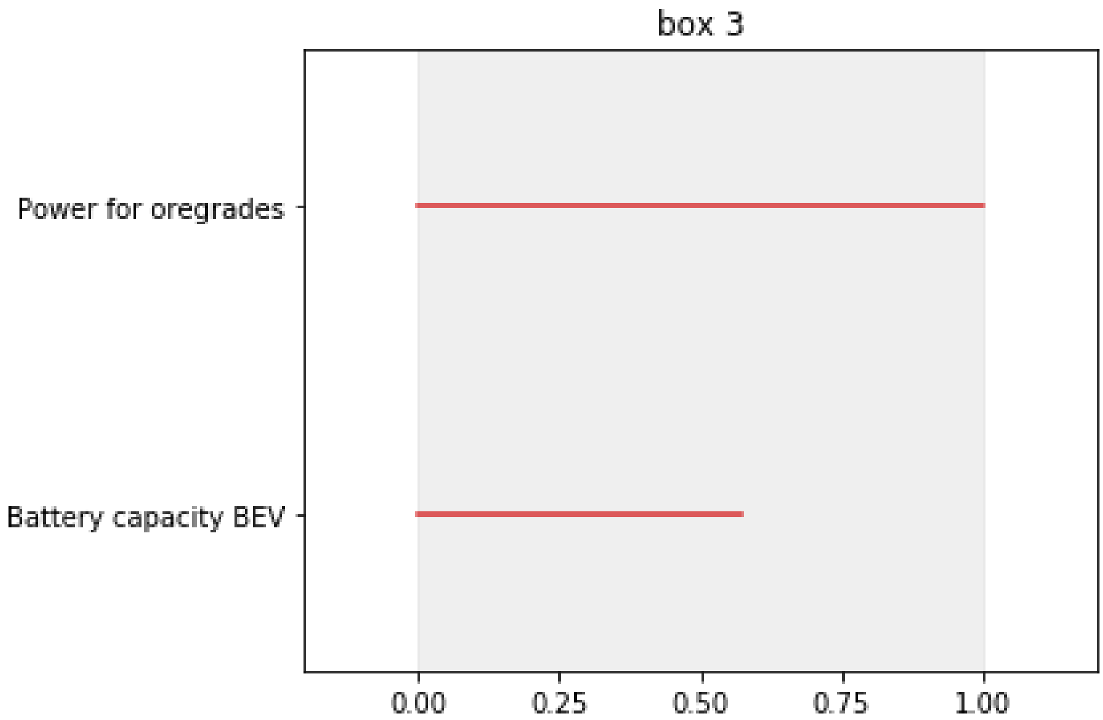




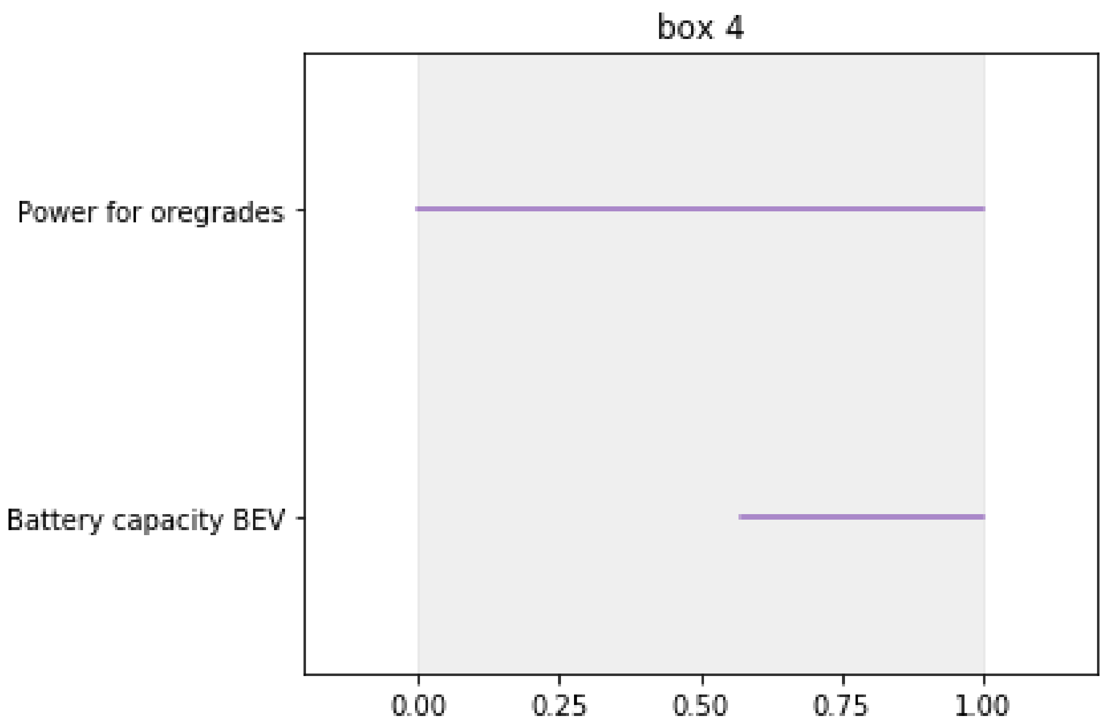
box 1
Power for oregrades
Battery capacity BEV
0.00
0.25
0.50
0.75
1.00



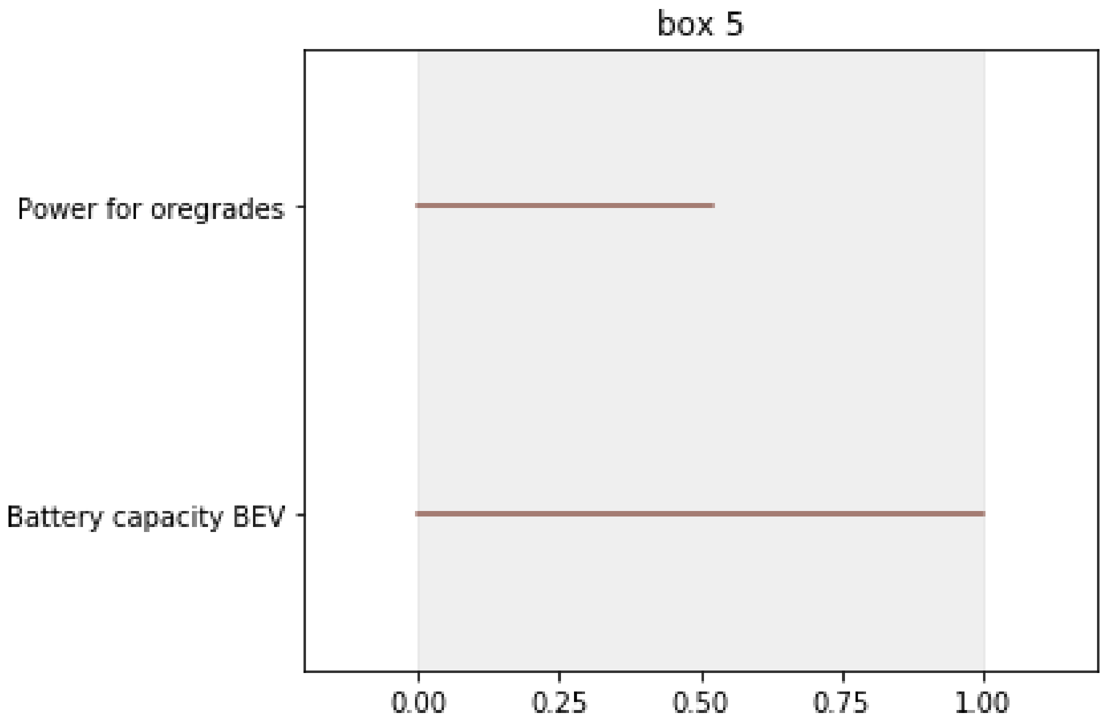
box 2
Power for oregrades
Battery capacity BEV
0.00
0.25
0.50
0.75
1.00

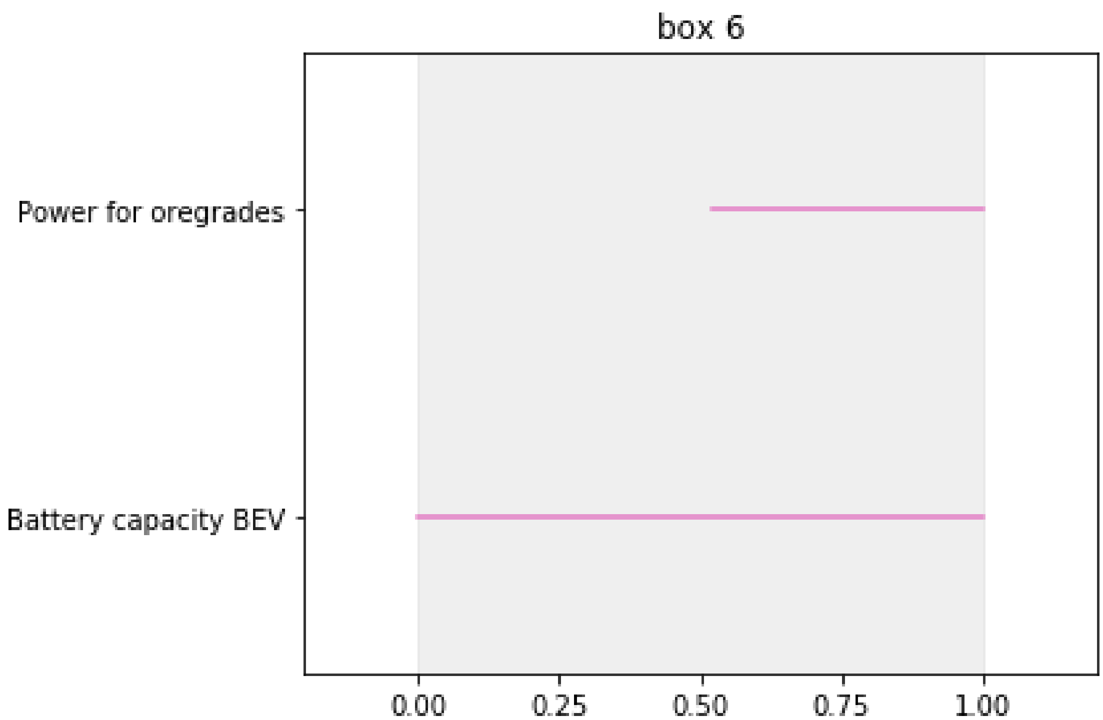


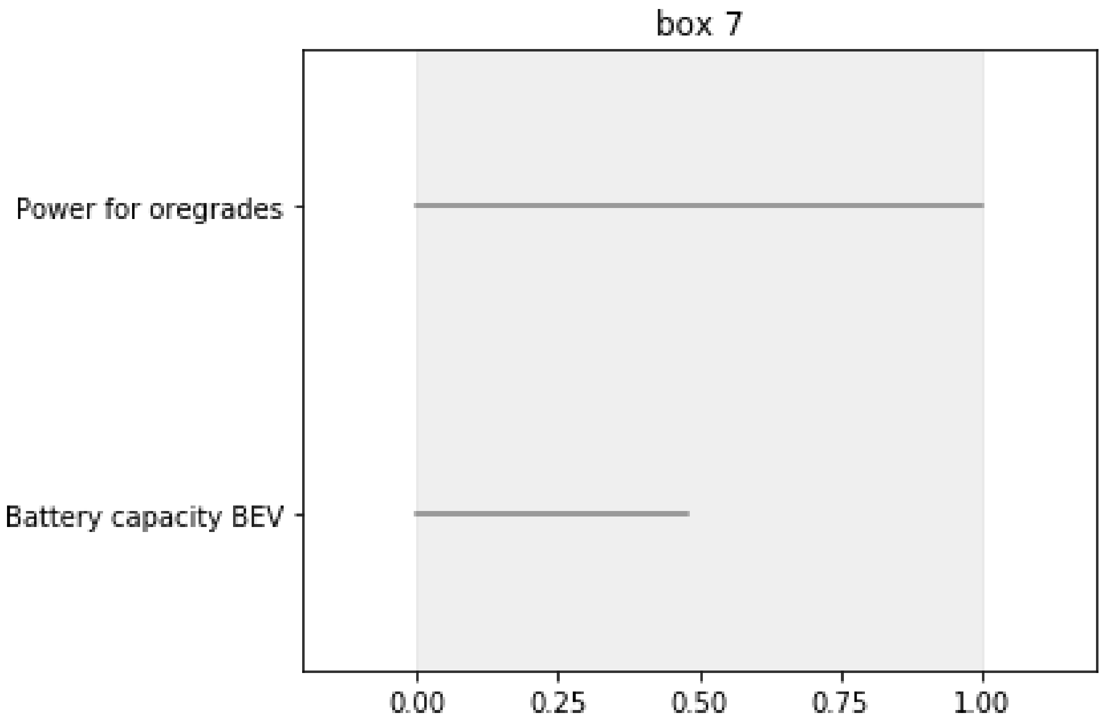
box 3
Power for oregrades
Battery capacity BEV
0.00
0.25
0.50
0.75
1.00

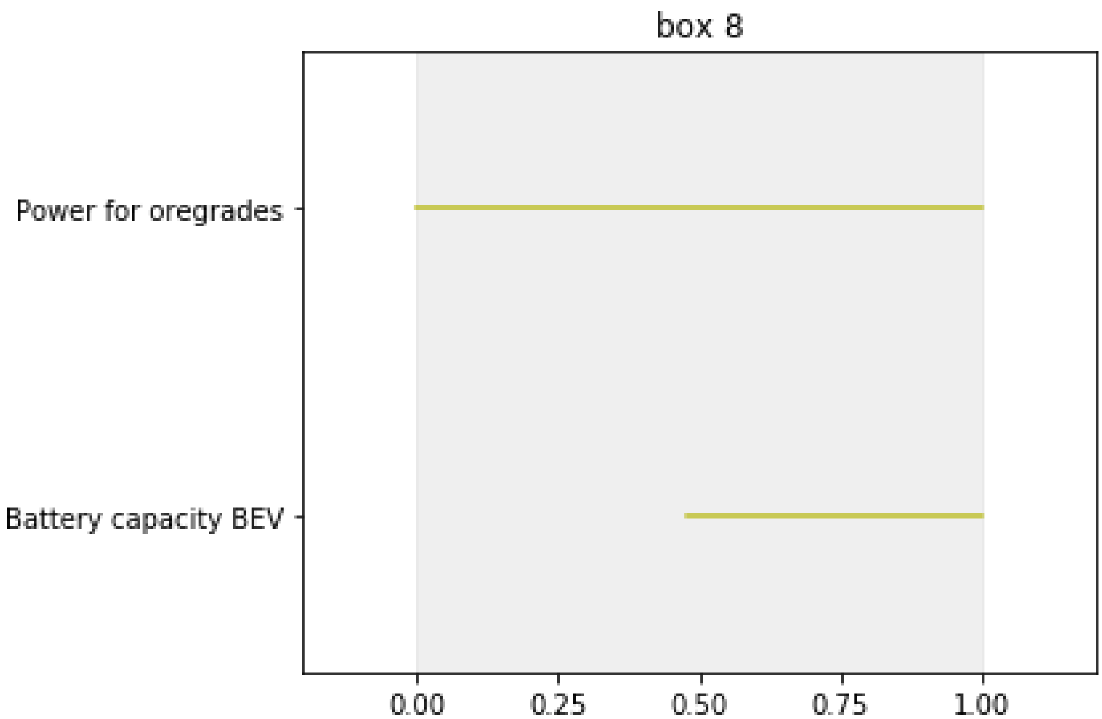


box 4
Power for oregrades
Battery capacity BEV
0.00
0.25
0.50
0.75
1.00

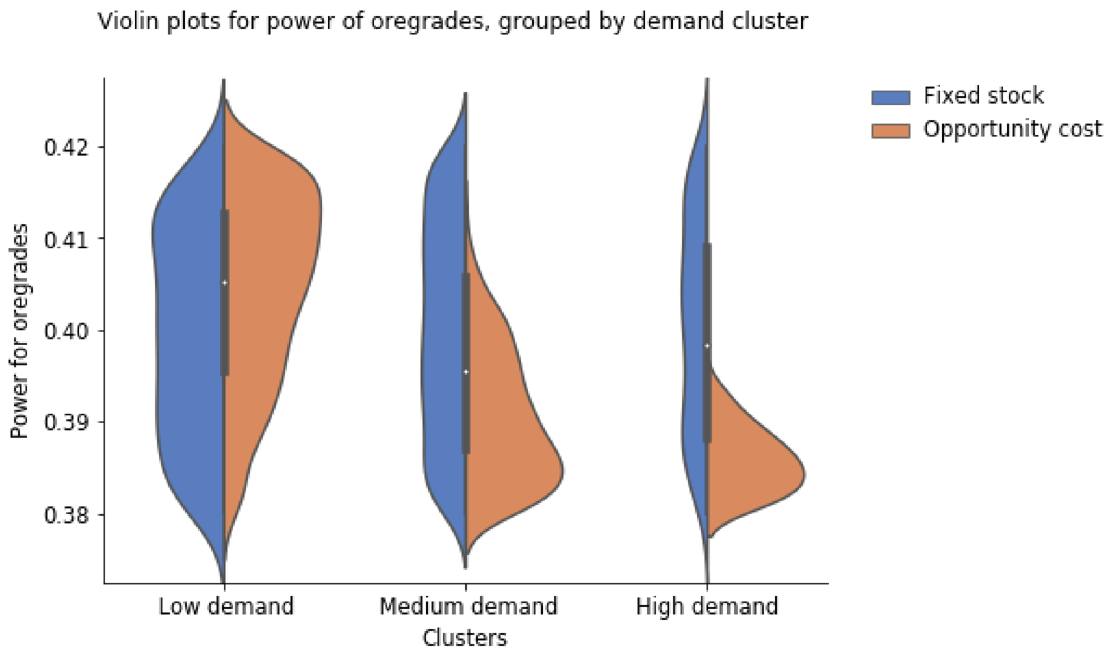

box 5
Power for oregrades
Battery capacity BEV
0.00
0.25
0.50
0.75
1.00


box 6
Power for oregrades
Battery capacity BEV
0.00
0.25
0.50
0.75
1.00


box 7
Power for oregrades
Battery capacity BEV
0.00
0.25
0.50
0.75
1.00

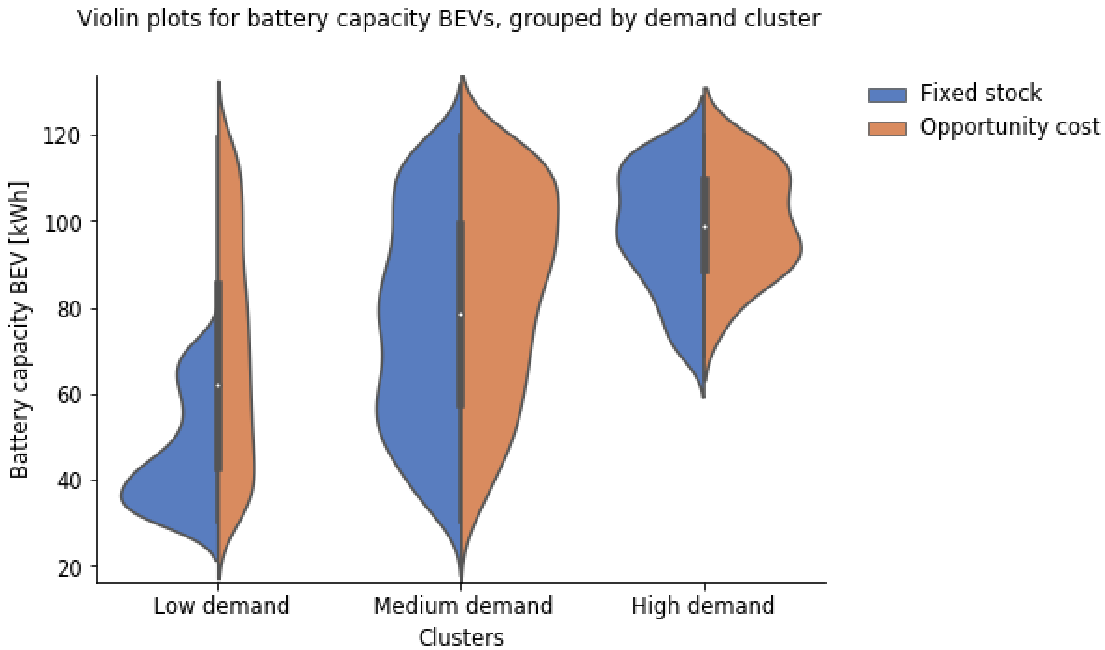

box 8
Power for oregrades
Battery capacity BEV
0.00
0.25
0.50
0.75
1.00

[32]:
```
ax = sns.violinplot(x="Clusters", y="Power for oregrades", hue="Paradigm␣
↪switch",
                    data=clustered_demand, palette="muted", split=True,
                   order = [' Low demand',' Medium demand', 'High demand'])
plt.legend(bbox_to_anchor=(1.05, 1), loc=2, borderaxespad=0.)
plt.suptitle('Violin plots for power of oregrades, grouped by demand cluster')
fig = plt.gcf()
fig.set_size_inches(7,5)
sns.despine()
change_fontsize(fig)
save_fig(fig,wd,'violinplot_poweroregrades')
plt.savefig(wd+'Violinplot_poweroregrades')
```



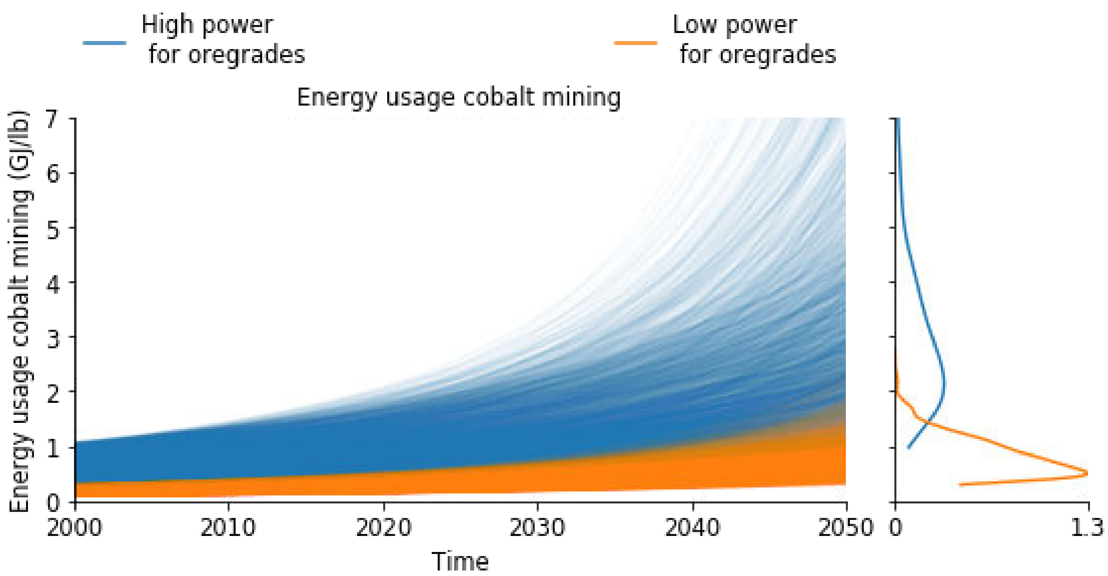
[33]:
```
ax = sns.violinplot(x="Clusters", y="Battery capacity BEV", hue="Paradigm␣
↪switch",
                    data=clustered_demand, palette="muted", split= True,
                   order = [' Low demand',' Medium demand', 'High demand'])
plt.suptitle('Violin plots for battery capacity BEVs, grouped by demand␣
↪cluster')
plt.legend(bbox_to_anchor=(1.05, 1), loc=2, borderaxespad=0.)
fig = plt.gcf()
plt.ylabel('Battery capacity BEV [kWh]')
fig.set_size_inches(7,5)
sns.despine()
change_fontsize(fig)
save_fig(fig,wd,'violinplot_poweroregrades')
```

```
plt.savefig(wd+'Violinplot_batterycapacity')
```

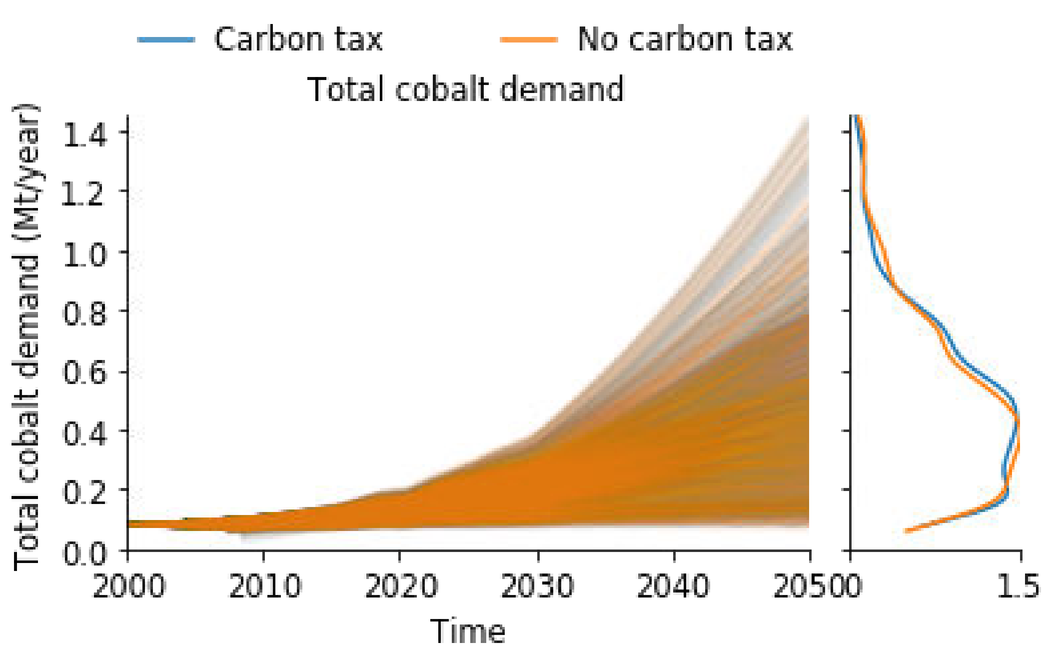


2.2 Visualize energy usage mining

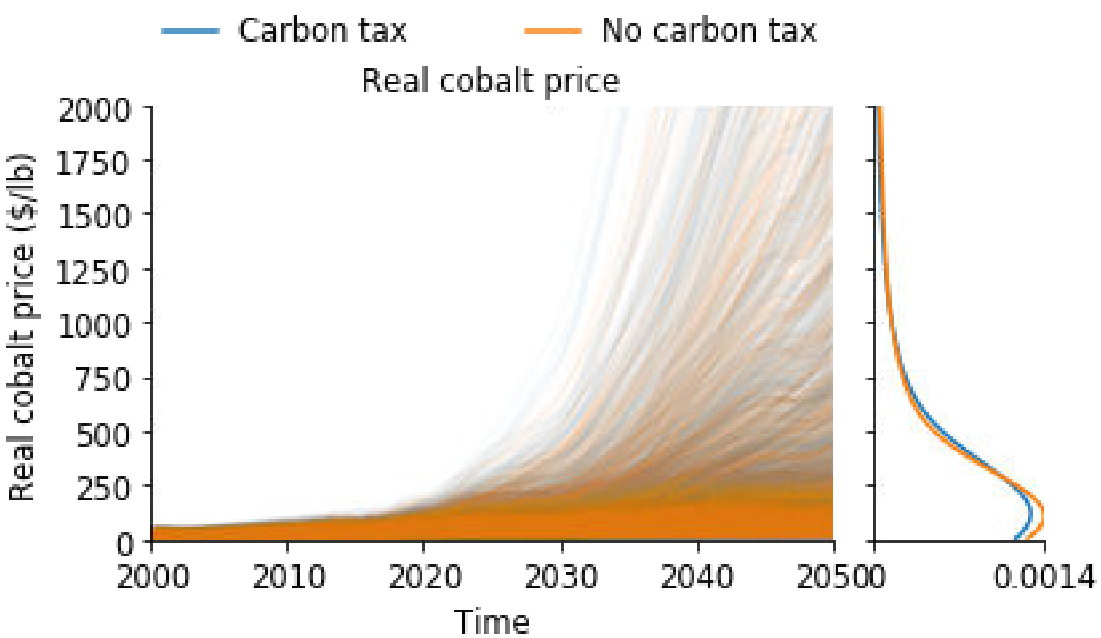
[223]:
```
nice_lines(exp_b,out_b, out_to_show = 'Energy usage mining[Cobalt]',
           group_by = 'High power for oregrades', density = Density.KDE,
           title = 'Energy usage cobalt mining',
           legend = True, paradigm = 'fs', alpha = 0.03, yupperlim = 7,
           zero = True, ylabel = 'Energy usage cobalt mining (GJ/lb)',
           grouping_specifiers = {'Low power \n for oregrades':0, 'High power␣
 ↪\n for oregrades':1},
           sizex = 9, sizey = 3.5)
fig.savefig(wd+'Energyusagemining.jpg')
save_fig(fig,wd,'Energyusagemining')
plt.show()
```



[224]:
```
nice_lines(exp_b,out_b,  out_to_show = 'Total demand[Cobalt]',
#             exp_to_show = exp_b[exp_b['Conditions low real price']].index.
 ↪values,
           group_by = 'Switch carbon policy', legend=True,
           grouping_specifiers = {'No carbon tax':0, 'Carbon tax':1},
           density = Density.KDE, convert_to_Mt = True,
           zero = True, ylabel = 'Total cobalt demand (Mt/year)',
           title = 'Total cobalt demand', alpha = 0.03)
```



[225]:
```
nice_lines(exp_b,out_b,  out_to_show = 'Real price[Cobalt]',
           group_by = 'Switch carbon policy', legend=True,
           grouping_specifiers = {'No carbon tax':0, 'Carbon tax':1},
           density = Density.KDE, zero = True, yupperlim = 2000,
           title = 'Real cobalt price', ylabel = 'Real cobalt price ($/lb)',␣
 ↪alpha = 0.03)
```



2.3 Visualize influence of energy price growth scenario and oregrade

2.3.1 Visualize influence of variables on price

[631]:
```
exp_b['High energy price'] = exp_b['Switch energy price growth scenario'] <3
exp_fs['High energy price'] = exp_fs['Switch energy price growth scenario'] <3
exp_oc['High energy price'] = exp_oc['Switch energy price growth scenario'] <3
```

```
C:\ProgramData\Anaconda3_32bits\lib\site-packages\ipykernel_launcher.py:2:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/indexing.html#indexing-view-versus-copy
```

```
C:\ProgramData\Anaconda3_32bits\lib\site-packages\ipykernel_launcher.py:3:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/indexing.html#indexing-view-versus-copy
  This is separate from the ipykernel package so we can avoid doing imports
until
```

[632]:

```
exp_b['High power for oregrades'] = exp_b['Power for oregrades'] >0.4
exp_b['High power for oregrades'] = exp_b['High power for oregrades'].
 ↪astype('object')
exp_fs['High power for oregrades'] = exp_fs['Power for oregrades'] >0.4
exp_fs['High power for oregrades'] = exp_fs['High power for oregrades'].
 ↪astype('object')
exp_oc['High power for oregrades'] = exp_oc['Power for oregrades'] >0.4
exp_oc['High power for oregrades'] = exp_oc['High power for oregrades'].
 ↪astype('object')
```

```
C:\ProgramData\Anaconda3_32bits\lib\site-packages\ipykernel_launcher.py:3:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/indexing.html#indexing-view-versus-copy
  This is separate from the ipykernel package so we can avoid doing imports
until
C:\ProgramData\Anaconda3_32bits\lib\site-packages\ipykernel_launcher.py:4:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/indexing.html#indexing-view-versus-copy
  after removing the cwd from sys.path.
C:\ProgramData\Anaconda3_32bits\lib\site-packages\ipykernel_launcher.py:5:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/indexing.html#indexing-view-versus-copy
  """
C:\ProgramData\Anaconda3_32bits\lib\site-packages\ipykernel_launcher.py:6:
SettingWithCopyWarning:
```

```
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/indexing.html#indexing-view-versus-copy
```

[633]:
```
exp_b['Conditions high real price'] = exp_b['High energy price'] & exp_b['High␣
↪power for oregrades']
exp_fs['Conditions high real price'] = exp_fs['High energy price'] &␣
↪exp_fs['High power for oregrades']
exp_oc['Conditions high real price'] = exp_oc['High energy price'] &␣
↪exp_oc['High power for oregrades']
```

```
C:\ProgramData\Anaconda3_32bits\lib\site-packages\ipykernel_launcher.py:2:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/indexing.html#indexing-view-versus-copy

C:\ProgramData\Anaconda3_32bits\lib\site-packages\ipykernel_launcher.py:3:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/indexing.html#indexing-view-versus-copy
  This is separate from the ipykernel package so we can avoid doing imports
until
```

[634]:
```
exp_b['Conditions high real price'] = exp_b['Conditions high real price'].
↪astype('object')
```

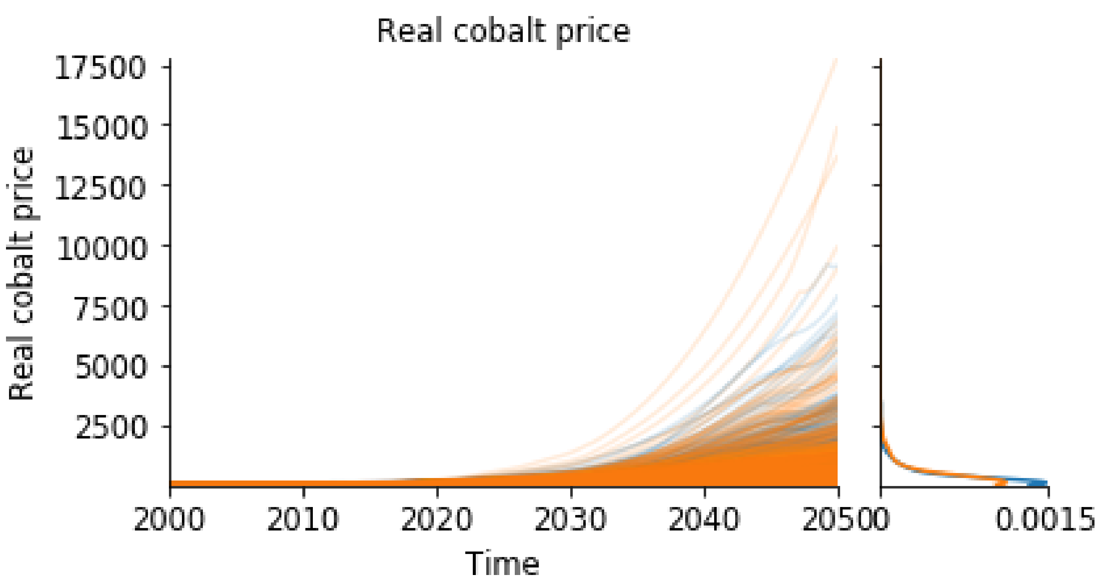
[635]:
```
exp_b['Low energy price'] = exp_b['Switch energy price growth scenario'] ==3
exp_b['Low power for oregrades'] = exp_b['Power for oregrades'] <0.39
exp_b['Conditions low real price'] = exp_b['Low energy price'] & exp_b['Low␣
↪power for oregrades']
```

[636]:
```
exp_b['Conditions low real price'] = np.invert(exp_b['Conditions high real␣
↪price'])
exp_fs['Conditions low real price'] = np.invert(exp_fs['Conditions high real␣
↪price'])
exp_oc['Conditions low real price'] = np.invert(exp_oc['Conditions high real␣
↪price'])
```

```
C:\ProgramData\Anaconda3_32bits\lib\site-packages\ipykernel_launcher.py:2:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/indexing.html#indexing-view-versus-copy

C:\ProgramData\Anaconda3_32bits\lib\site-packages\ipykernel_launcher.py:3:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/indexing.html#indexing-view-versus-copy
  This is separate from the ipykernel package so we can avoid doing imports
until
```

[626]:

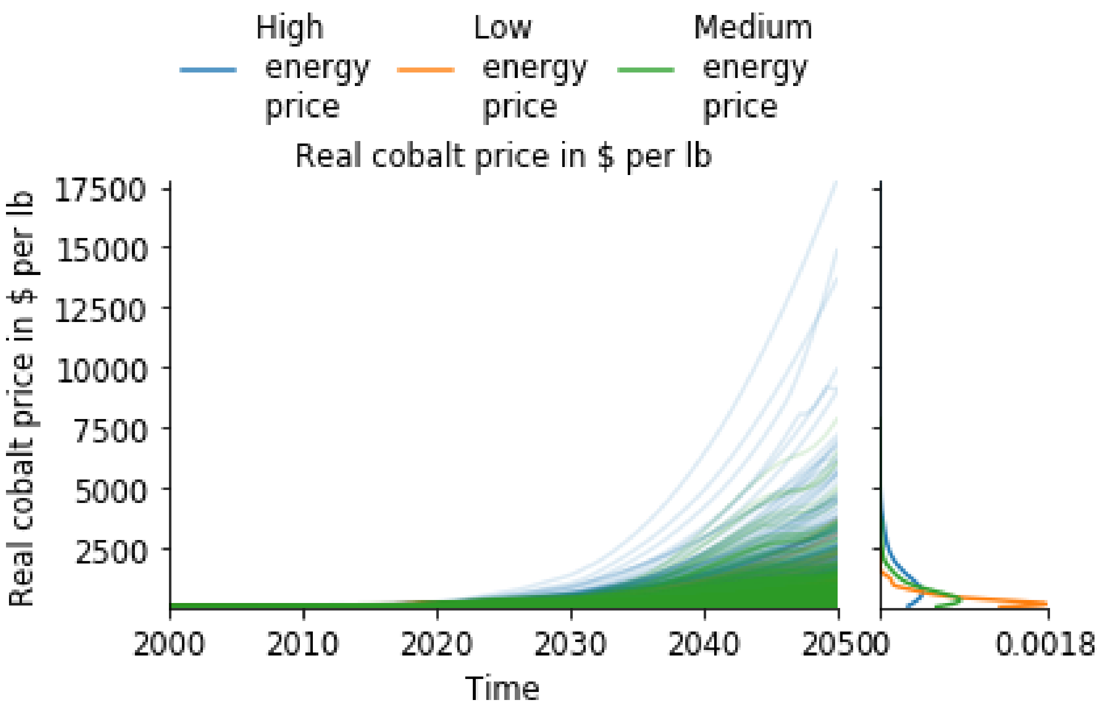
```
nice_lines(exp_b,out_b,  out_to_show = 'Real price[Cobalt]',
           exp_to_show = exp_b['Conditions high real price'].index.values,
           group_by = 'Switch carbon policy', density = Density.KDE,
          title = 'Real cobalt price')
```



[627]:

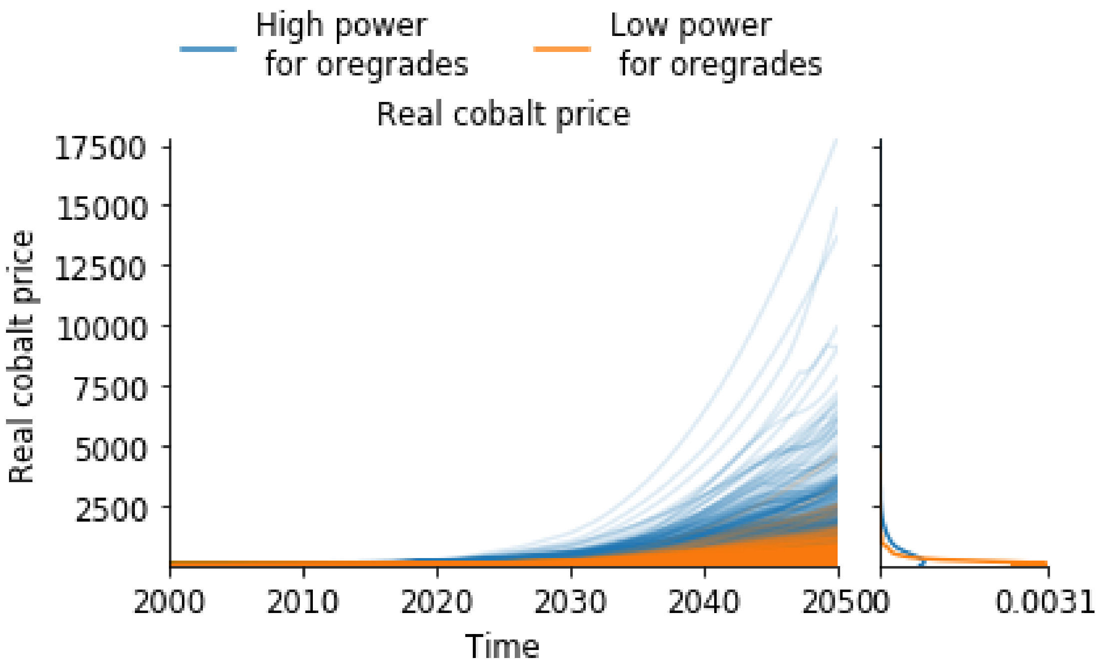
```
nice_lines(exp_fs,out_fs,out_to_show = 'Real price[Cobalt]',
          group_by = 'Switch energy price growth scenario',
           grouping_specifiers = {'Medium \n energy \n price':2, 'High \n␣
 ↪energy \n price':1,'Low \n energy \n price':3},
           legend  = True,
```

```
          density = Density.KDE, title = 'Real cobalt price in $ per lb')
```

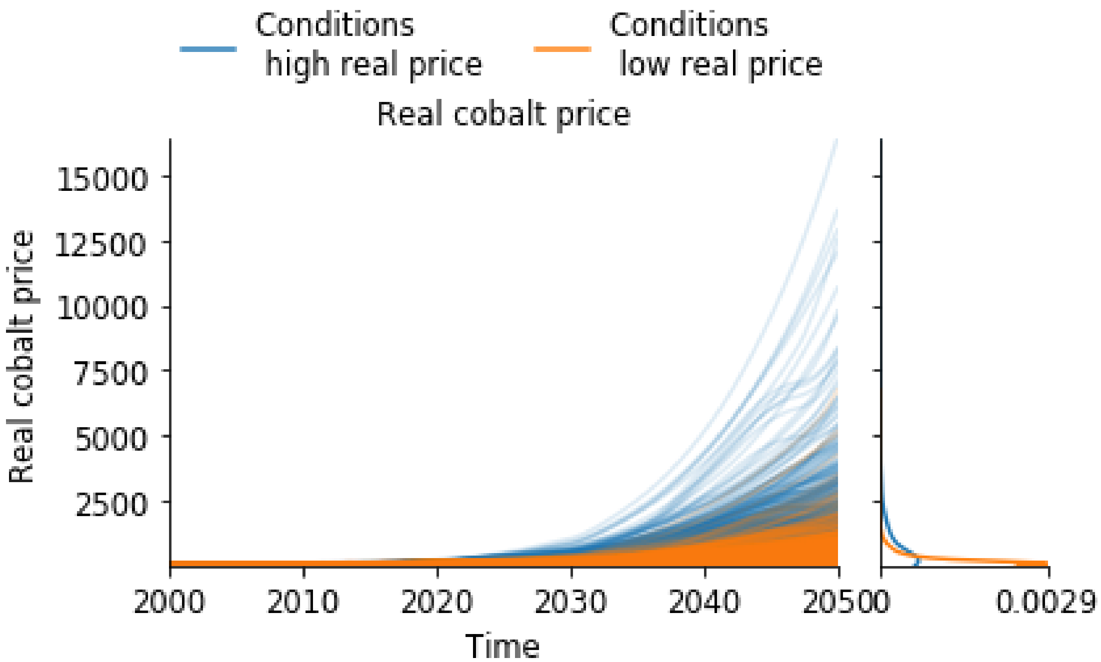


[628]:
```
exp_b['Low power for oregrades'] = np.invert(exp_b['High power for oregrades'])
```

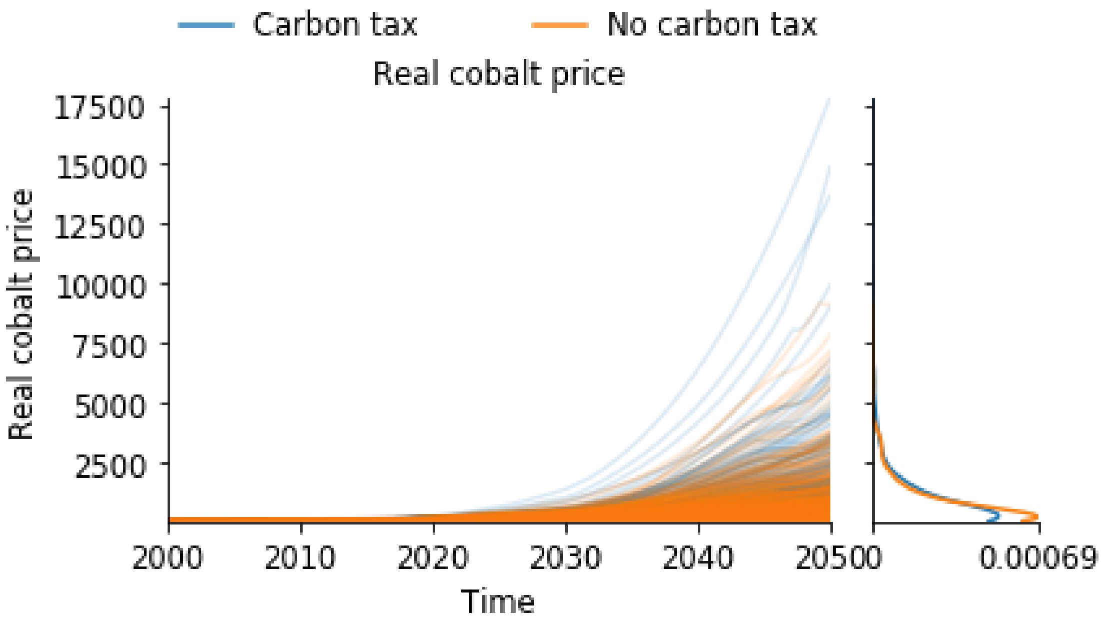
[629]:
```
nice_lines(exp_b,out_b,out_to_show = 'Real price[Cobalt]',
          group_by = 'Low power for oregrades',
           grouping_specifiers = {'High power \n for oregrades':-2, 'Low power␣
 ↪\n for oregrades':-1},
           legend  = True,
          density = Density.KDE, title = 'Real cobalt price')
```



[219]:
```
nice_lines(exp_b,out_b,out_to_show = 'Real price[Cobalt]',
          group_by = 'Conditions low real price',
           grouping_specifiers = {'Conditions \n high real price':-2,␣
 ↪'Conditions \n low real price':-1},
           legend  = True,
          density = Density.KDE, title = 'Real cobalt price')
```



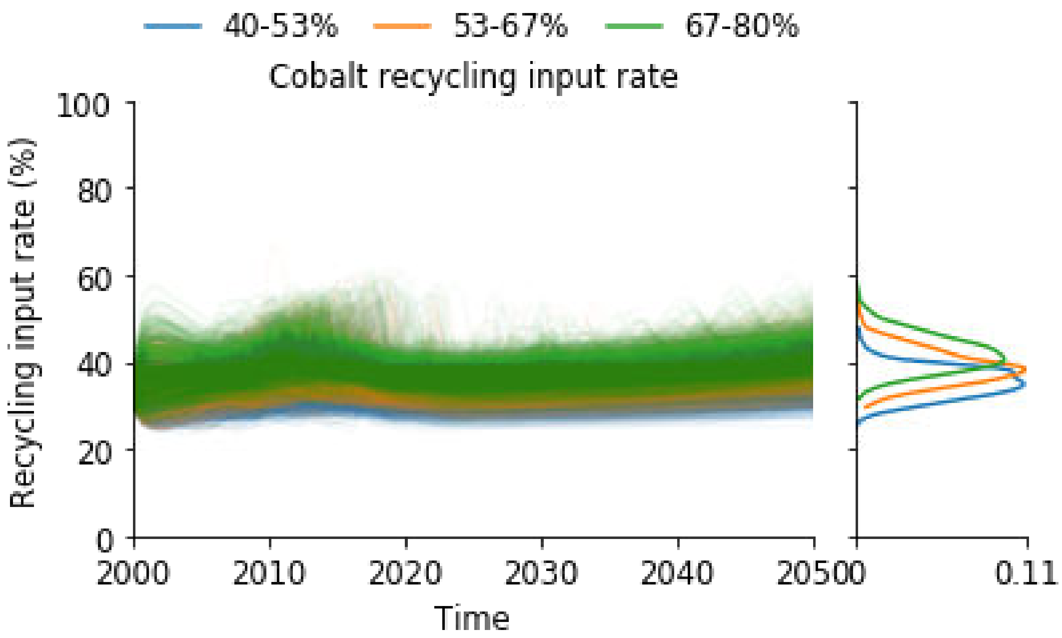
[638]:
```
nice_lines(exp_b,out_b,  out_to_show = 'Real price[Cobalt]',
           exp_to_show = exp_b[exp_b['Conditions high real price']].index.
 ↪values,
           group_by = 'Switch carbon policy', legend=True,
           grouping_specifiers = {'No carbon tax':0, 'Carbon tax':1},
           density = Density.KDE,
           title = 'Real cobalt price')
```



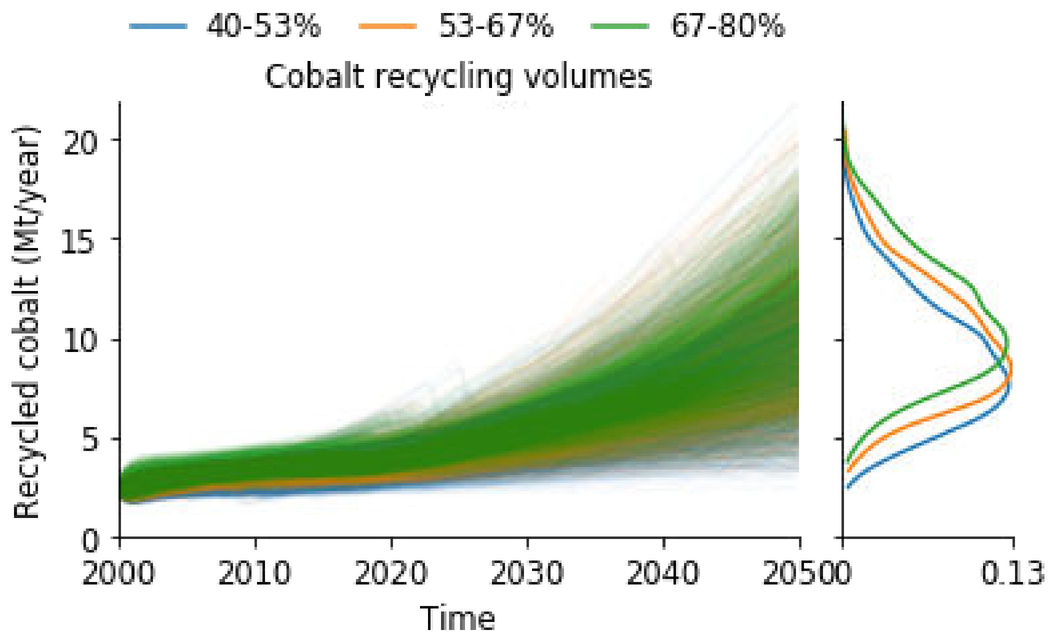
2.4 Visualize recycling input rate

[639]:
```
exp_b['Collection rate cobalt products'] = pd.cut(exp_b['Collection rate metal␣
↪products'],
                                                  [0.4,0.533,0.666,0.8],
                                                ␣
↪labels=['40-53%','53-67%','67-80%'])
```

[640]:
```
out_b['Recycling input rate cobalt'] = out_b['Recycling input rate[Cobalt]']*100
nice_lines(exp_b,out_b, out_to_show = 'Recycling input rate cobalt',
           group_by = 'Collection rate cobalt products', density = Density.KDE,
           title = 'Cobalt recycling input rate',
           legend = True, zero = True, alpha = 0.03,
            yupperlim = 100, ylabel = 'Recycling input rate (%)')
fig.savefig(wd+'cobaltrecyclinginputrate.jpg')
plt.show()
```



[231]:
```
out_b['Recycled cobalt'] = out_b['Metal recovered from scrap[Cobalt]']*100
nice_lines(exp_b,out_b, out_to_show = 'Recycled cobalt',
           group_by = 'Collection rate cobalt products', density = Density.KDE,
           title = 'Cobalt recycling volumes',
           legend = True, zero = True, alpha = 0.03, convert_to_Mt = True,
           ylabel = 'Recycled cobalt (Mt/year)')
fig.savefig(wd+'cobaltrecyclingvolumes.jpg')
plt.show()
```



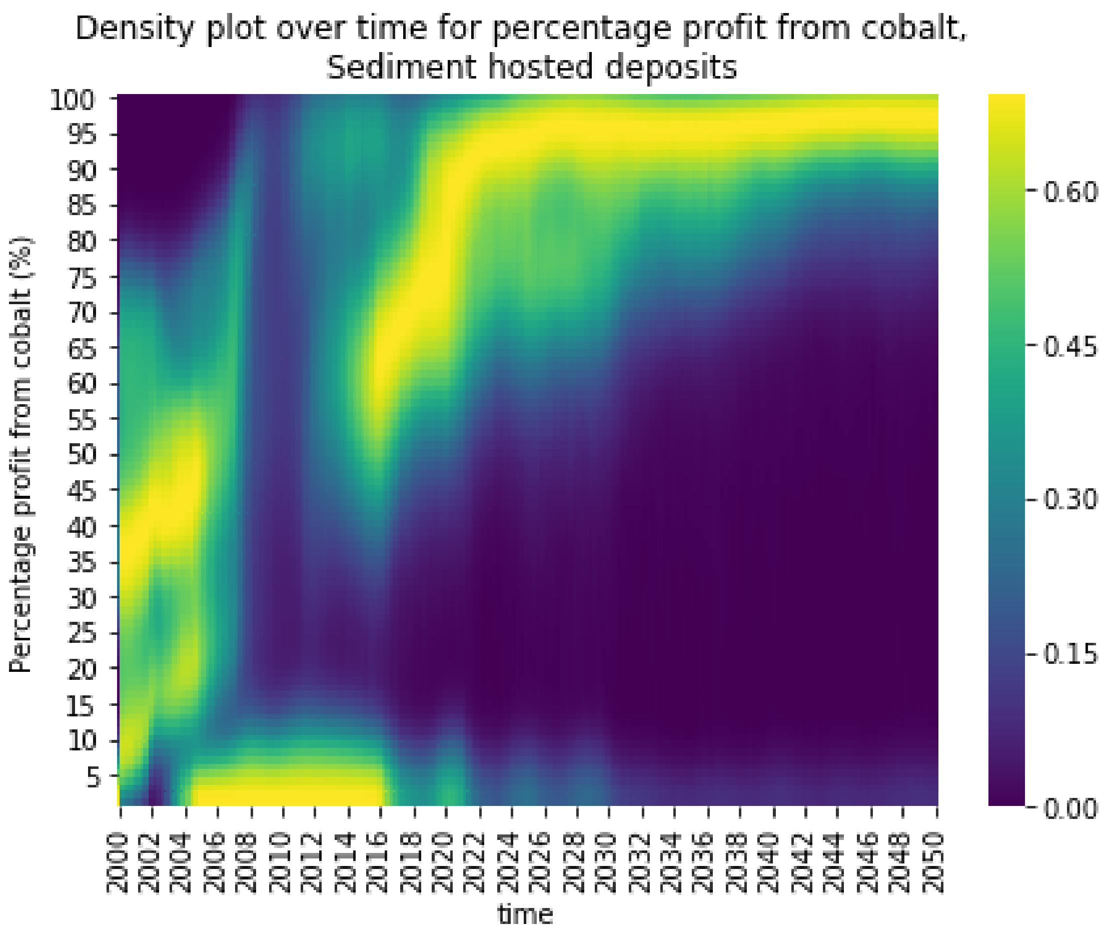
2.5 Visualize profit industrial mining

[257]:
```
plt.rcParams['axes.xmargin'] = 0.01
plt.rcParams['axes.ymargin'] = 0.01
```

[129]:
```
kde_over_time(exp_b,out_b,
              outcomes_to_show = 'Percentage profit from cobalt, Sediment␣
 ↪hosted deposit')
plt.title('Density plot over time for percentage profit from cobalt, \n␣
 ↪Sediment hosted deposits')
fig = plt.gcf()
fig.set_size_inches(7,5)
ax = fig.get_axes()
ax[0].set_xticklabels(np.arange(2000, 2051, 2))
ax[0].set_ylabel('Percentage profit from cobalt (%)')
ax[0].set_yticklabels(100-np.arange(0, 100, 5))
```

[129]:
```
[Text(0, 0.5, '100'),
 Text(0, 5.5, '95'),
 Text(0, 10.5, '90'),
 Text(0, 15.5, '85'),
 Text(0, 20.5, '80'),
 Text(0, 25.5, '75'),
 Text(0, 30.5, '70'),
 Text(0, 35.5, '65'),
 Text(0, 40.5, '60'),
```

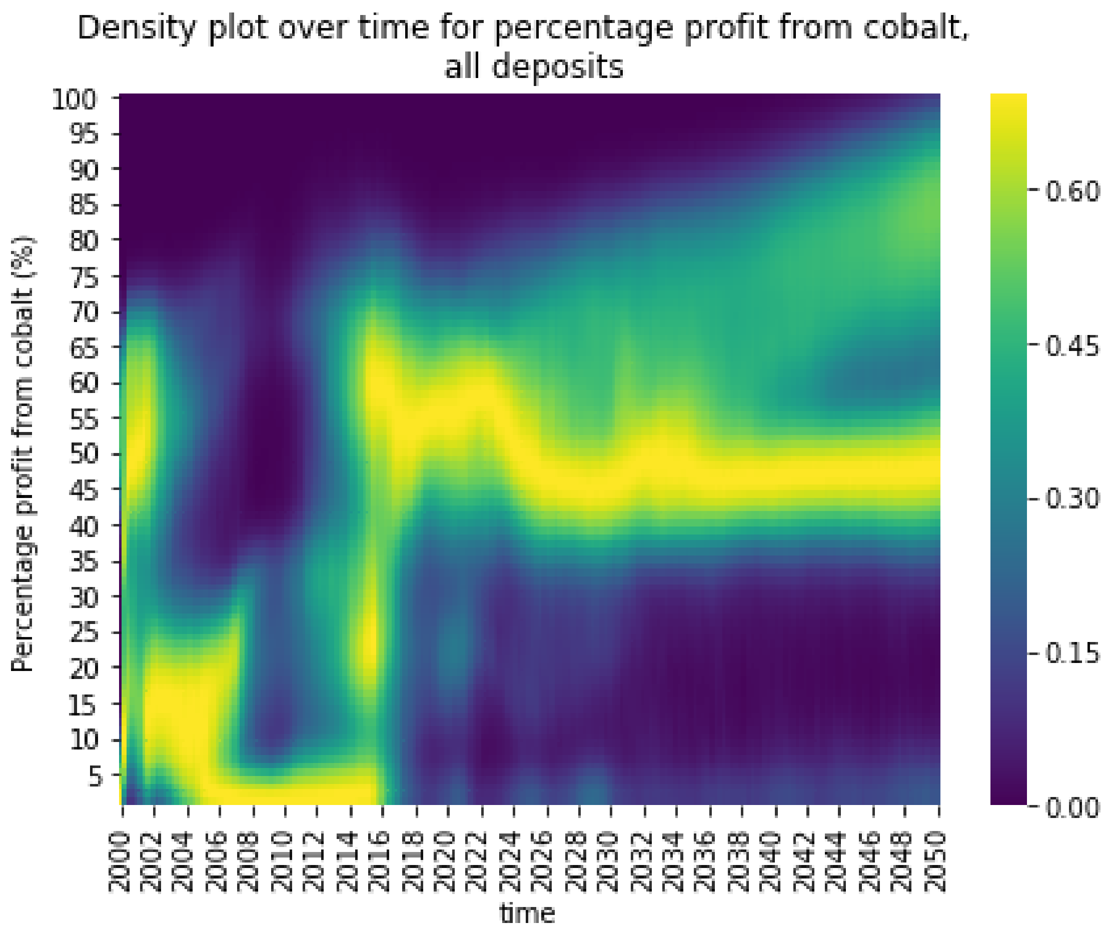
```
 Text(0, 45.5, '55'),
 Text(0, 50.5, '50'),
 Text(0, 55.5, '45'),
 Text(0, 60.5, '40'),
 Text(0, 65.5, '35'),
 Text(0, 70.5, '30'),
 Text(0, 75.5, '25'),
 Text(0, 80.5, '20'),
 Text(0, 85.5, '15'),
 Text(0, 90.5, '10'),
 Text(0, 95.5, '5')]
```



[130]:
```
kde_over_time(exp_b,out_b,
               outcomes_to_show = 'Percentage profit industrial mining from␣
 ↪Cobalt')
plt.title('Density plot over time for percentage profit from cobalt, \n all␣
 ↪deposits')
fig = plt.gcf()
```

```
fig.set_size_inches(7,5)
ax = fig.get_axes()
ax[0].set_xticklabels(np.arange(2000, 2051, 2))
ax[0].set_ylabel('Percentage profit from cobalt (%)')
ax[0].set_yticklabels(100-np.arange(0, 100, 5))
```

[130]:
```
[Text(0, 0.5, '100'),
 Text(0, 5.5, '95'),
 Text(0, 10.5, '90'),
 Text(0, 15.5, '85'),
 Text(0, 20.5, '80'),
 Text(0, 25.5, '75'),
 Text(0, 30.5, '70'),
 Text(0, 35.5, '65'),
 Text(0, 40.5, '60'),
 Text(0, 45.5, '55'),
 Text(0, 50.5, '50'),
 Text(0, 55.5, '45'),
 Text(0, 60.5, '40'),
 Text(0, 65.5, '35'),
 Text(0, 70.5, '30'),
 Text(0, 75.5, '25'),
 Text(0, 80.5, '20'),
 Text(0, 85.5, '15'),
 Text(0, 90.5, '10'),
 Text(0, 95.5, '5')]
```

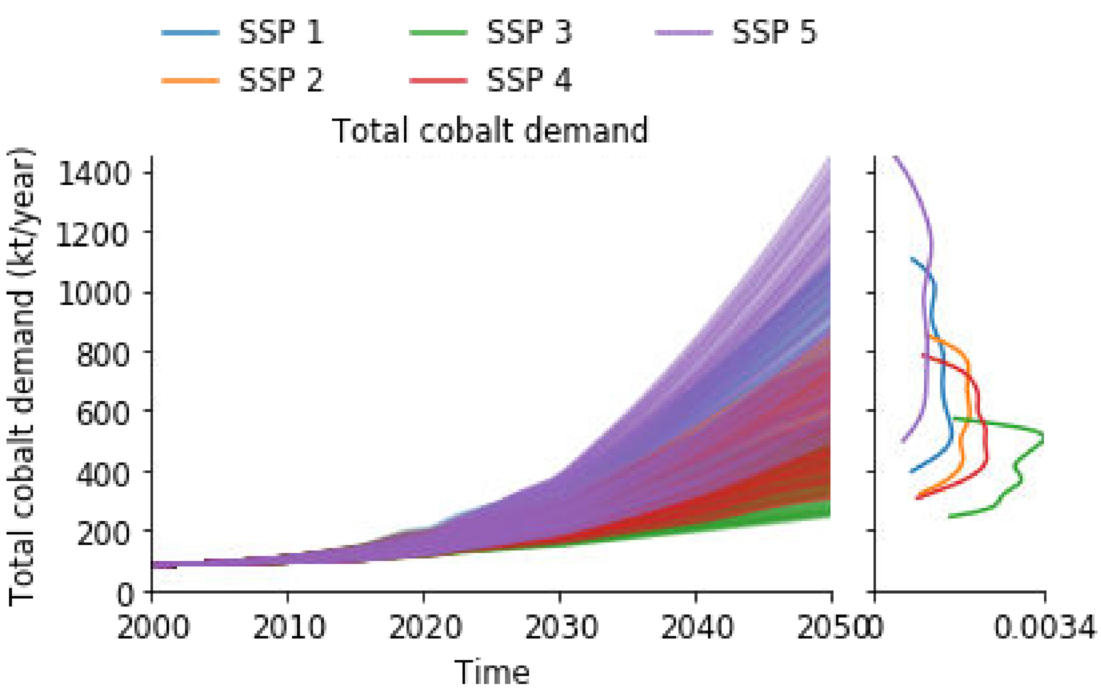


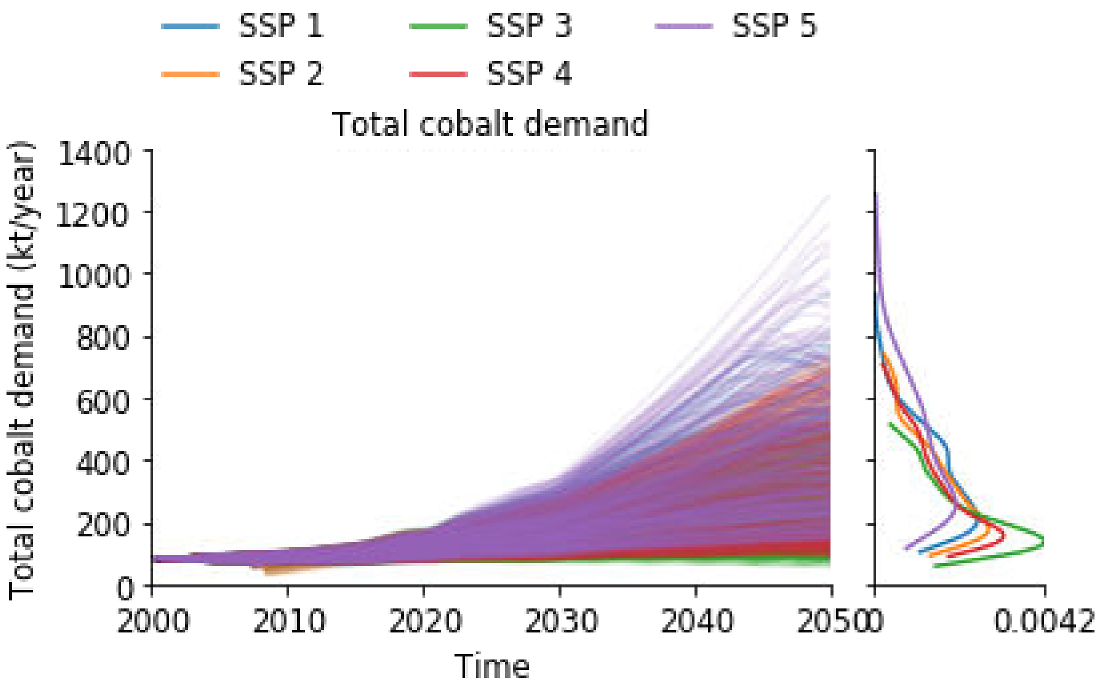
2.6 Visualize influence of paradigm on key supply and demand variables

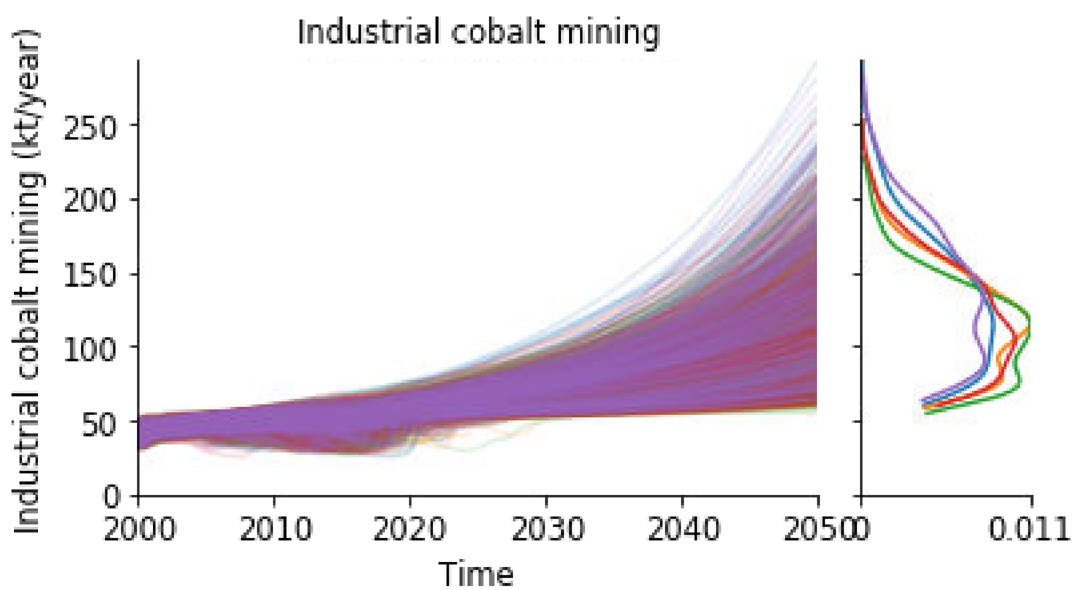
[625]:
```
nice_lines(exp_fs,out_fs, out_to_show = 'Total demand[Cobalt]',
           group_by = 'Switch SSP', density = Density.KDE,
           title = 'Total cobalt demand',
           legend = True, paradigm = 'fs',
           convert_to_kt = True, zero = True, ylabel = 'Total cobalt demand (kt/
↪year)',
           grouping_specifiers = {'SSP 1': 1 , 'SSP 2': 2 ,'SSP 3': 3 ,'SSP 4':␣
↪4 ,'SSP 5': 5 })
nice_lines(exp_oc,out_oc, paradigm = 'oc',out_to_show = 'Total demand[Cobalt]',
           group_by = 'Switch SSP', density = Density.KDE,
          title = 'Total cobalt demand', legend = True, ylabel = 'Total cobalt␣
↪demand (kt/year)',
           convert_to_kt = True, zero = True, yupperlim = 1400,
          grouping_specifiers = {'SSP 1': 1 , 'SSP 2': 2 ,'SSP 3': 3 ,'SSP 4':␣
↪4 ,'SSP 5': 5 })
```

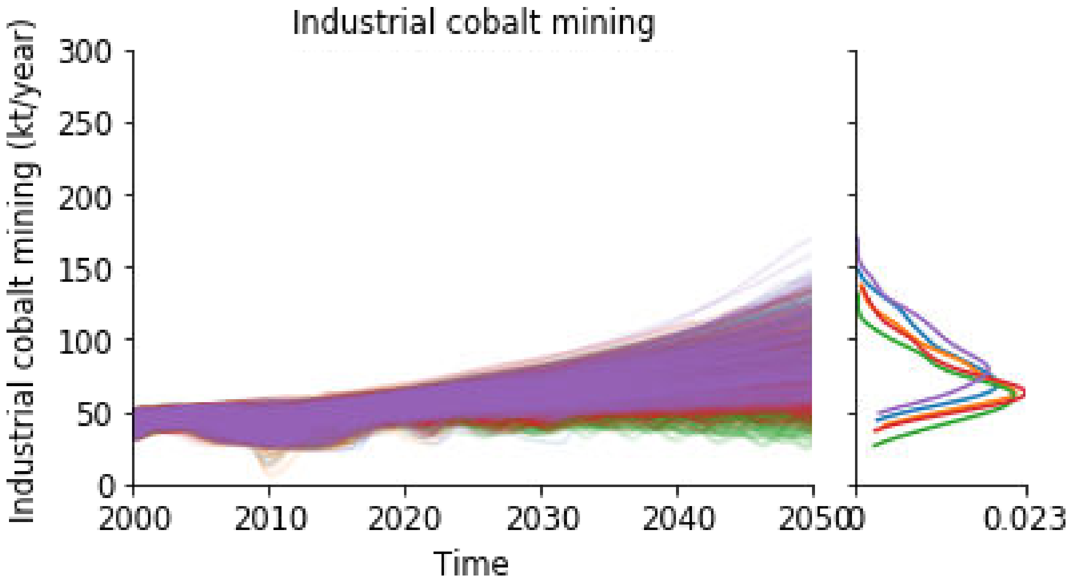
```
nice_lines(exp_fs,out_fs, out_to_show = 'Industrial Ore mining[Cobalt]',
           group_by = 'Switch SSP', paradigm ='fs', density = Density.KDE, zero␣
 ↪= True,
           title = 'Industrial cobalt mining',convert_to_kt = True,
           ylabel = 'Industrial cobalt mining (kt/year)',)
nice_lines(exp_oc,out_oc,  paradigm ='oc',out_to_show = 'Industrial Ore␣
 ↪mining[Cobalt]',
           group_by = 'Switch SSP', density = Density.KDE, zero = True,␣
 ↪yupperlim = 300,
           title = 'Industrial cobalt mining',convert_to_kt = True,
           ylabel = 'Industrial cobalt mining (kt/year)')

nice_lines(exp_fs,out_fs, paradigm = 'fs',out_to_show = 'Reserves[Cobalt]',
           group_by = 'Switch SSP', density = Density.KDE, zero = True,␣
 ↪yupperlim = 110,
          title = 'Cobalt reserves',convert_to_Mt = True,
          ylabel = 'Cobalt reserves (Mt)')
nice_lines(exp_oc,out_oc, paradigm = 'oc',out_to_show = 'Reserves[Cobalt]',
           group_by = 'Switch SSP', density = Density.KDE, zero = True,
          title = 'Cobalt reserves',convert_to_Mt = True,
          ylabel = 'Cobalt reserves (Mt)')

nice_lines(exp_fs,out_fs,  paradigm ='fs',out_to_show = 'Resources[Cobalt]',
           group_by = 'Switch SSP', density = Density.KDE, zero = True,␣
 ↪yupperlim = 45,
          title = 'Cobalt resources',convert_to_Mt = True, ylabel = 'Cobalt␣
 ↪resources (Mt)')
nice_lines(exp_oc,out_oc,  paradigm ='oc',out_to_show = 'Resources[Cobalt]',
           group_by = 'Switch SSP', density = Density.KDE, zero = True,
          title = 'Cobalt resources',convert_to_Mt = True, ylabel = 'Cobalt␣
 ↪resources (Mt)')

nice_lines(exp_fs,out_fs, paradigm = 'fs',out_to_show = 'R over P␣
 ↪ratio[Cobalt]',
           group_by = 'Switch SSP', density = Density.KDE, zero = True,␣
 ↪yupperlim = 1100,
          title = 'R over P ratio cobalt', ylabel = 'R over P ratio cobalt␣
 ↪(year)')
nice_lines(exp_oc,out_oc, paradigm = 'oc',out_to_show = 'R over P␣
 ↪ratio[Cobalt]',
           group_by = 'Switch SSP', density = Density.KDE, zero = True,␣
 ↪yupperlim = 1100,
          title = 'R over P ratio cobalt',  ylabel = 'R over P ratio cobalt␣
 ↪(year)')
```

```
nice_lines(exp_fs,out_fs,  paradigm ='fs',out_to_show = 'Relative part␣
↪artisanal mining[Cobalt]',
           group_by = 'Switch SSP', density = Density.KDE, zero = True,
          title = 'Part of cobalt mining coming from artisanal miners')
nice_lines(exp_oc,out_oc, paradigm = 'oc',out_to_show = 'Relative part␣
↪artisanal mining[Cobalt]',
           group_by = 'Switch SSP', density = Density.KDE, zero = True,
          title = 'Part of cobalt mining coming from artisanal miners')

nice_lines(exp_fs,out_fs, paradigm = 'fs',out_to_show = 'Average Co recovery␣
↪rate',
           group_by = 'Switch SSP', density = Density.KDE, zero = True,
          title = 'Average cobalt recovery rate (%)')
nice_lines(exp_oc,out_oc,  paradigm ='oc',out_to_show = 'Average Co recovery␣
↪rate',
           group_by = 'Switch SSP', density = Density.KDE, zero = True,
          title = 'Average cobalt recovery rate')
```

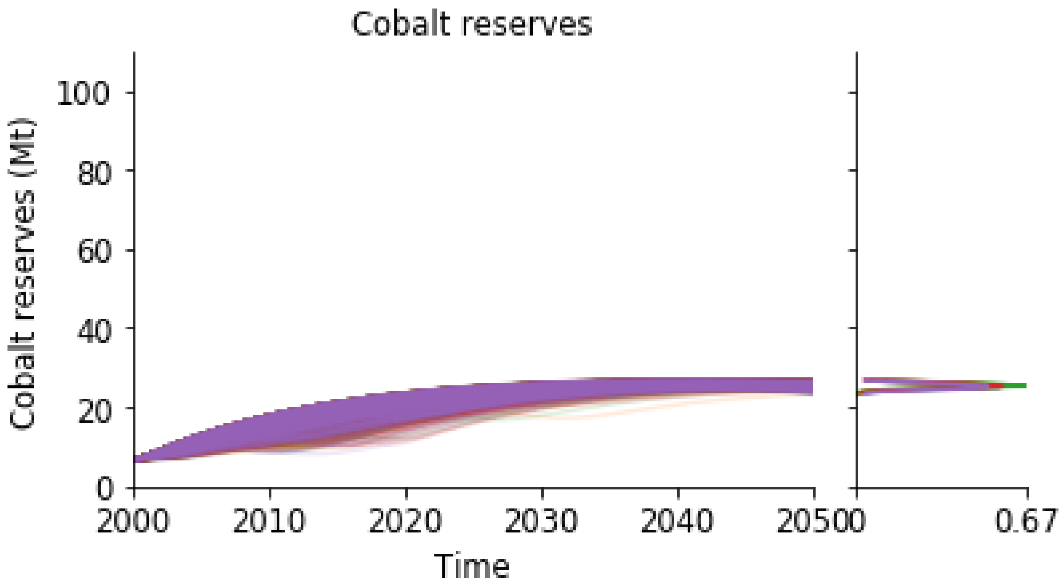



SSP 1
SSP 2
SSP 3
SSP 4
SSP 5
Total cobalt demand
Total cobalt demand (kt/year)
0
200
400
600
800
1000
1200
1400
2000
2010
2020
2030
2040
2050
0
0.0042
Time

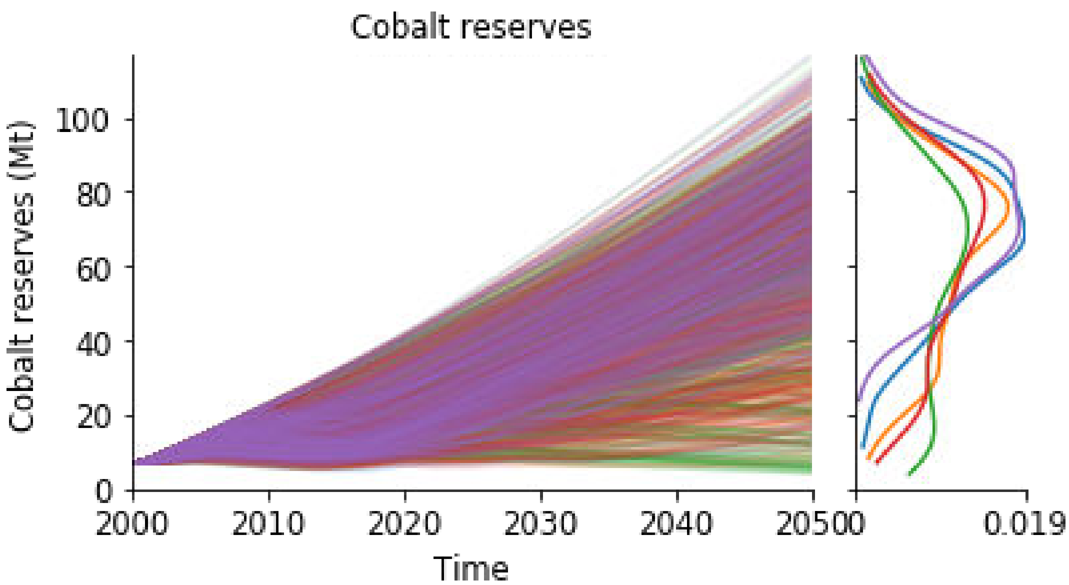

Industrial cobalt mining
Industrial cobalt mining (kt/year)
0
50
100
150
200
250
2000
2010
2020
2030
2040
2050
0
0.011
Time

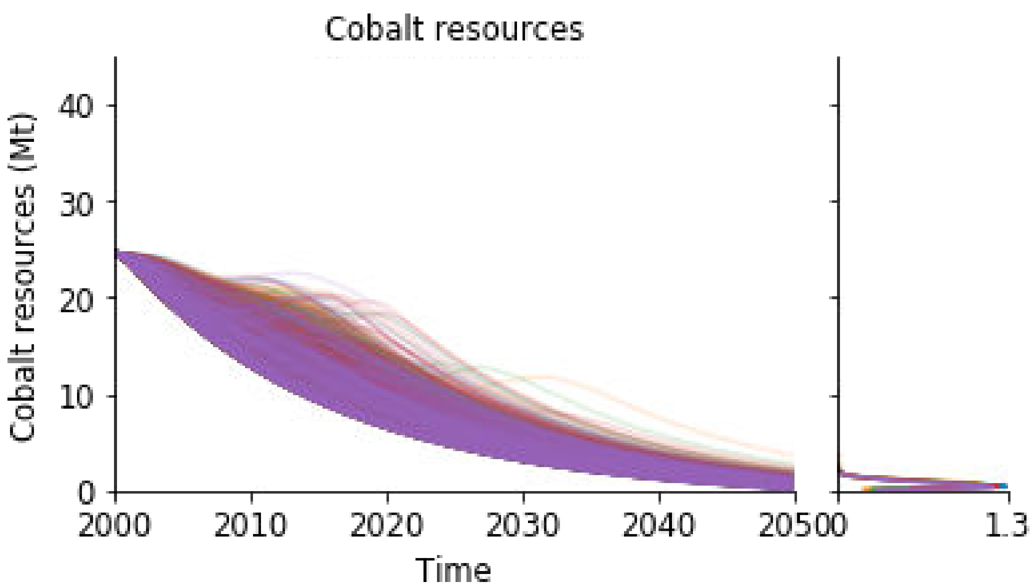


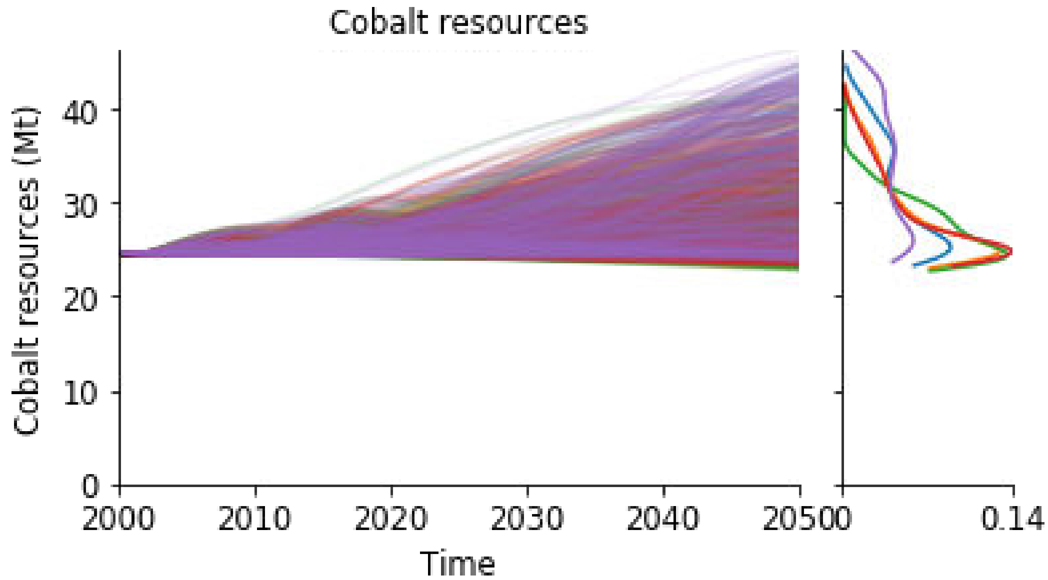
Industrial cobalt mining
Industrial cobalt mining (kt/year)
300
250
200
150
100
50
0
2000
2010
2020
2030
2040
2050
0
0.023
Time



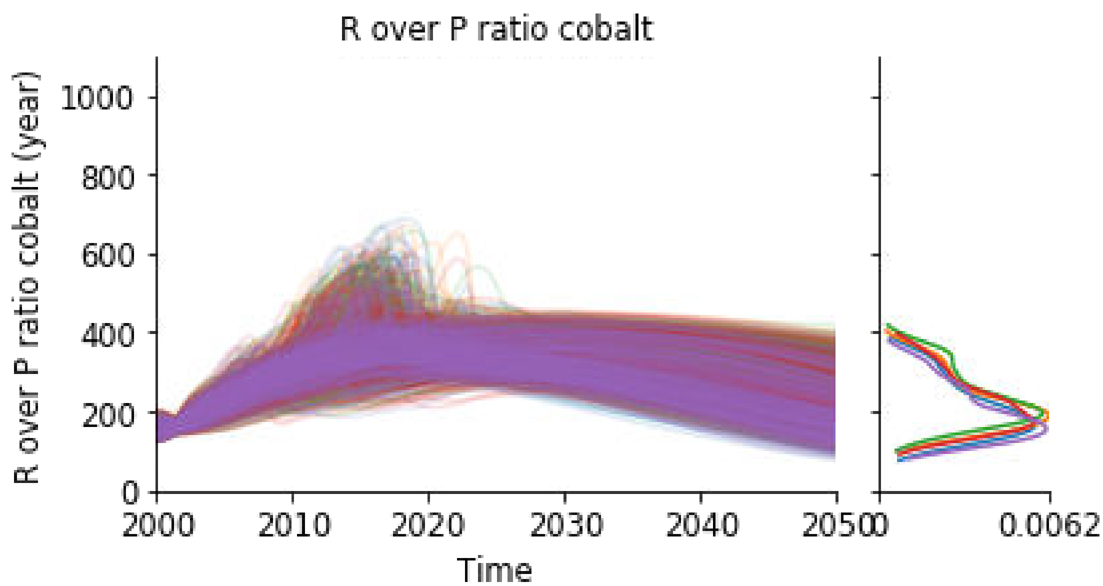
Cobalt reserves
Cobalt reserves (Mt)
100
80
60
40
20
0
2000
2010
2020
2030
2040
2050
0
0.67
Time


Cobalt reserves
Cobalt reserves (Mt)
0
20
40
60
80
100
2000
2010
2020
2030
2040
2050
Time
0
0.019

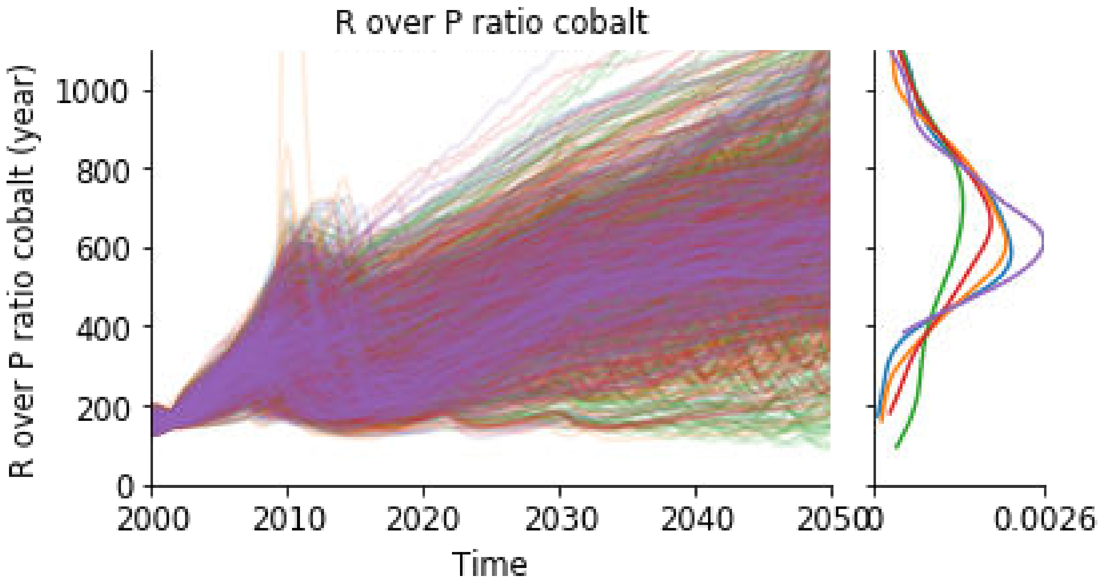

Cobalt resources
Cobalt resources (Mt)
0
10
20
30
40
2000
2010
2020
2030
2040
2050
Time
0
1.3

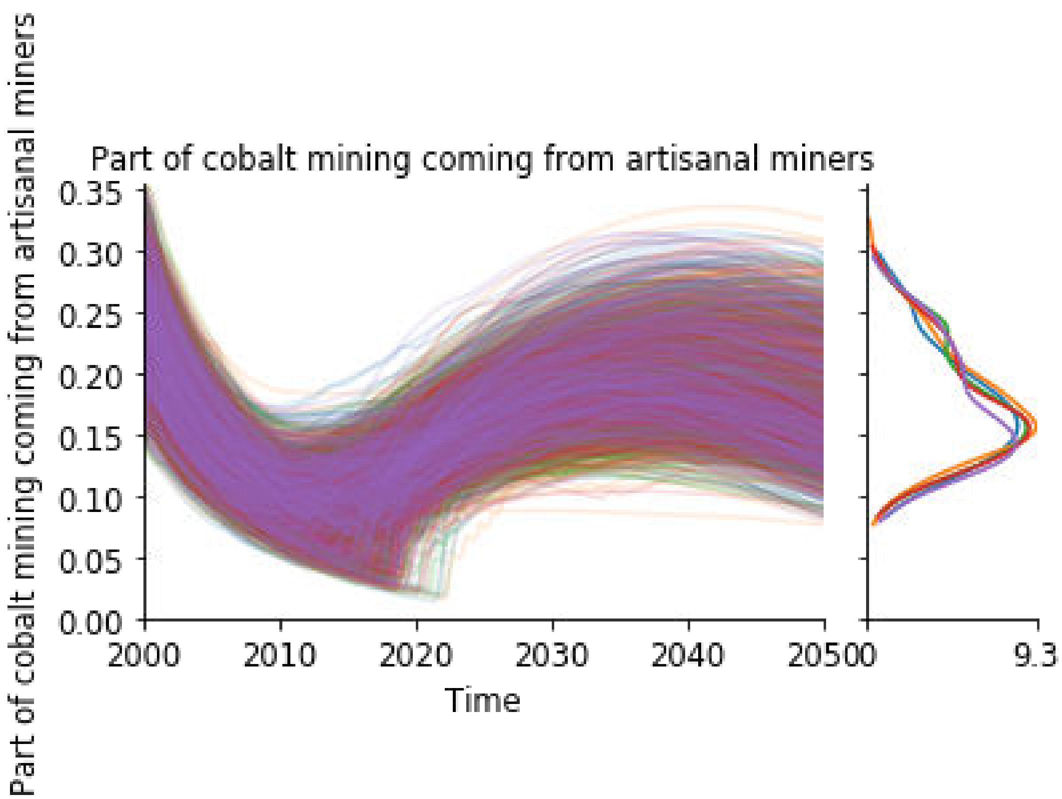


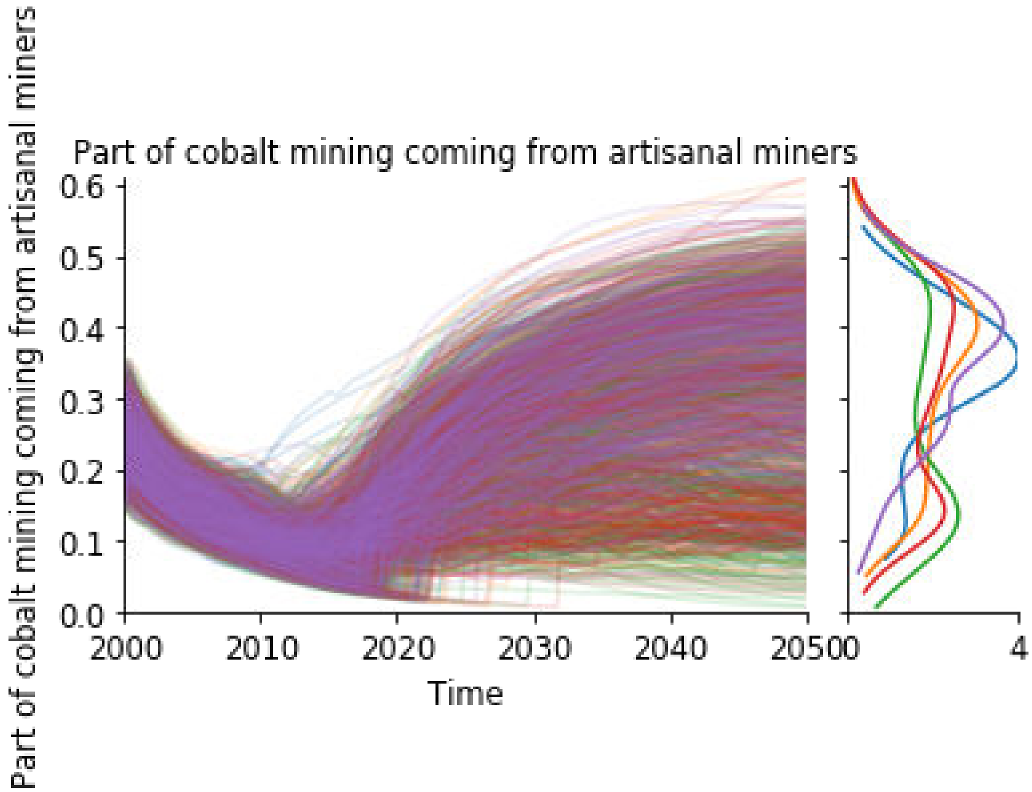
Cobalt resources
Cobalt resources (Mt)
0
10
20
30
40
2000
2010
2020
2030
2040
2050
Time
0
0.14

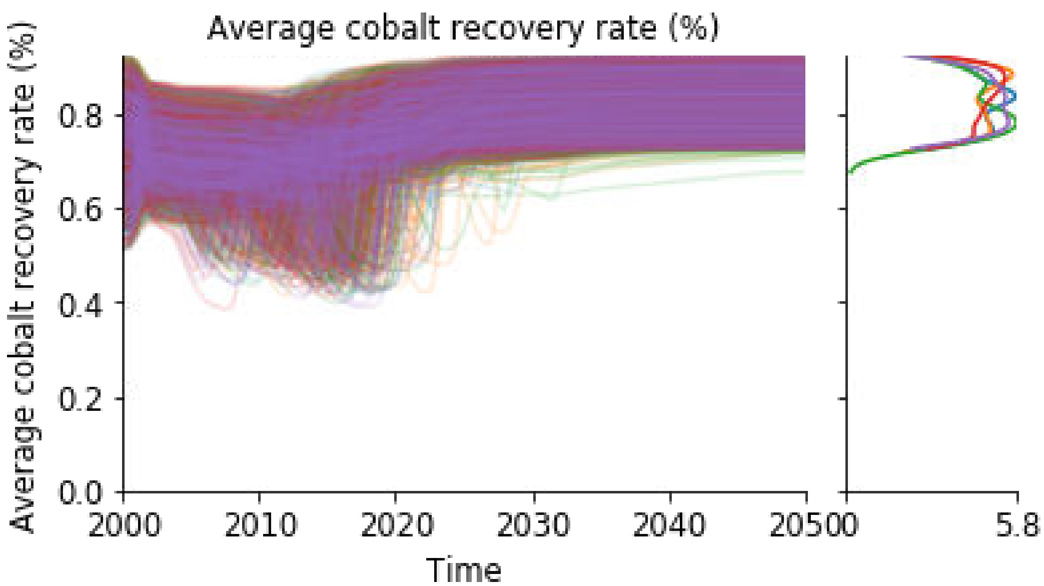


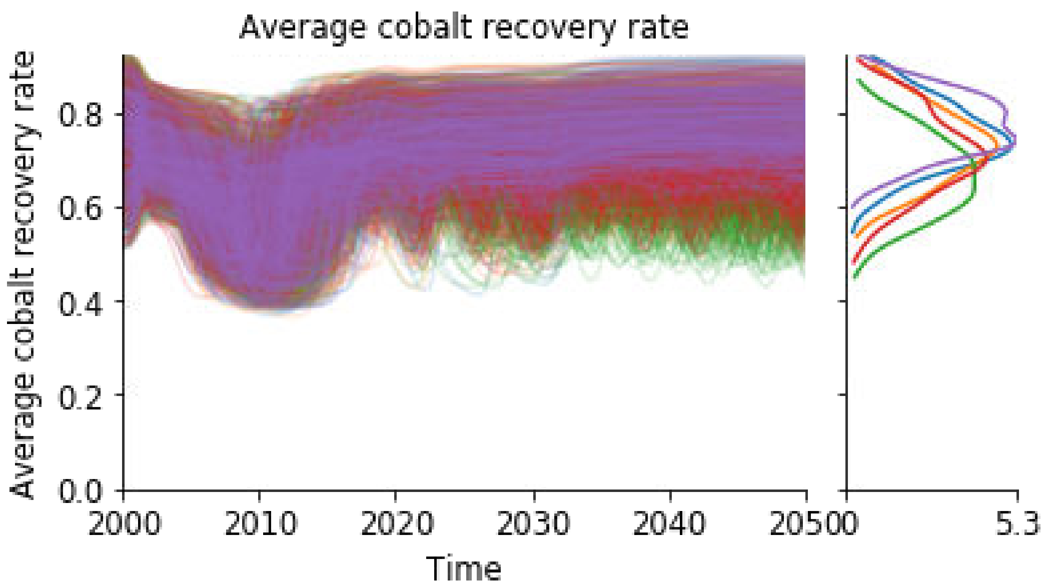
R over P ratio cobalt
R over P ratio cobalt (year)
0
200
400
600
800
1000
2000
2010
2020
2030
2040
2050
Time
0
0.0062


R over P ratio cobalt
R over P ratio cobalt (year)
1000
800
600
400
200
0
2000
2010
2020
2030
2040
2050
0
0.0026
Time


Part of cobalt mining coming from artisanal miners
Part of cobalt mining coming from artisanal miners
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
2000
2010
2020
2030
2040
2050
0
9.3
Time

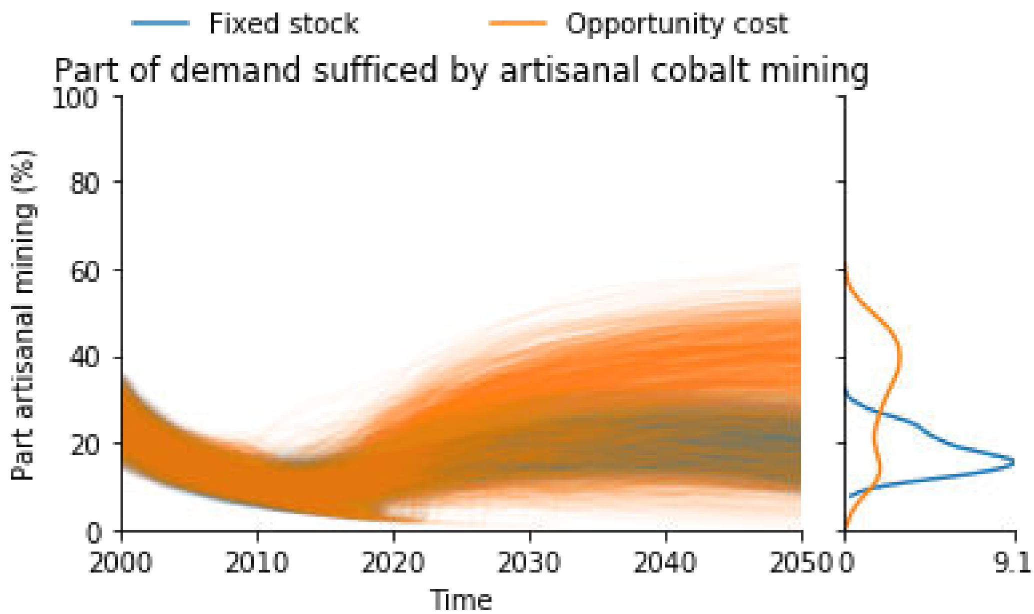

Part of cobalt mining coming from artisanal miners
Part of cobalt mining coming from artisanal miners
0.0
0.1
0.2
0.3
0.4
0.5
0.6
2000
2010
2020
2030
2040
2050
0
4
Time


Average cobalt recovery rate (%)
Average cobalt recovery rate (%)
0.0
0.2
0.4
0.6
0.8
2000
2010
2020
2030
2040
2050
0
5.8
Time

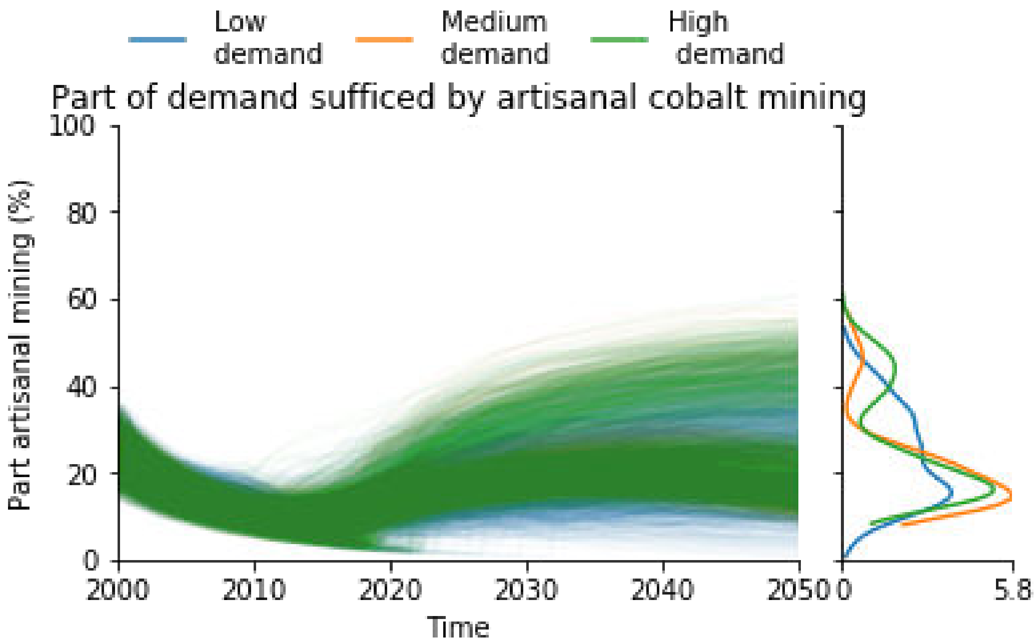


2.7 Visualize swing factors in production

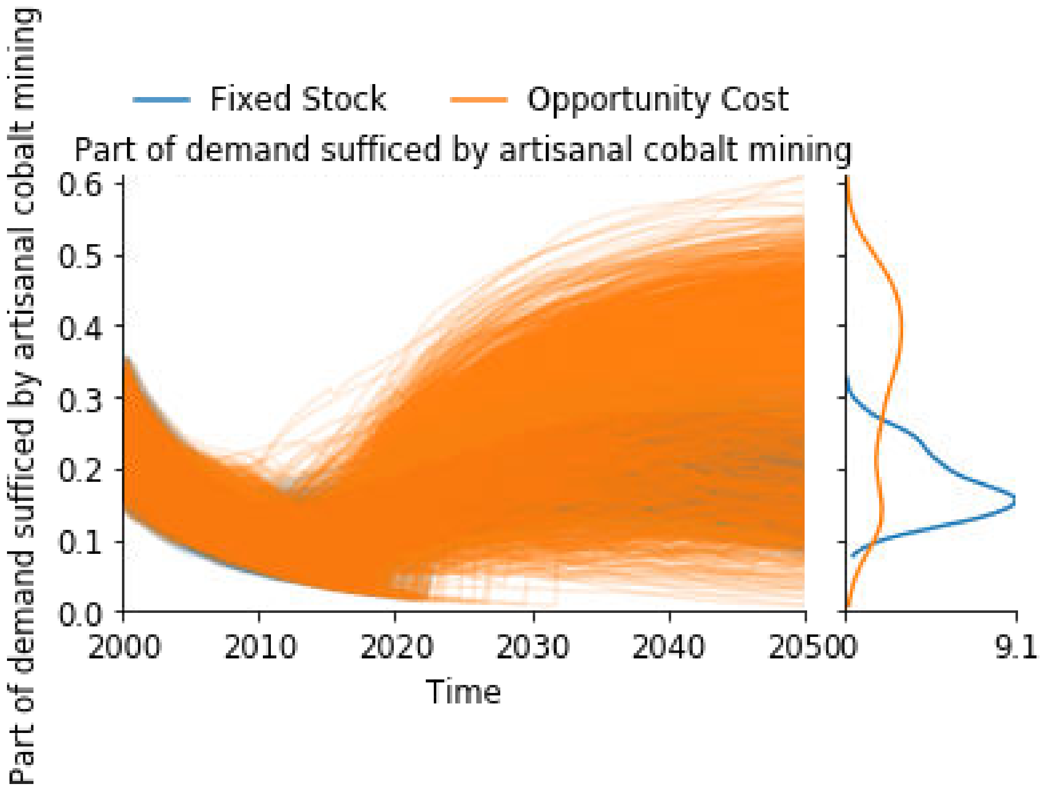
[123]:
```
out_b['Part of demand sufficed by artisanal cobalt mining'] = out_b['Relative␣
↪part artisanal mining[Cobalt]']
lines(exp_b,out_b,outcomes_to_show = 'Part of demand sufficed by artisanal␣
↪cobalt mining',
     group_by = 'Switch opportunity cost fixed stock',
      grouping_specifiers = {'Fixed stock':1,'Opportunity cost':2},
      density = Density.KDE)
fig = plt.gcf()
# fig.suptitle('Part of demand sufficed by \n artisanal cobalt mining')
fig.set_size_inches(6,3)
ax = fig.get_axes()
ax[0].set_xticklabels(labels_time)
ax[0].set_yticklabels(np.arange(0,101,20))
ax[0].set_ylabel('Part artisanal mining (%)')
for line in ax[0].get_lines():
    line.set_alpha(0.035)
ax[0].set_ylim([0,1])
sns.despine()
save_fig(fig, wd, 'co_relativpartartisanal_paradigm')
plt.show()
```



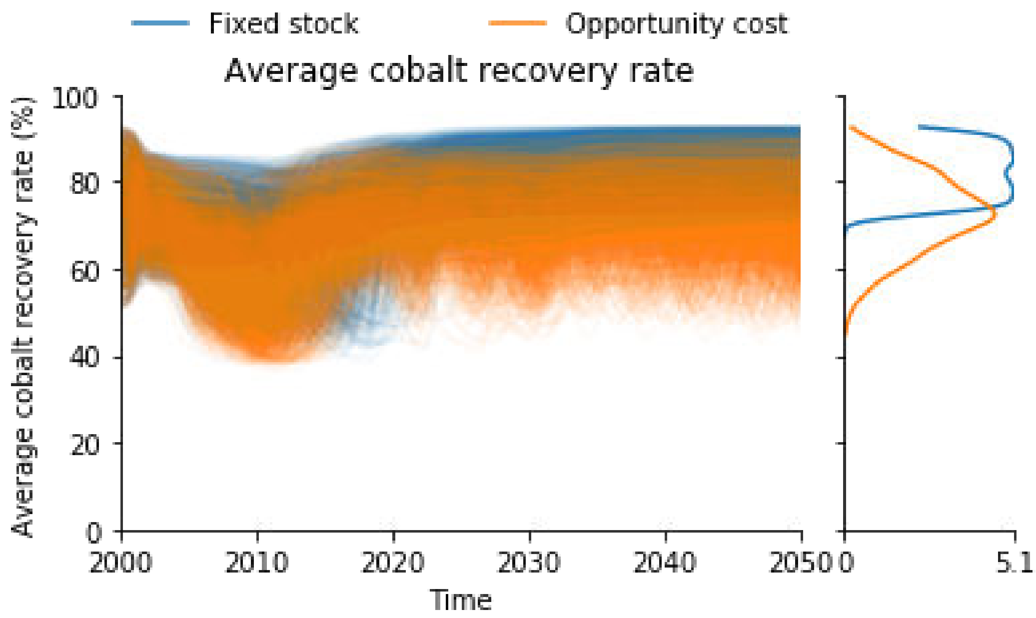
[135]:
```
lines(clustered_demand,out_b,outcomes_to_show = 'Part of demand sufficed by␣
↪artisanal cobalt mining',
     group_by = 'clusters',
      grouping_specifiers = {'High \n demand':0,' Medium \n demand':1, ' Low \n␣
↪demand':2},
      density = Density.KDE)
fig = plt.gcf()
# fig.suptitle('Part of demand sufficed by artisanal cobalt mining')
fig.set_size_inches(6,3)
ax = fig.get_axes()
ax[0].set_xticklabels(labels_time)
ax[0].set_yticklabels(np.arange(0,101,20))
ax[0].set_ylabel('Part artisanal mining (%)')
for line in ax[0].get_lines():
    line.set_alpha(0.03)
ax[0].set_ylim([0,1])
sns.despine()
save_fig(fig, wd, 'co_relativpartartisanal_demand')
plt.show()
```



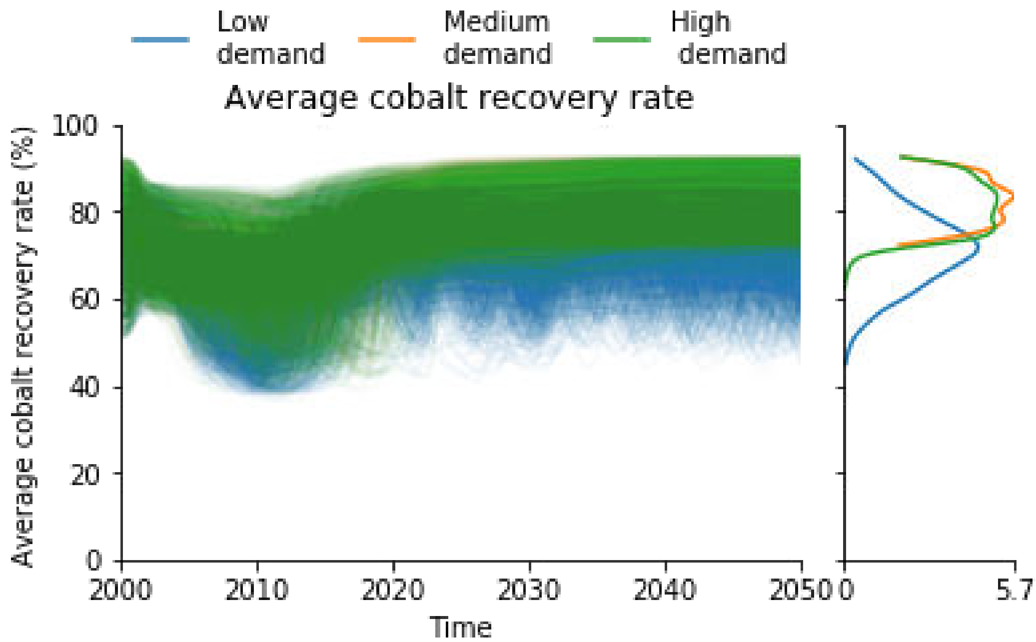
[117]:
```
nice_lines(exp_b,out_b,  paradigm ='both',out_to_show = 'Relative part␣
↪artisanal mining[Cobalt]',
           group_by = 'Switch opportunity cost fixed stock', density = Density.
↪KDE,
          title = 'Part of demand sufficed by artisanal cobalt mining', legend␣
↪= True,
          grouping_specifiers = {'Fixed Stock':1, 'Opportunity Cost':2}, zero =␣
↪True )
```



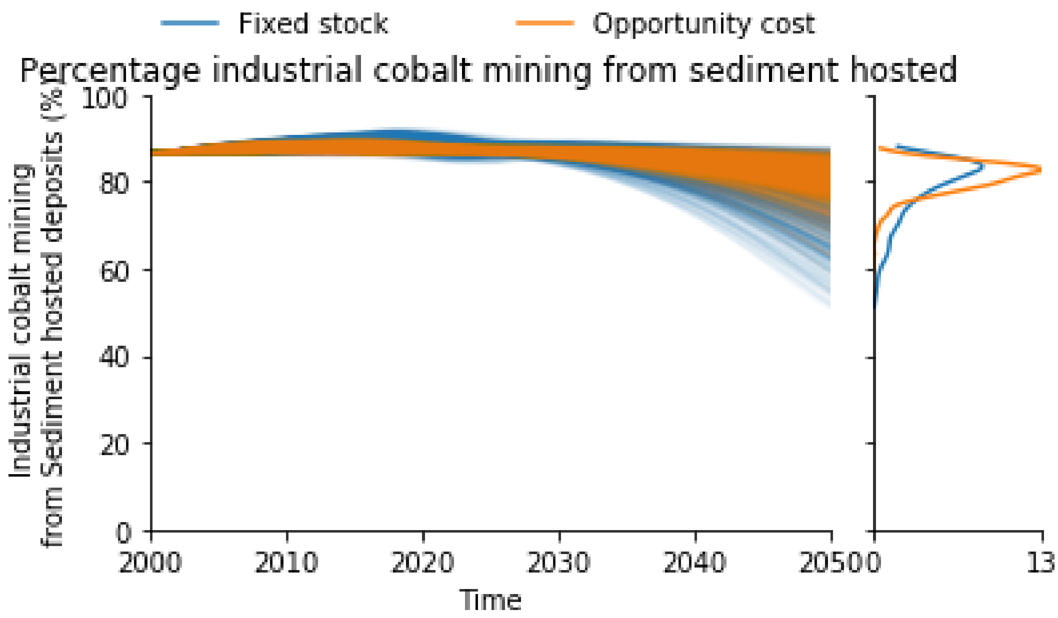
[97]:
```
lines(exp_b,out_b,outcomes_to_show = 'Average cobalt recovery rate',
     group_by = 'Switch opportunity cost fixed stock',
      grouping_specifiers = {'Fixed stock':1,'Opportunity cost':2},
      density = Density.KDE)
fig = plt.gcf()
# fig.suptitle('Percentage industrial cobalt mining \n from Sediment hosted␣
 ↪deposits')
fig.set_size_inches(6,3)
ax = fig.get_axes()
ax[0].set_xticklabels(labels_time)
ax[0].set_yticklabels(np.arange(0,101,20))
ax[0].set_ylabel('Average cobalt recovery rate (%)')
for line in ax[0].get_lines():
    line.set_alpha(0.04)
ax[0].set_ylim([0,1])
sns.despine()
save_fig(fig, wd, 'co_recovrate_paradigm')
plt.show()
```



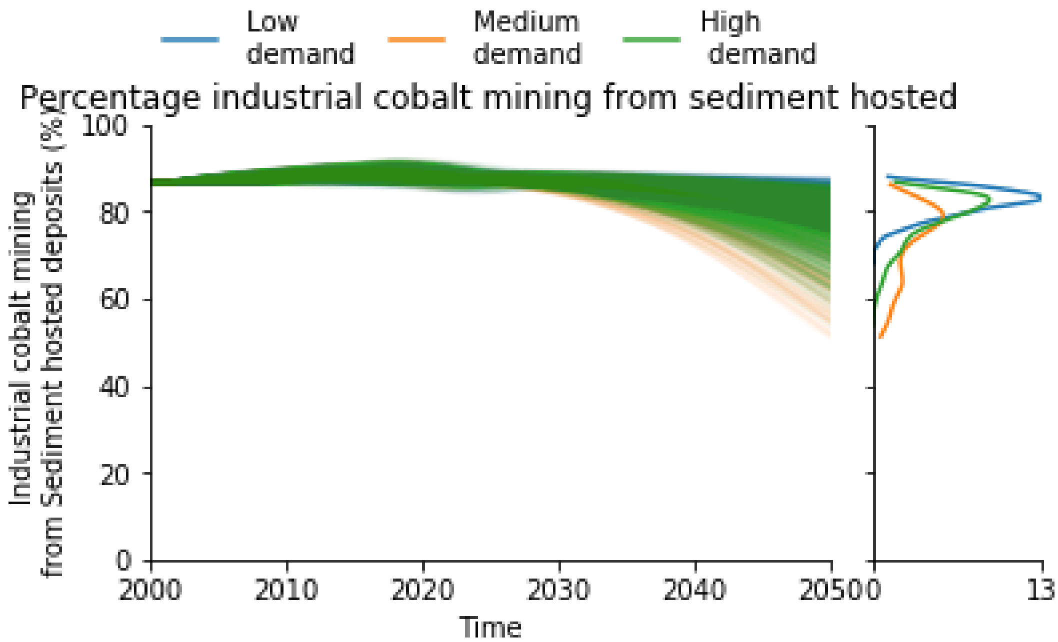
[95]:
```
lines(clustered_demand,out_b,outcomes_to_show = 'Average cobalt recovery rate',
     group_by = 'clusters',
      grouping_specifiers = {'High \n demand':0,' Medium \n demand':1, ' Low \n␣
 ↪demand':2},
      density = Density.KDE)
fig = plt.gcf()
# plt.suptitle('Percentage industrial cobalt mining \n from Sediment hosted␣
 ↪deposits')
fig.set_size_inches(6,3)
ax = fig.get_axes()
ax[0].set_xticklabels(labels_time)
ax[0].set_yticklabels(np.arange(0,101,20))
ax[0].set_ylabel('Average cobalt recovery rate (%)')
for line in ax[0].get_lines():
    line.set_alpha(0.04)
ax[0].set_ylim([0,1])
sns.despine()
save_fig(fig, wd, 'co_recovrate_demand')
plt.show()
```



[94]:
```
lines(exp_b,out_b,outcomes_to_show = 'Percentage industrial cobalt mining from␣
↪sediment hosted',
     group_by = 'Switch opportunity cost fixed stock',
      grouping_specifiers = {'Fixed stock':1,'Opportunity cost':2},
      density = Density.KDE)
fig = plt.gcf()
# plt.suptitle('Percentage industrial cobalt mining \n from Sediment hosted␣
↪deposits')
fig.set_size_inches(6,3)
ax = fig.get_axes()
ax[0].set_xticklabels(labels_time)
ax[0].set_ylim([0,1])
ax[0].set_yticklabels(np.arange(0,101,20))
ax[0].set_ylabel('Industrial cobalt mining \n from Sediment hosted deposits␣
↪(%)')
for line in ax[0].get_lines():
    line.set_alpha(0.04)
sns.despine()
save_fig(fig, wd, 'perc_sedhost_paradigm')
plt.show()
```

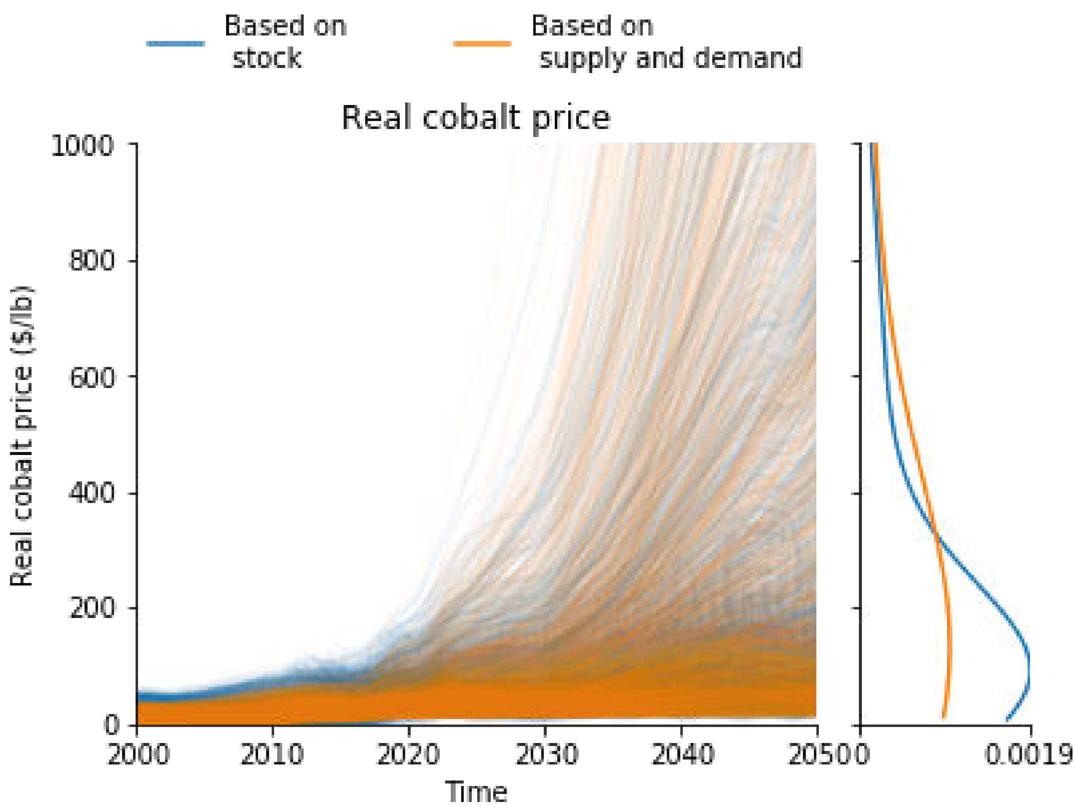


[96]:
```
lines(clustered_demand,out_b,outcomes_to_show = 'Percentage industrial cobalt␣
 ↪mining from sediment hosted',
     group_by = 'clusters',
      grouping_specifiers = {'High \n demand':0,' Medium \n demand':1, ' Low \n␣
 ↪demand':2},
      density = Density.KDE)
fig = plt.gcf()
# plt.suptitle('Percentage industrial cobalt mining \n from Sediment hosted␣
 ↪deposits')
fig.set_size_inches(6,3)
ax = fig.get_axes()
ax[0].set_xticklabels(labels_time)
ax[0].set_ylim([0,1])
ax[0].set_yticklabels(np.arange(0,101,20))
ax[0].set_ylabel('Industrial cobalt mining \n from Sediment hosted deposits␣
 ↪(%)')
for line in ax[0].get_lines():
    line.set_alpha(0.04)
sns.despine()
save_fig(fig, wd, 'perc_sedhost_demand')
plt.show()
```

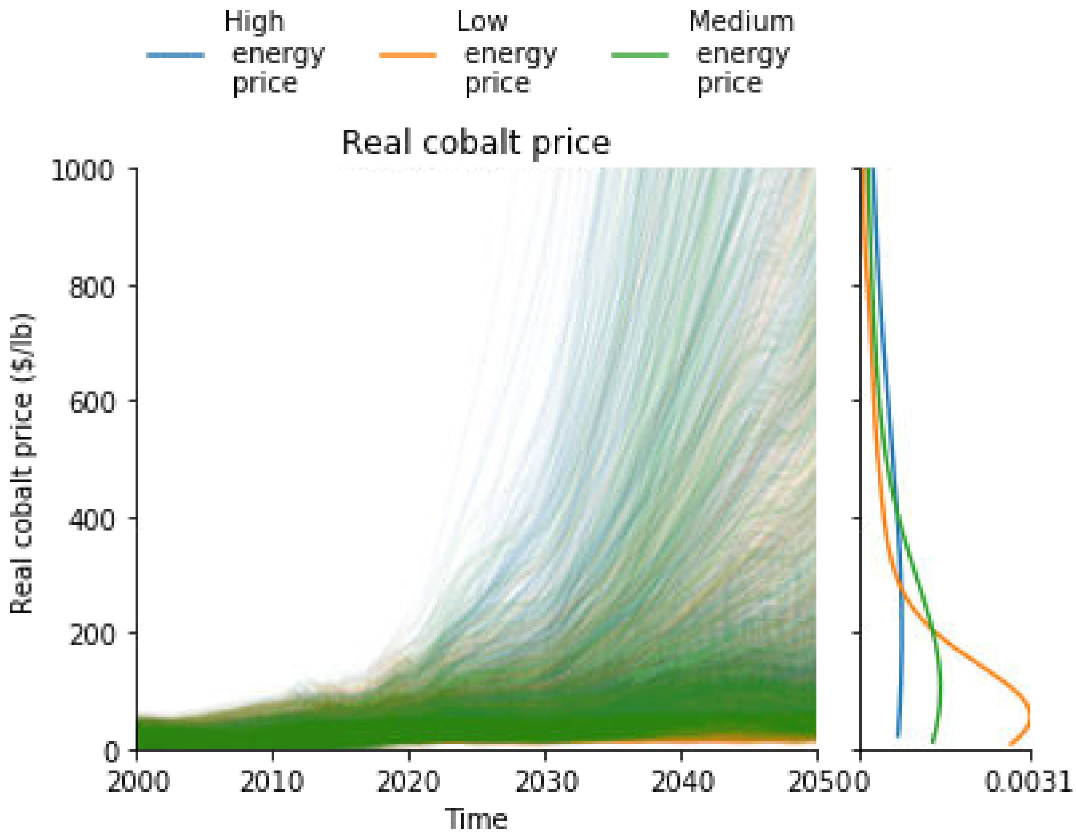


2.8 Visualize cobalt price

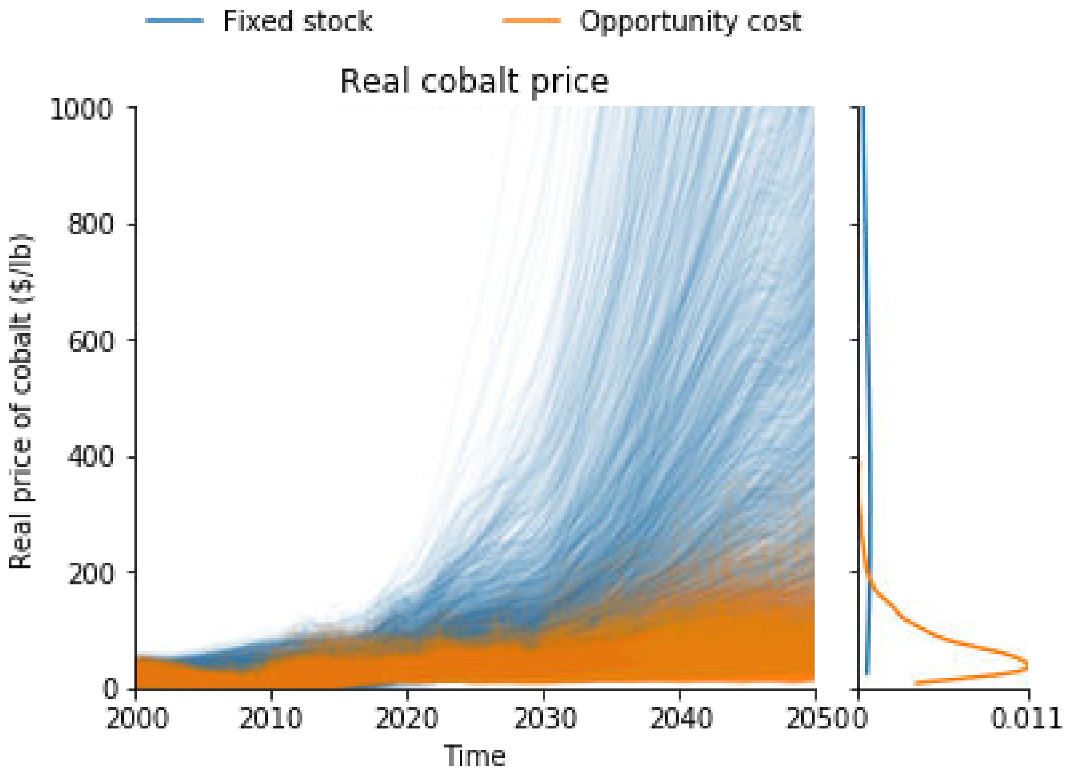
[261]:
```
out_b['Real cobalt price'] = out_b['Real price[Cobalt]']
lines(exp_b, out_b, outcomes_to_show = 'Real cobalt price',
      group_by='Switch real price',
      grouping_specifiers = {'Based on \n stock':1, 'Based on \n supply and␣
↪demand':2},
      density = Density.KDE)
fig = plt.gcf()
fig.set_size_inches(6,4)
# plt.yscale('log')
ax = fig.get_axes()
ax[0].set_xticklabels(labels_time)
ax[0].set_ylim([0,1000])
ax[0].set_ylabel('Real cobalt price ($/lb)')
for line in ax[0].get_lines():
    line.set_alpha(0.035)
sns.despine()
save_fig(fig,wd,'cobaltprice_switchformula')
plt.show()
```



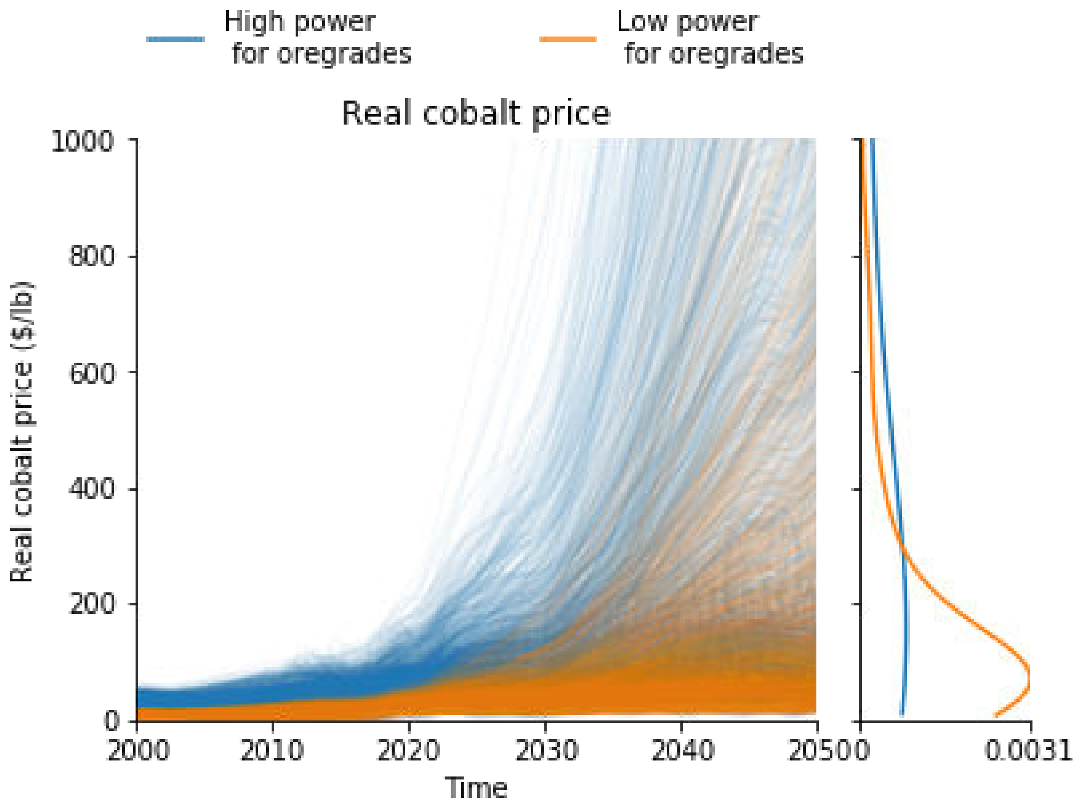
[262]:
```
lines(exp_b, out_b, outcomes_to_show = 'Real cobalt price',
      group_by = 'Switch energy price growth scenario',
      grouping_specifiers = {'Medium \n energy \n price':2, 'High \n energy \n␣
 ↪price':1,'Low \n energy \n price':3},
      density = Density.KDE)
fig = plt.gcf()
fig.set_size_inches(6,4)
# plt.yscale('log')
ax = fig.get_axes()
ax[0].set_xticklabels(labels_time)
ax[0].set_ylim([0,1000])
ax[0].set_ylabel('Real cobalt price ($/lb)')
for line in ax[0].get_lines():
    line.set_alpha(0.035)
sns.despine()
save_fig(fig,wd,'cobaltprice_switchenergyprice')
plt.show()
```



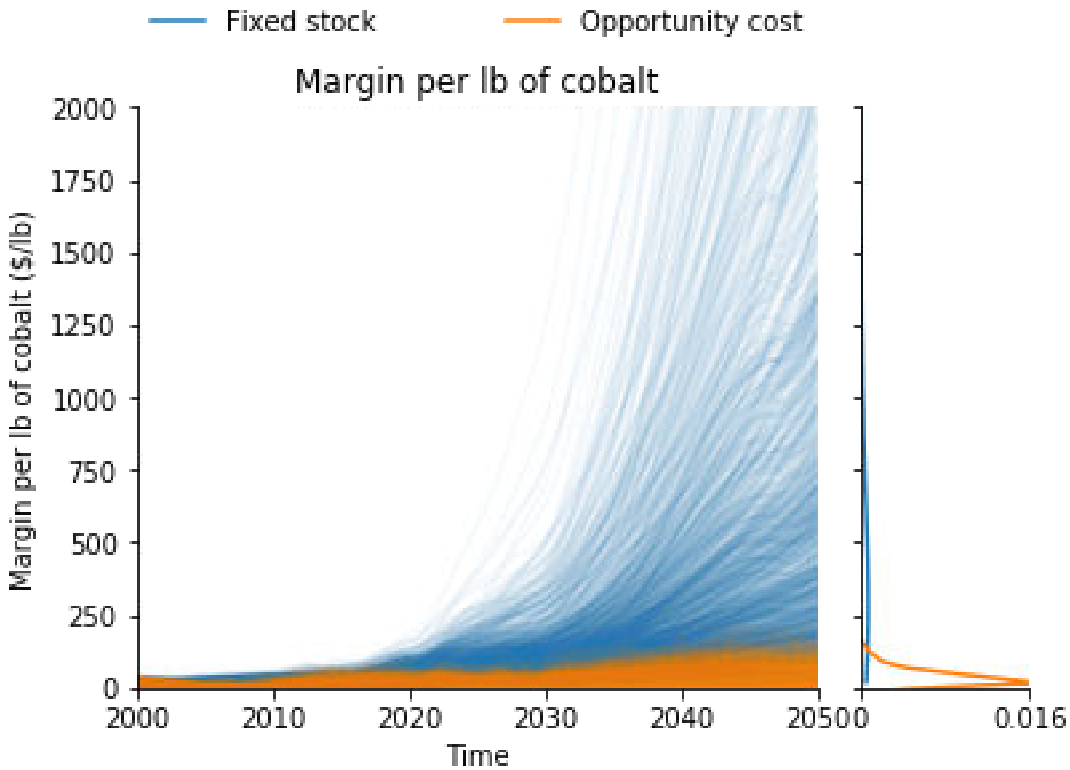
[263]:
```
lines(exp_b,out_b, outcomes_to_show = 'Real cobalt price',
      group_by='Switch opportunity cost fixed stock',
      grouping_specifiers = {'Fixed stock':1,'Opportunity cost':2},
      density = Density.KDE)
fig = plt.gcf()
# fig.set_size_inches(6,3)
ax = fig.get_axes()
ax[0].set_xticklabels(labels_time)
ax[0].set_ylim([0,1000])
ax[0].set_ylabel('Real price of cobalt ($/lb)')
for line in ax[0].get_lines():
    line.set_alpha(0.04)
sns.despine()
save_fig(fig,wd,'cobaltprice_paradigm')
plt.show()
```



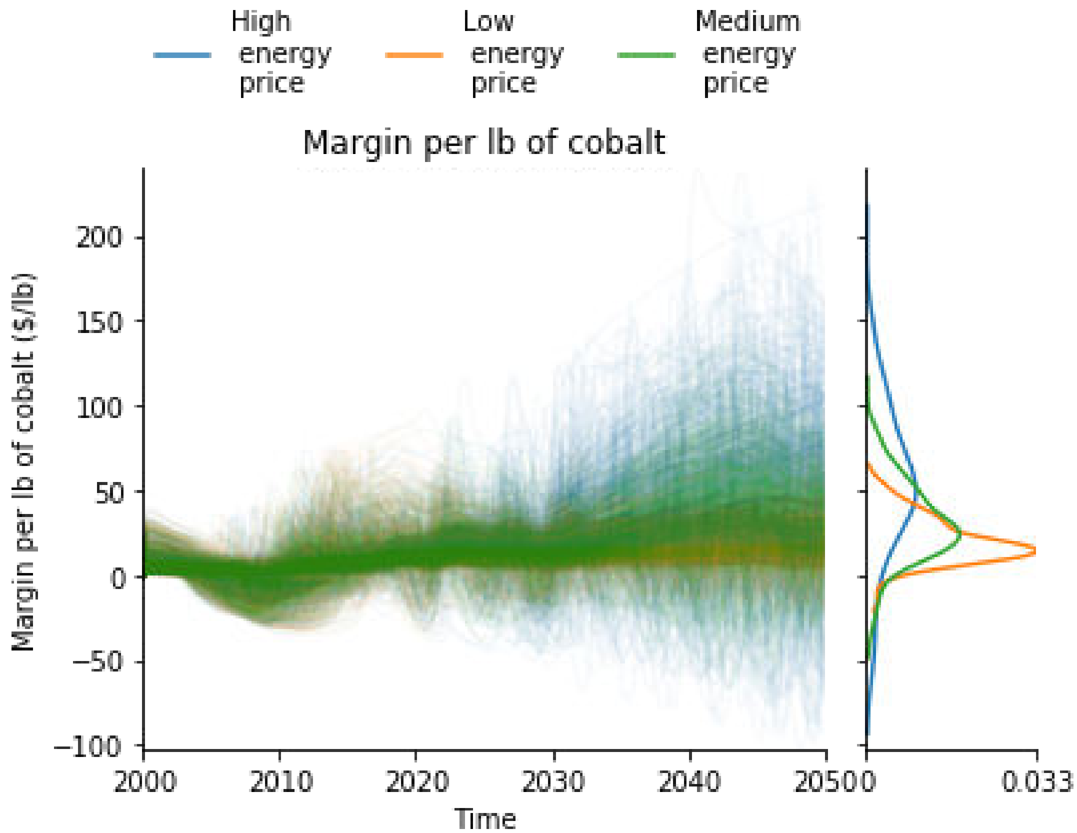
[331]:
```
lines(exp_b, out_b, outcomes_to_show = 'Real cobalt price',
      group_by = 'High power for oregrades',
      grouping_specifiers = {'High power \n for oregrades ': 1,'Low power \n␣
 ↪for oregrades':0},
      density = Density.KDE)
fig = plt.gcf()
fig.set_size_inches(6,4)
# plt.yscale('log')
ax = fig.get_axes()
ax[0].set_xticklabels(labels_time)
ax[0].set_ylim([0,1000])
for line in ax[0].get_lines():
    line.set_alpha(0.035)
ax[0].set_ylabel('Real cobalt price ($/lb)')
save_fig(fig,wd,'cobaltprice_oregrade')
sns.despine()
plt.show()
```



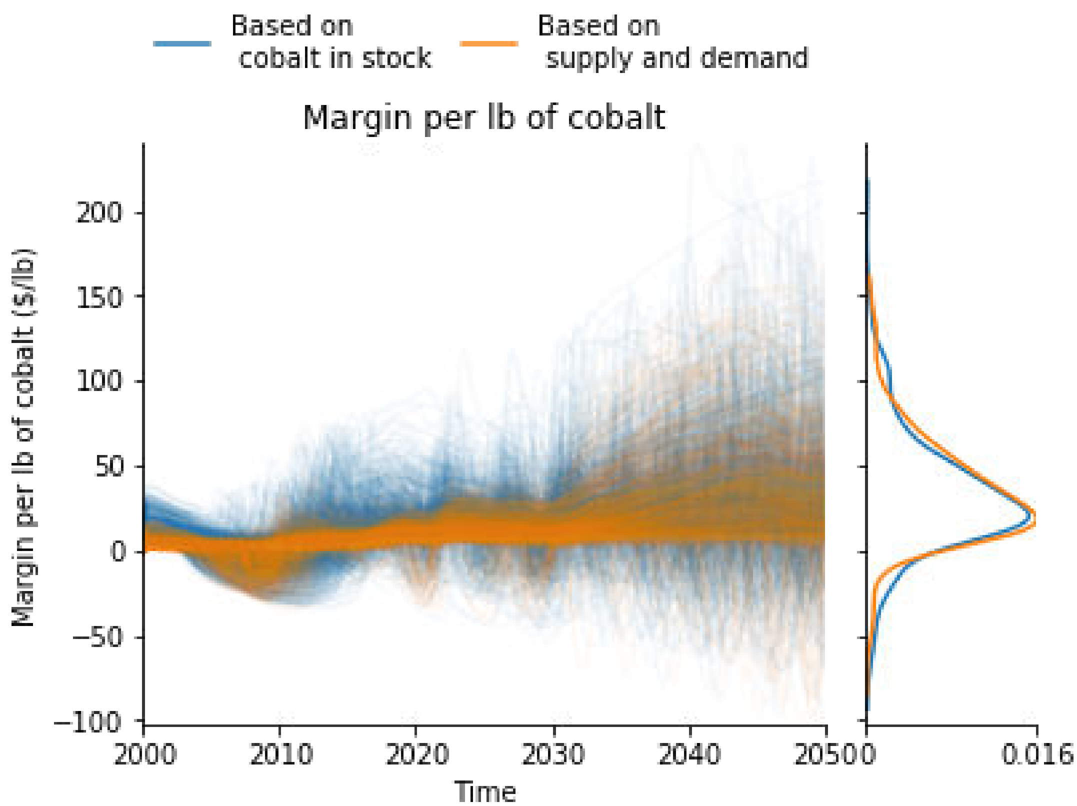
[256]:
```
out_b['Margin per lb of cobalt'] = out_b['Marge per lb[Cobalt]']
lines(exp_b,out_b, outcomes_to_show = 'Margin per lb of cobalt',
      group_by='Switch opportunity cost fixed stock',
      grouping_specifiers = {'Fixed stock':1,'Opportunity cost':2},
      density = Density.KDE)
fig = plt.gcf()
# fig.set_size_inches(6,3)
ax = fig.get_axes()
ax[0].set_xticklabels(labels_time)
ax[0].set_ylim([0,2000])
ax[0].set_ylabel('Margin per lb of cobalt ($/lb)')
for line in ax[0].get_lines():
    line.set_alpha(0.04)
sns.despine()
save_fig(fig,wd,'marginperlb_paradigm')
plt.show()
```



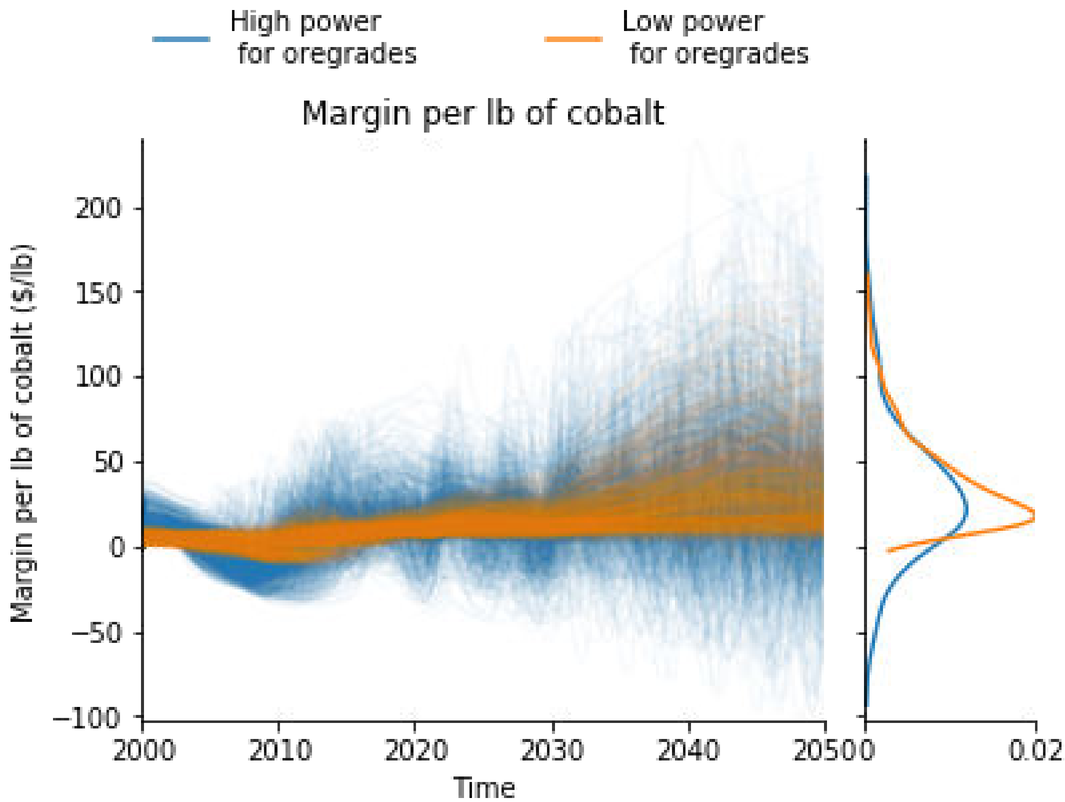
[249]:
```
lines(exp_b,out_b, outcomes_to_show = 'Margin per lb of cobalt',
      experiments_to_show = exp_b[exp_b['Switch opportunity cost fixed␣
 ↪stock']==2].index.values,
      group_by='Switch energy price growth scenario',
      grouping_specifiers = {'High \n energy \n price': 1,'Medium \n energy \n␣
 ↪price':2,'Low \n energy \n price':3},
      density = Density.KDE)
fig = plt.gcf()
ax = fig.get_axes()
ax[0].set_xticklabels(labels_time)
ax[0].set_ylabel('Margin per lb of cobalt ($/lb)')
for line in ax[0].get_lines():
    line.set_alpha(0.03)
sns.despine()
save_fig(fig,wd,'marginperlb_energy')
plt.show()
```



[250]:
```
lines(exp_b,out_b, outcomes_to_show = 'Margin per lb of cobalt',
      experiments_to_show = exp_b[exp_b['Switch opportunity cost fixed␣
 ↪stock']==2].index.values,
      group_by='Switch real price', #energy price growth scenario',
      grouping_specifiers = {'Based on \n cobalt in stock': 1,'Based on \n␣
 ↪supply and demand':2,},
      density = Density.KDE)
fig = plt.gcf()
ax = fig.get_axes()
ax[0].set_xticklabels(labels_time)
ax[0].set_ylabel('Margin per lb of cobalt ($/lb)')
for line in ax[0].get_lines():
    line.set_alpha(0.03)
sns.despine()
save_fig(fig,wd,'marginperlb_priceformula')
plt.show()
```



[251]:
```
lines(exp_b,out_b, outcomes_to_show = 'Margin per lb of cobalt',
      experiments_to_show = exp_b[exp_b['Switch opportunity cost fixed␣
↪stock']==2].index.values,
      group_by='High power for oregrades', #energy price growth scenario',
      grouping_specifiers = {'High power \n for oregrades ': 1,'Low power \n␣
↪for oregrades':0},
      density = Density.KDE)
fig = plt.gcf()
ax = fig.get_axes()
ax[0].set_xticklabels(labels_time)
ax[0].set_ylabel('Margin per lb of cobalt ($/lb)')
for line in ax[0].get_lines():
    line.set_alpha(0.03)
sns.despine()
save_fig(fig,wd,'marginperlb_oregrade')
plt.show()
```



2.9 Visualize individual runs

[643]:
```
# clustered_demand[clustered_demand['Paradigm switch'] == 'Fixed␣
↪stock'][clustered_demand['clusters']==1][clustered_demand['Power for␣
↪oregrades']>0.41][clustered_demand['Battery capacity␣
↪BEV']>90][clustered_demand['Switch energy price growth scenario']==3]
```

[644]:
```
# clustered_demand[clustered_demand['Paradigm switch'] == 'Fixed␣
↪stock'][clustered_demand['clusters']==2][clustered_demand['Power for␣
↪oregrades']<0.39][clustered_demand['Battery capacity␣
↪BEV']<60][clustered_demand['Switch energy price growth scenario']==1]
```

[289]:
```
row1 = exp_b.index.values == 19
row2 = exp_b.index.values == 1519
row3 = exp_b.index.values == 12
row2 = exp_b.index.values == 1512
```

[291]:
```
duh = np.array(np.array([row1 | row2],dtype='int'),dtype= 'object')
```

[313]:
```
exp_b['dugh'] = 0
```

[314]:
```
exp_b['dugh'][19] = 1
exp_b['dugh'][1519] = 2
exp_b['dugh'][12] = 3
exp_b['dugh'][1512] = 4
```

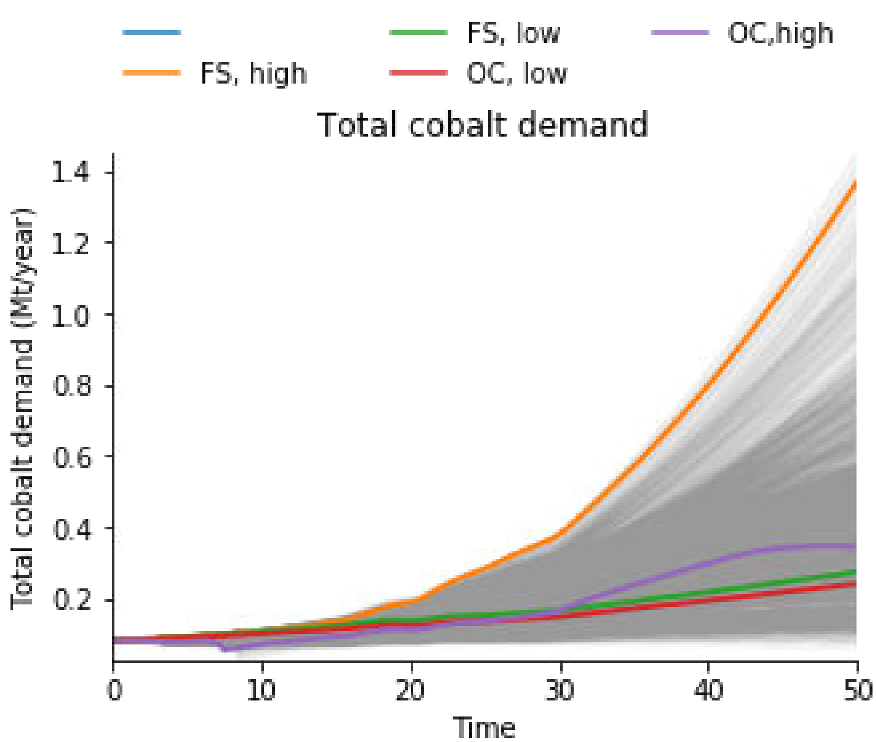
```
C:\ProgramData\Anaconda3_32bits\lib\site-packages\ipykernel_launcher.py:1:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/indexing.html#indexing-view-versus-copy
  """Entry point for launching an IPython kernel.
C:\ProgramData\Anaconda3_32bits\lib\site-packages\ipykernel_launcher.py:2:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/indexing.html#indexing-view-versus-copy

C:\ProgramData\Anaconda3_32bits\lib\site-packages\ipykernel_launcher.py:3:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/indexing.html#indexing-view-versus-copy
  This is separate from the ipykernel package so we can avoid doing imports
until
C:\ProgramData\Anaconda3_32bits\lib\site-packages\ipykernel_launcher.py:4:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/indexing.html#indexing-view-versus-copy
  after removing the cwd from sys.path.
```

[315]:
```
sum(exp_b['dugh'])
```

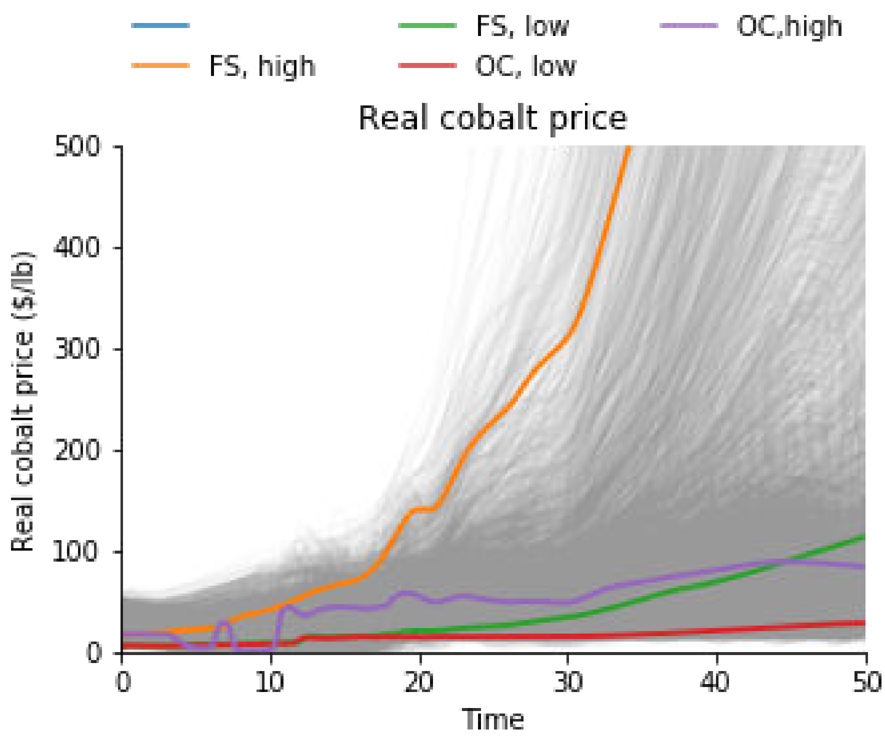
[315]: 10

[327]:
```
out_b['Total cobalt demand'] = out_b['Total demand[Cobalt]']/2204622620
lines(exp_b, out_b, 'Total cobalt demand',group_by = 'dugh' , legend = True ,
      grouping_specifiers= {'FS, high': 1, 'OC,high ':2, '':0, 'FS, low': 3,␣
 ↪'OC, low':4} )
fig = plt.gcf()
ax = fig.get_axes()
fig.set_size_inches(5,3.5)
find_colors(ax[0])
for line in ax[0].get_lines():
```

```
    if line.get_color() == (0.12156862745098039, 0.4666666666666667, 0.
↪7058823529411765):
        line.set_color((0.6,0.6,0.6))
        line.set_alpha(0.03)
    if line.get_color() == (1.0, 0.4980392156862745, 0.054901960784313725):
        line.set_alpha(1)
        line.set_linewidth(2)
    if line.get_color() == (0.17254901960784313, 0.6274509803921569, 0.
↪17254901960784313):
        line.set_alpha(1)
        line.set_linewidth(2)
    if line.get_color() == (0.8392156862745098, 0.15294117647058825, 0.
↪1568627450980392):
        line.set_alpha(1)
        line.set_linewidth(2)
    if line.get_color() == (0.5803921568627451, 0.403921568627451, 0.
↪7411764705882353):
        line.set_alpha(1)
        line.set_linewidth(2)
ax[0].set_ylabel('Total cobalt demand (Mt/year)')
sns.despine()
save_fig(fig,wd,'specificruns_demand')
```

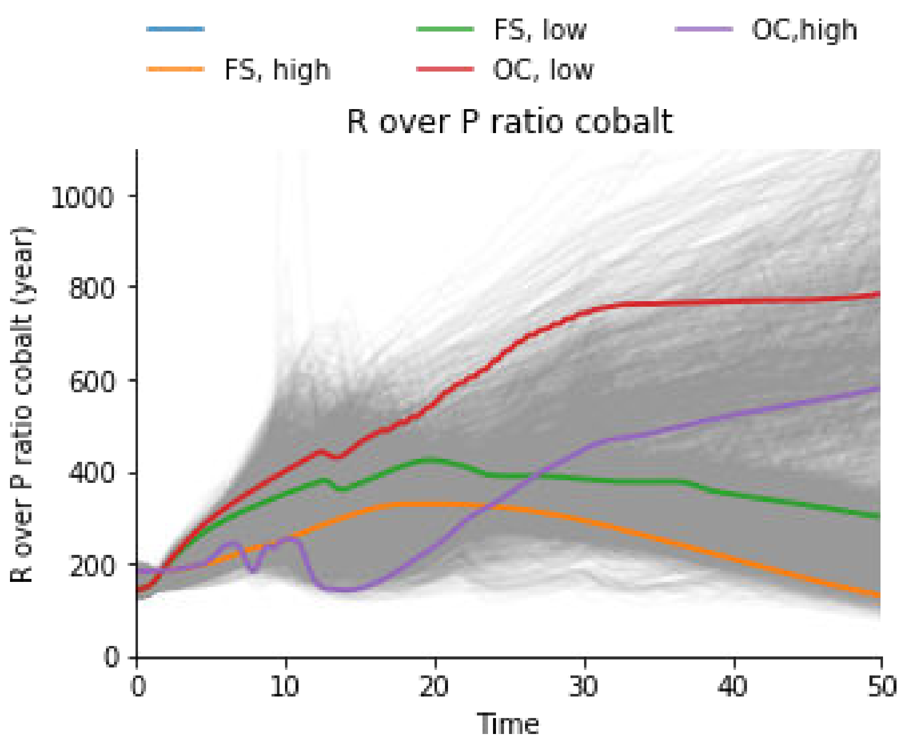


[328]:
```
out_b['Real cobalt price'] = out_b['Real price[Cobalt]']
lines(exp_b, out_b, 'Real cobalt price',group_by = 'dugh' , legend = True,
      grouping_specifiers= {'FS, high': 1, 'OC,high ':2, '':0, 'FS, low': 3,␣
 ↪'OC, low':4}  )
fig = plt.gcf()
ax = fig.get_axes()
fig.set_size_inches(5,3.5)
find_colors(ax[0])
for line in ax[0].get_lines():
    if line.get_color() == (0.12156862745098039, 0.4666666666666667, 0.
 ↪7058823529411765):
        line.set_color((0.6,0.6,0.6))
        line.set_alpha(0.05)
    if line.get_color() == (1.0, 0.4980392156862745, 0.054901960784313725):
        line.set_alpha(1)
        line.set_linewidth(2)
    if line.get_color() == (0.17254901960784313, 0.6274509803921569, 0.
 ↪17254901960784313):
        line.set_alpha(1)
        line.set_linewidth(2)
    if line.get_color() == (0.8392156862745098, 0.15294117647058825, 0.
 ↪1568627450980392):
        line.set_alpha(1)
        line.set_linewidth(2)
    if line.get_color() == (0.5803921568627451, 0.403921568627451, 0.
 ↪7411764705882353):
        line.set_alpha(1)
        line.set_linewidth(2)
ax[0].set_ylim([0,500])
ax[0].set_ylabel('Real cobalt price ($/lb)')
sns.despine()
save_fig(fig,wd,'specificruns_price')
```



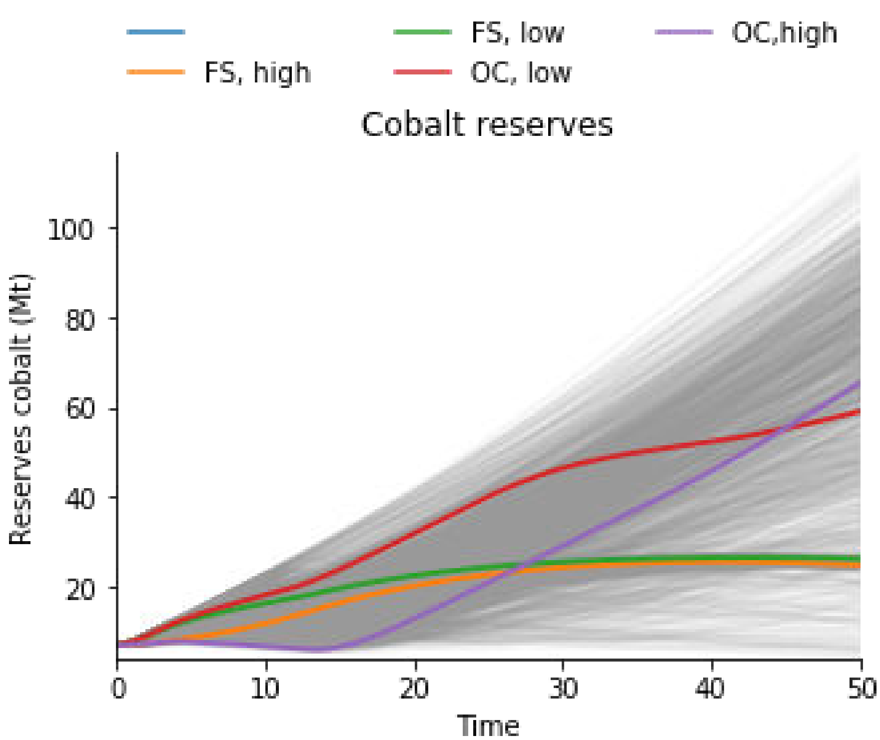
[329]:
```
out_b['R over P ratio cobalt'] = out_b['R over P ratio[Cobalt]']
lines(exp_b, out_b, 'R over P ratio cobalt',group_by = 'dugh' , legend = True,
      grouping_specifiers= {'FS, high': 1, 'OC,high ':2, '':0, 'FS, low': 3,␣
 ↪'OC, low':4}  )
fig = plt.gcf()
ax = fig.get_axes()
fig.set_size_inches(5,3.5)
find_colors(ax[0])
for line in ax[0].get_lines():
    if line.get_color() == (0.12156862745098039, 0.4666666666666667, 0.
 ↪7058823529411765):
        line.set_color((0.6,0.6,0.6))
        line.set_alpha(0.05)
    if line.get_color() == (1.0, 0.4980392156862745, 0.054901960784313725):
        line.set_alpha(1)
        line.set_linewidth(2)
    if line.get_color() == (0.17254901960784313, 0.6274509803921569, 0.
 ↪17254901960784313):
        line.set_alpha(1)
        line.set_linewidth(2)
    if line.get_color() == (0.8392156862745098, 0.15294117647058825, 0.
 ↪1568627450980392):
        line.set_alpha(1)
```

```
        line.set_linewidth(2)
    if line.get_color() == (0.5803921568627451, 0.403921568627451, 0.
↪7411764705882353):
        line.set_alpha(1)
        line.set_linewidth(2)
ax[0].set_ylim([0,1100])
ax[0].set_ylabel('R over P ratio cobalt (year)')
sns.despine()
save_fig(fig,wd,'specificruns_roverp')
```



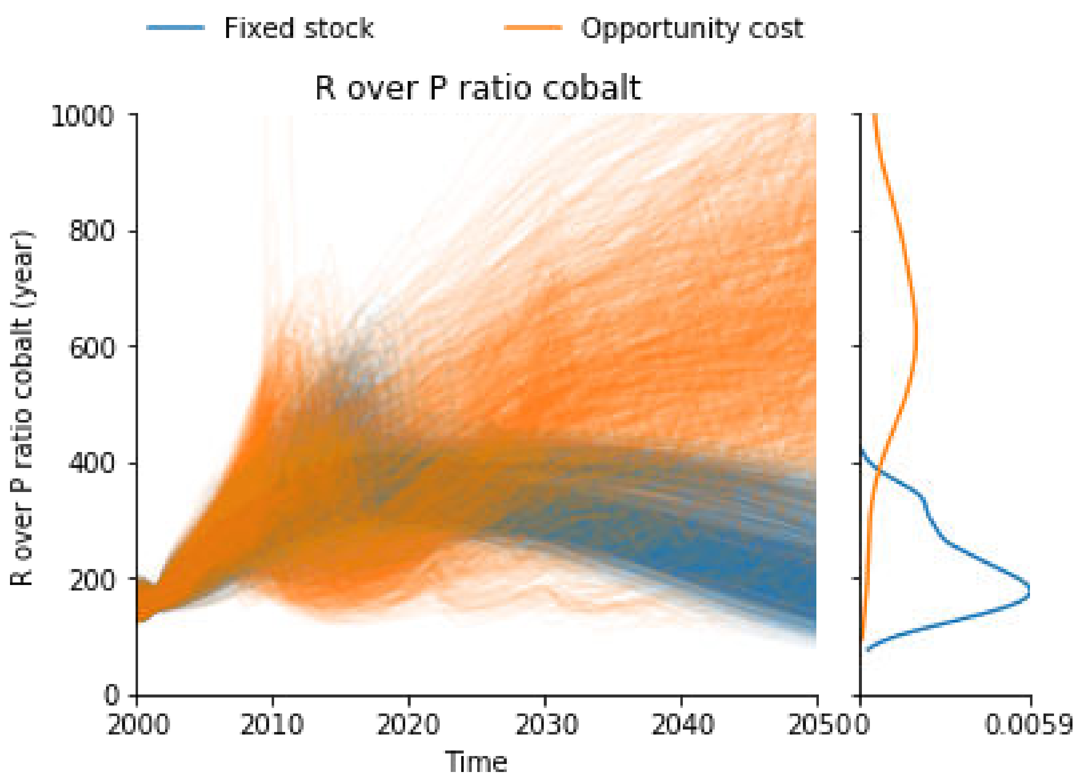
[330]:
```
out_b['Cobalt reserves'] = out_b['Reserves[Cobalt]']/2204622620
lines(exp_b, out_b, 'Cobalt reserves',group_by = 'dugh' ,  legend = True,
      grouping_specifiers= {'FS, high': 1, 'OC,high ':2, '':0, 'FS, low': 3,␣
↪'OC, low':4}  )
fig = plt.gcf()
ax = fig.get_axes()
fig.set_size_inches(5,3.5)
find_colors(ax[0])
for line in ax[0].get_lines():
    if line.get_color() == (0.12156862745098039, 0.4666666666666667, 0.
↪7058823529411765):
        line.set_color((0.6,0.6,0.6))
        line.set_alpha(0.05)
```

```
    if line.get_color() == (1.0, 0.4980392156862745, 0.054901960784313725):
        line.set_alpha(1)
        line.set_linewidth(2)
    if line.get_color() == (0.17254901960784313, 0.6274509803921569, 0.
↪17254901960784313):
        line.set_alpha(1)
        line.set_linewidth(2)
    if line.get_color() == (0.8392156862745098, 0.15294117647058825, 0.
↪1568627450980392):
        line.set_alpha(1)
        line.set_linewidth(2)
    if line.get_color() == (0.5803921568627451, 0.403921568627451, 0.
↪7411764705882353):
        line.set_alpha(1)
        line.set_linewidth(2)
ax[0].set_ylabel('Reserves cobalt (Mt)')
sns.despine()
save_fig(fig,wd,'specificruns_reserves')
```



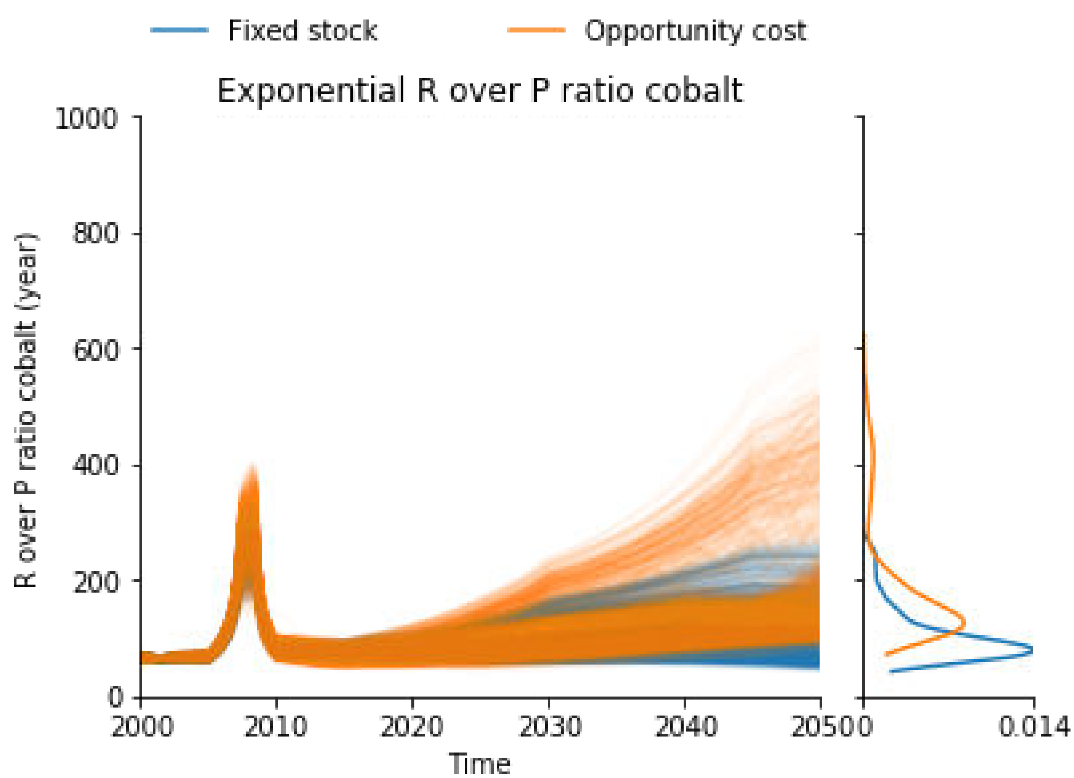
2.9.1 Visualize difference R over P ratio and exponential R over P ratio

[325]:
```
lines(exp_b,out_b, outcomes_to_show = 'R over P ratio cobalt',
      group_by='Switch opportunity cost fixed stock',
      grouping_specifiers = {'Fixed stock':1,'Opportunity cost':2},
      density = Density.KDE)
fig = plt.gcf()
# fig.set_size_inches(6,3)
ax = fig.get_axes()
ax[0].set_xticklabels(labels_time)
ax[0].set_ylabel('R over P ratio cobalt (year)')
for line in ax[0].get_lines():
    line.set_alpha(0.04)
ax[0].set_ylim([0,1000])
sns.despine()
save_fig(fig,wd,'roverpratio_paradigm')
plt.show()
```



[326]:
```
out_b['Exponential R over P ratio cobalt'] = out_b['Exponential index of␣
↪depletion[Cobalt]']

lines(exp_b,out_b, outcomes_to_show = 'Exponential R over P ratio cobalt',
```

```
        group_by='Switch opportunity cost fixed stock',
        grouping_specifiers = {'Fixed stock':1,'Opportunity cost':2},
        density = Density.KDE)
fig = plt.gcf()
# fig.set_size_inches(6,3)
ax = fig.get_axes()
ax[0].set_xticklabels(labels_time)
ax[0].set_ylabel('R over P ratio cobalt (year)')
for line in ax[0].get_lines():
    line.set_alpha(0.04)
ax[0].set_ylim([0,1000])
sns.despine()
save_fig(fig,wd,'roverpratio_paradigm')
plt.show()
```

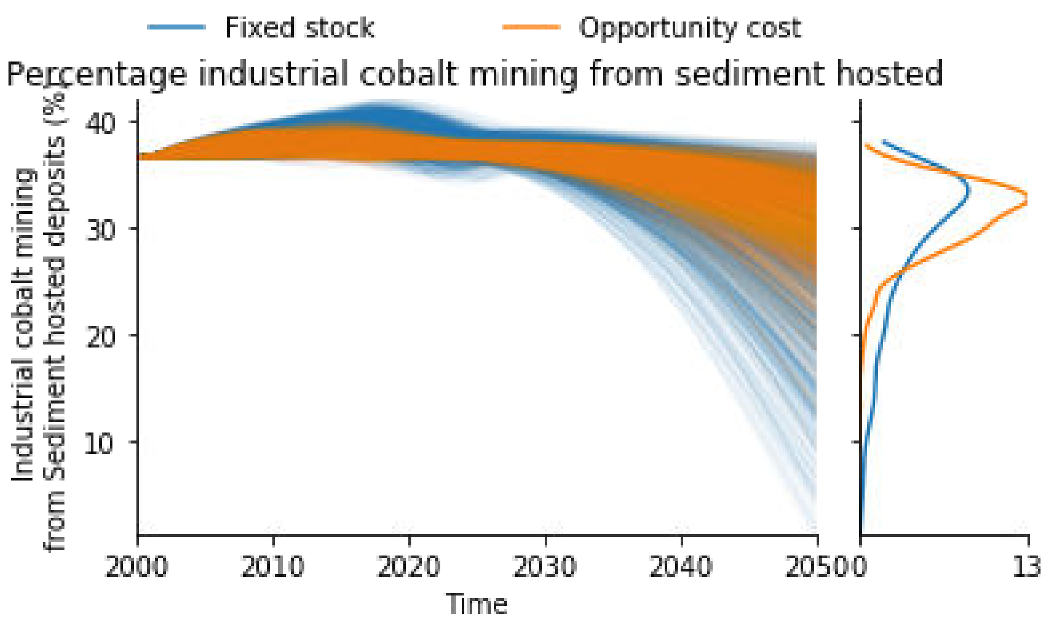


2.10 Visualize cobalt mining capacity % sediment hosted

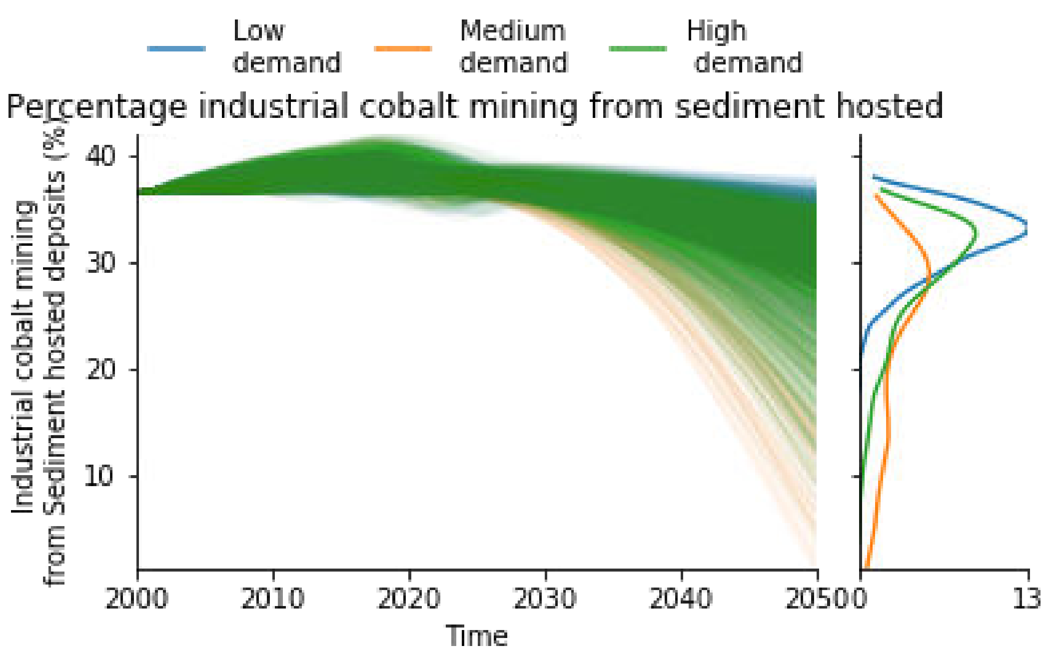
[34]:
```
out_b['Indstrial mining capacity cobalt, sediment hosted (Mt/year)'] =␣
 ↪out_b['Industrial mining capacity[Sed hosted Co]']/2204622620 * 0.054
out_b['Indstrial mining capacity cobalt, Ni laterite (Mt/year)'] =␣
 ↪out_b['Industrial mining capacity[Ni laterite Co]']/2204622620 * 0.0482
```

```
out_b['Indstrial mining capacity cobalt, Magmatic sulfide (Mt/year)'] =␣
↪out_b['Industrial mining capacity[Magm sulfide Co]']/2204622620 * 0.0061

out_b['Percentage industrial cobalt mining from sediment hosted'] =␣
↪out_b['Indstrial mining capacity cobalt, sediment hosted (Mt/year)'] /␣
↪(out_b['Indstrial mining capacity cobalt, sediment hosted (Mt/year)'] +␣
↪out_b['Indstrial mining capacity cobalt, Ni laterite (Mt/year)'] +␣
↪out_b['Indstrial mining capacity cobalt, Magmatic sulfide (Mt/year)'])
```

[77]:
```
lines(exp_b,out_b,outcomes_to_show = 'Percentage industrial cobalt mining from␣
↪sediment hosted',
     group_by = 'Switch opportunity cost fixed stock',
      grouping_specifiers = {'Fixed stock':1,'Opportunity cost':2},
      density = Density.KDE)
fig = plt.gcf()
# plt.suptitle('Percentage industrial cobalt mining \n from Sediment hosted␣
↪deposits')
fig.set_size_inches(6,3)
ax = fig.get_axes()
ax[0].set_xticklabels(labels_time)
ax[0].set_yticklabels(np.arange(0,100,10))
ax[0].set_ylabel('Industrial cobalt mining \n from Sediment hosted deposits␣
↪(%)')
for line in ax[0].get_lines():
    line.set_alpha(0.04)
sns.despine()
save_fig(fig, wd, 'perc_sedhost_paradigm')
plt.show()
```

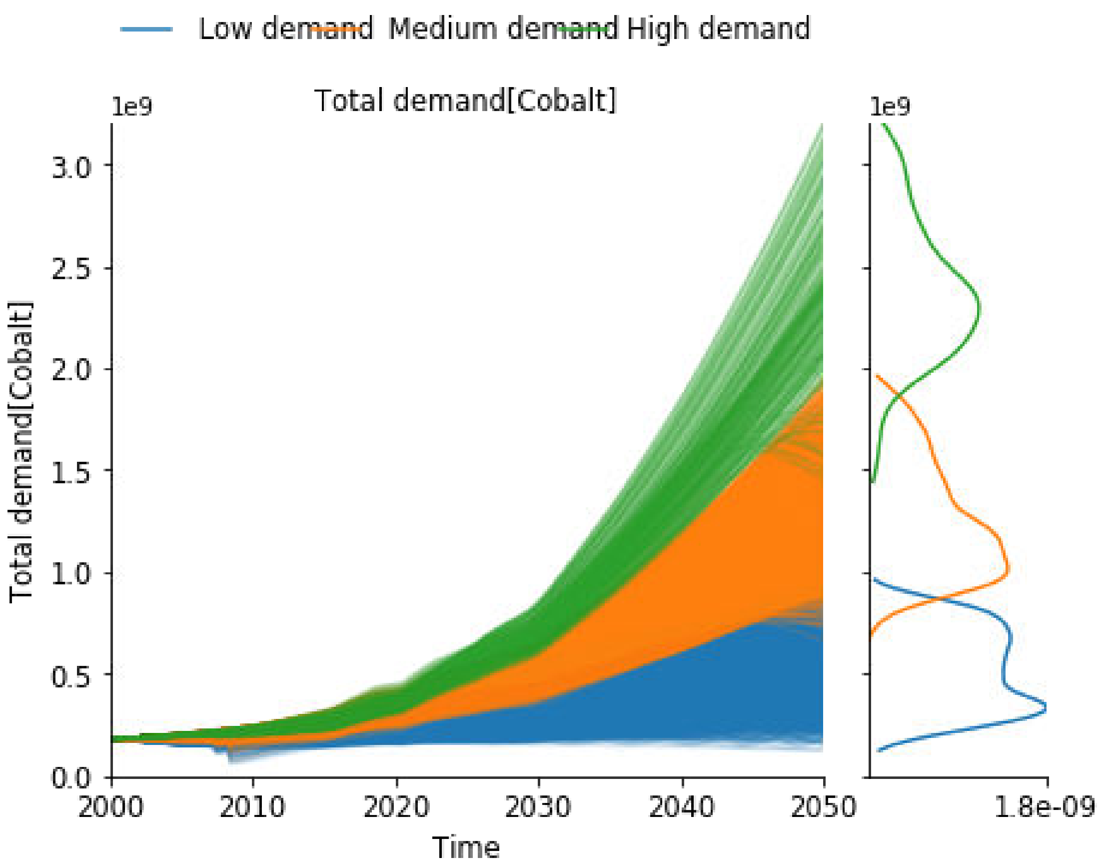


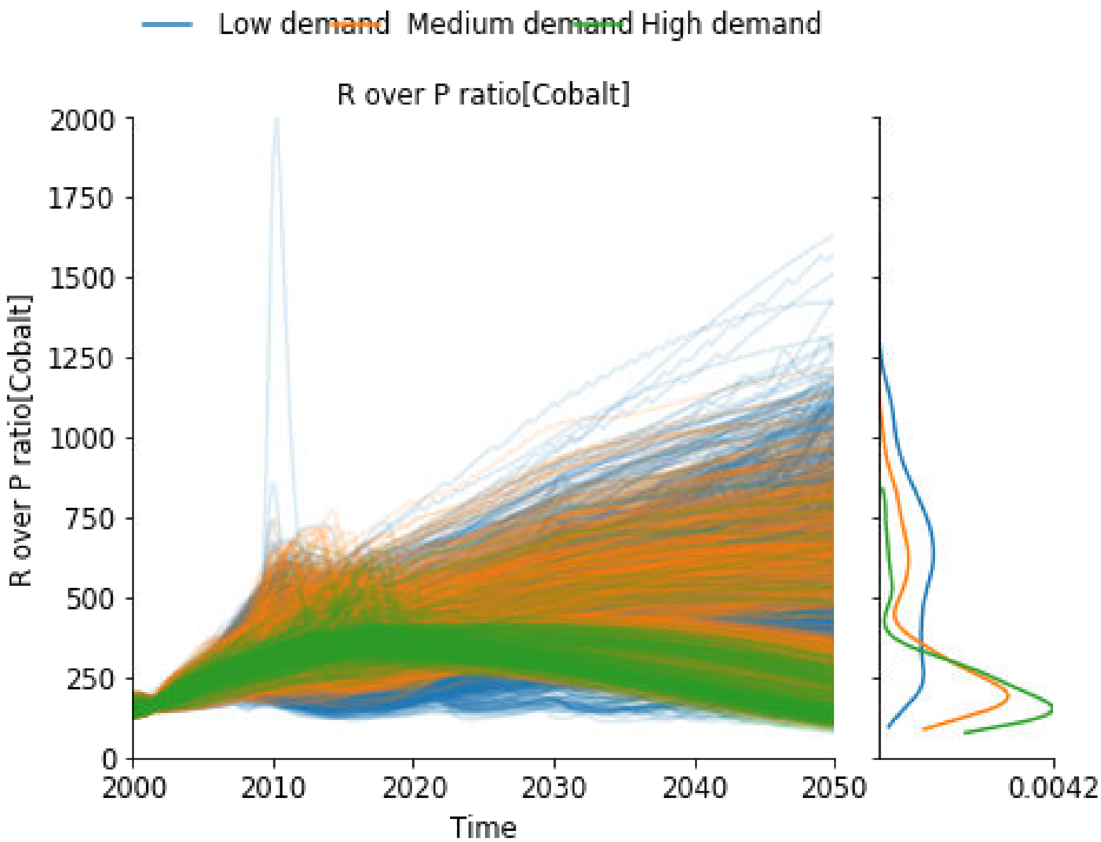
[76]:
```
lines(clustered_demand,out_b,outcomes_to_show = 'Percentage industrial cobalt␣
↪mining from sediment hosted',
      group_by = 'clusters',
       grouping_specifiers = {'High \n demand':0,' Medium \n demand':1, ' Low \n␣
↪demand':2},
       density = Density.KDE)
fig = plt.gcf()
# plt.suptitle('Percentage industrial cobalt mining \n from Sediment hosted␣
↪deposits')
fig.set_size_inches(6,3)
ax = fig.get_axes()
ax[0].set_xticklabels(labels_time)
ax[0].set_yticklabels(np.arange(0,100,10))
ax[0].set_ylabel('Industrial cobalt mining \n from Sediment hosted deposits␣
↪(%)')
for line in ax[0].get_lines():
    line.set_alpha(0.04)
sns.despine()
save_fig(fig, wd, 'perc_sedhost_demand')
plt.show()
```



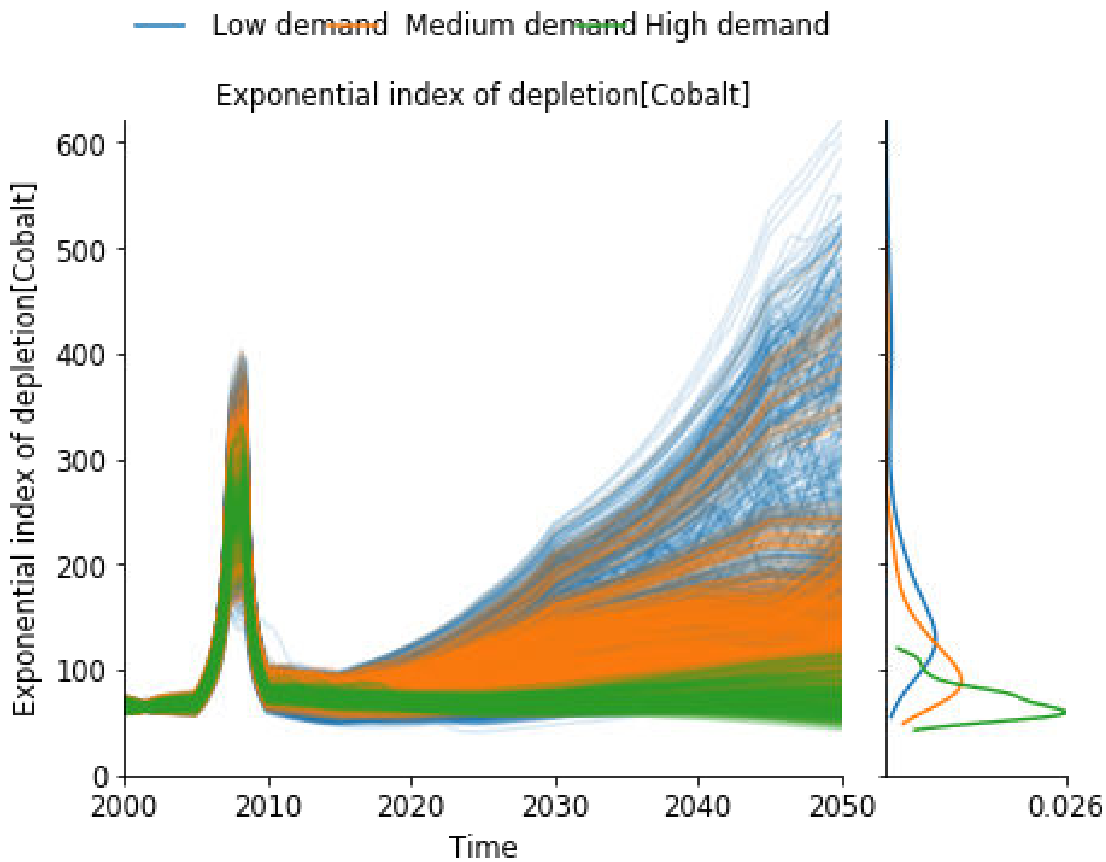
2.11 Graph dump

[641]:
```
for i in out_b:
    if i != 'TIME':
        if i == 'Normalised profit forecast[Copper]':
            fig,axes=plot_clusters('both', i , clustered_demand, zero= False)
        elif i == 'Normalised profit forecast[Nickel]':
            fig,axes=plot_clusters('both', i , clustered_demand, zero= False)
        elif i == 'Normalised profit forecast[Cobalt]':
            fig,axes=plot_clusters('both', i , clustered_demand, zero= False)
        else:
            fig,axes = plot_clusters('both', i , clustered_demand, zero= True )
        plt.show()
```

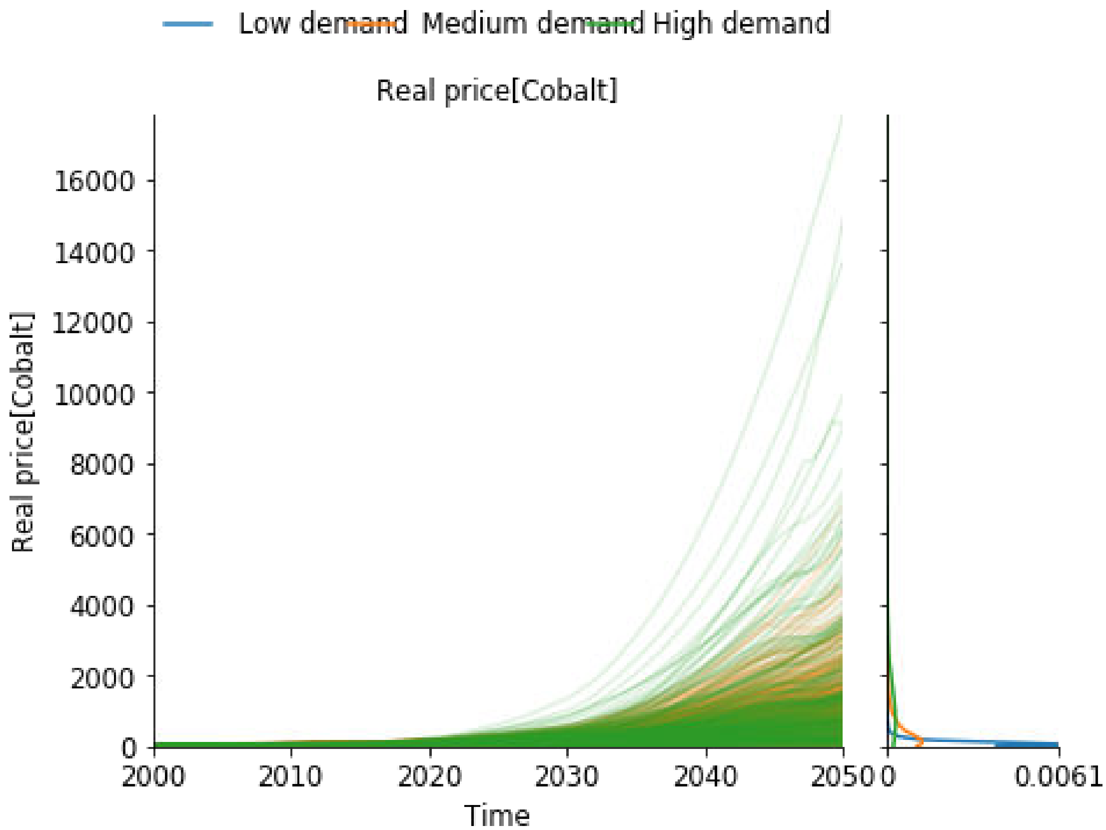




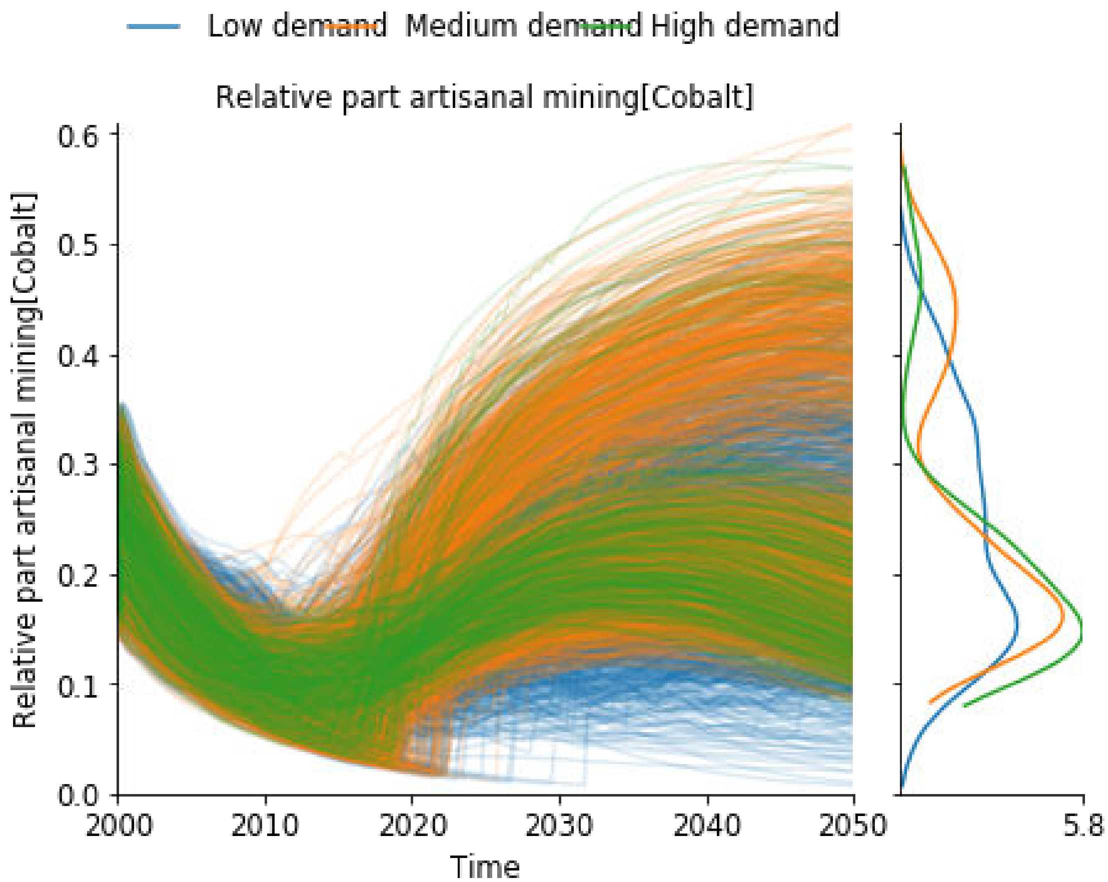
Low demand
Medium demand
High demand
R over P ratio[Cobalt]
R over P ratio[Cobalt]
2000
1750
1500
1250
1000
750
500
250
0
2000
2010
2020
2030
2040
2050
Time
0.0042

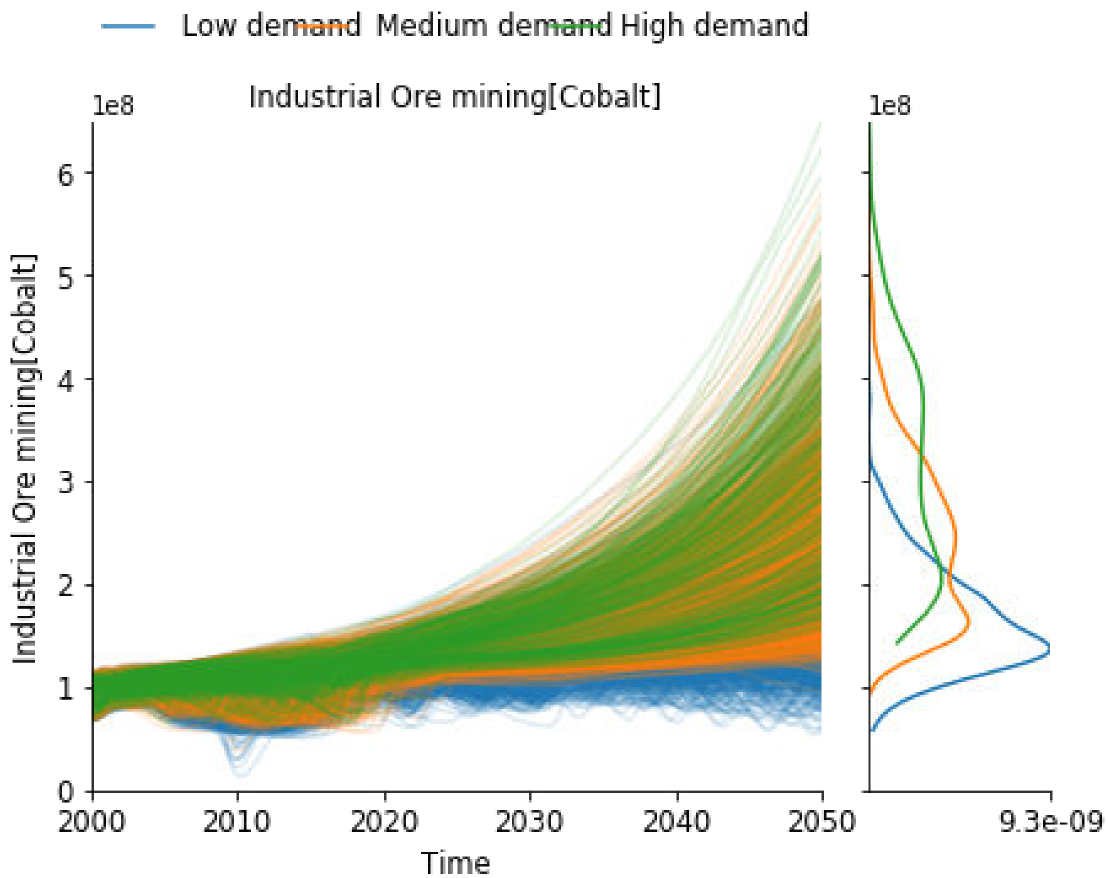


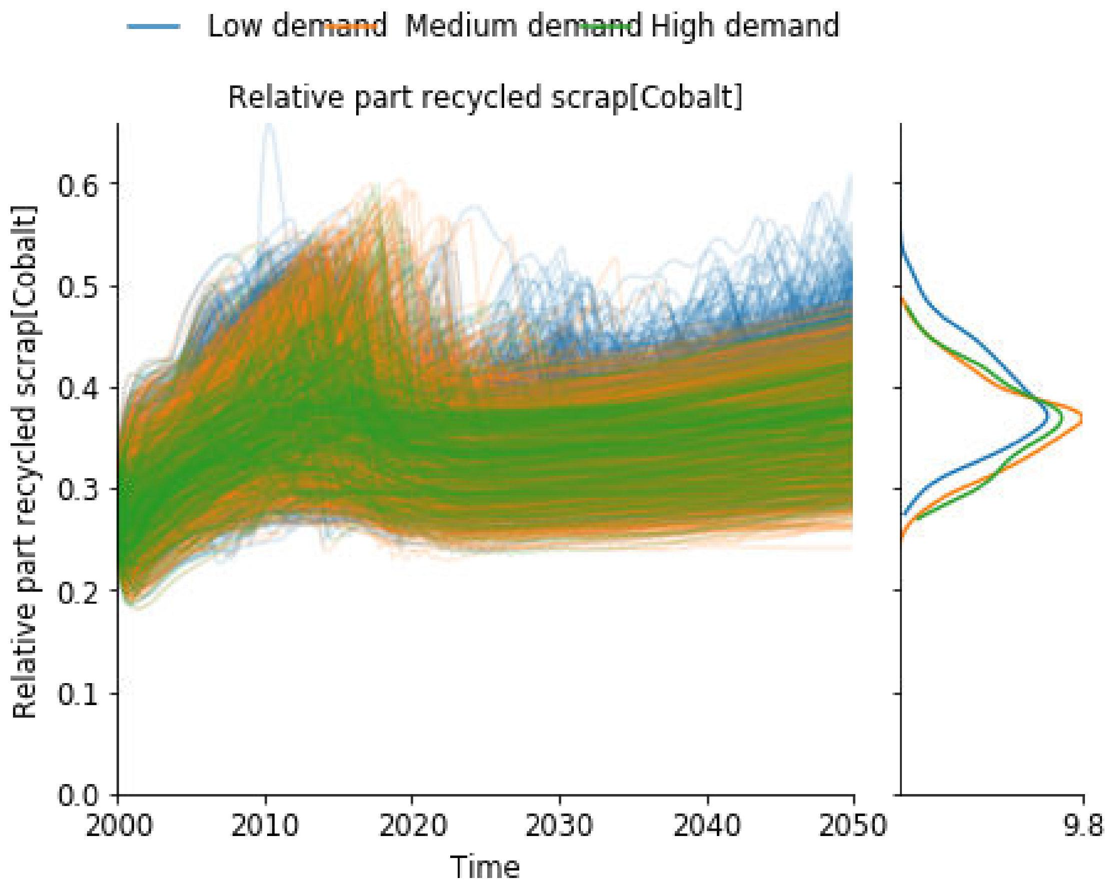
Low demand
Medium demand
High demand
Exponential index of depletion[Cobalt]
Exponential index of depletion[Cobalt]
0
100
200
300
400
500
600
2000
2010
2020
2030
2040
2050
Time
0.026



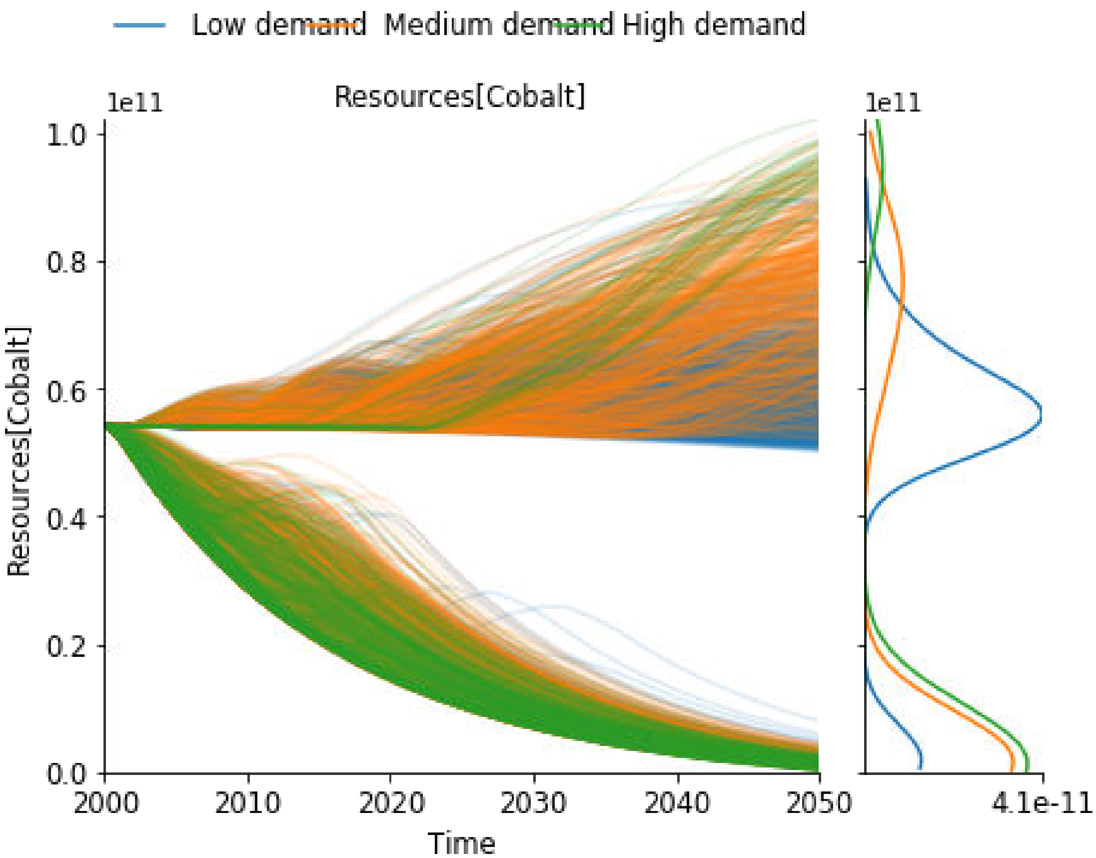
Low demand
Medium demand
High demand
Real price[Cobalt]
16000
14000
12000
10000
8000
6000
4000
2000
0
Real price[Cobalt]
2000
2010
2020
2030
2040
2050
Time
0
0.0061

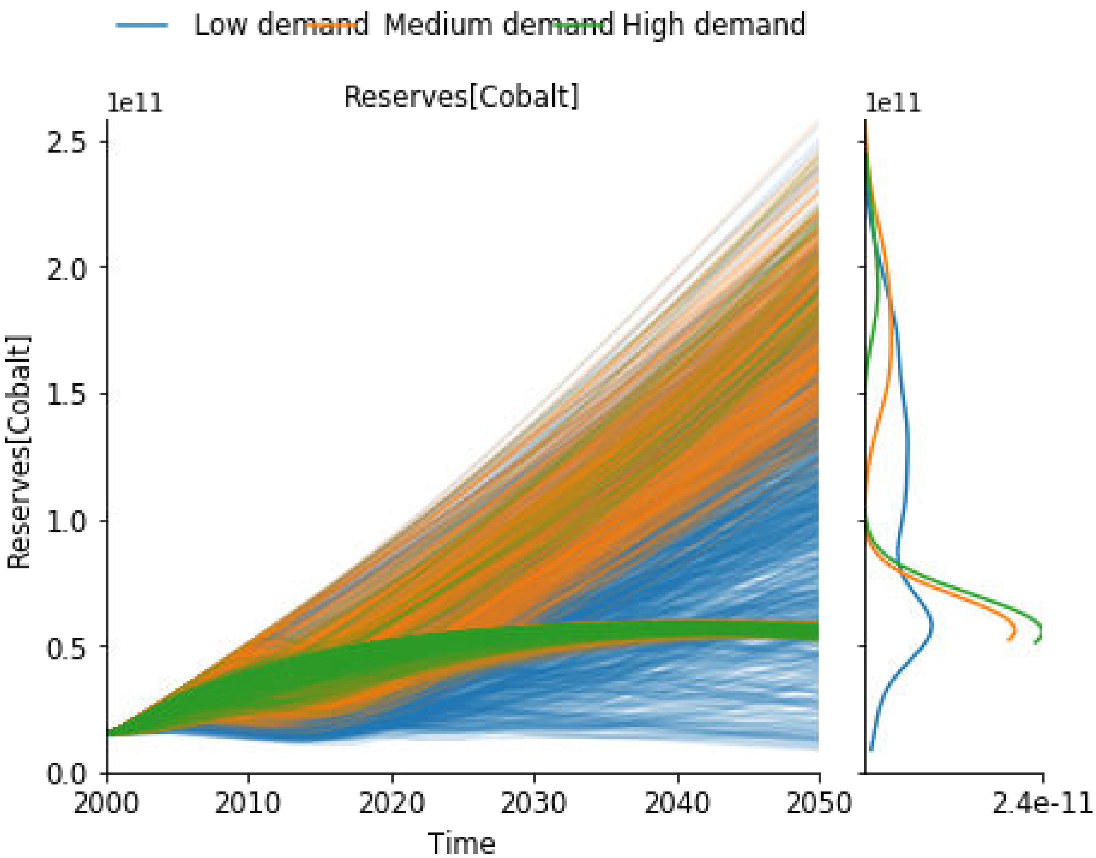

Low demand
Medium demand
High demand
Relative part artisanal mining[Cobalt]
Relative part artisanal mining[Cobalt]
0.6
0.5
0.4
0.3
0.2
0.1
0.0
2000
2010
2020
2030
2040
2050
Time
5.8


Low demand
Medium demand
High demand
Industrial Ore mining[Cobalt]
1e8
Industrial Ore mining[Cobalt]
0
1
2
3
4
5
6
2000
2010
2020
2030
2040
2050
Time
1e8
9.3e-09

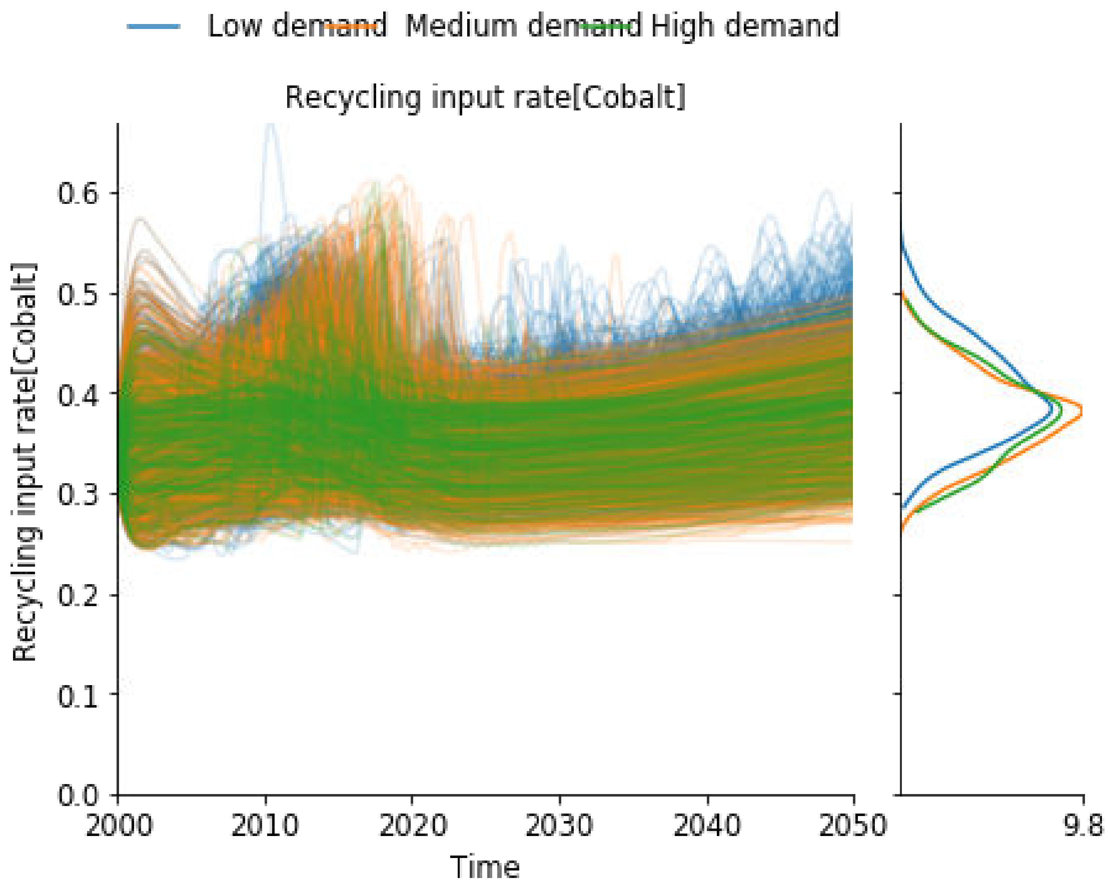


Low demand
Medium demand
High demand
Relative part recycled scrap[Cobalt]
Relative part recycled scrap[Cobalt]
0.0
0.1
0.2
0.3
0.4
0.5
0.6
2000
2010
2020
2030
2040
2050
Time
9.8

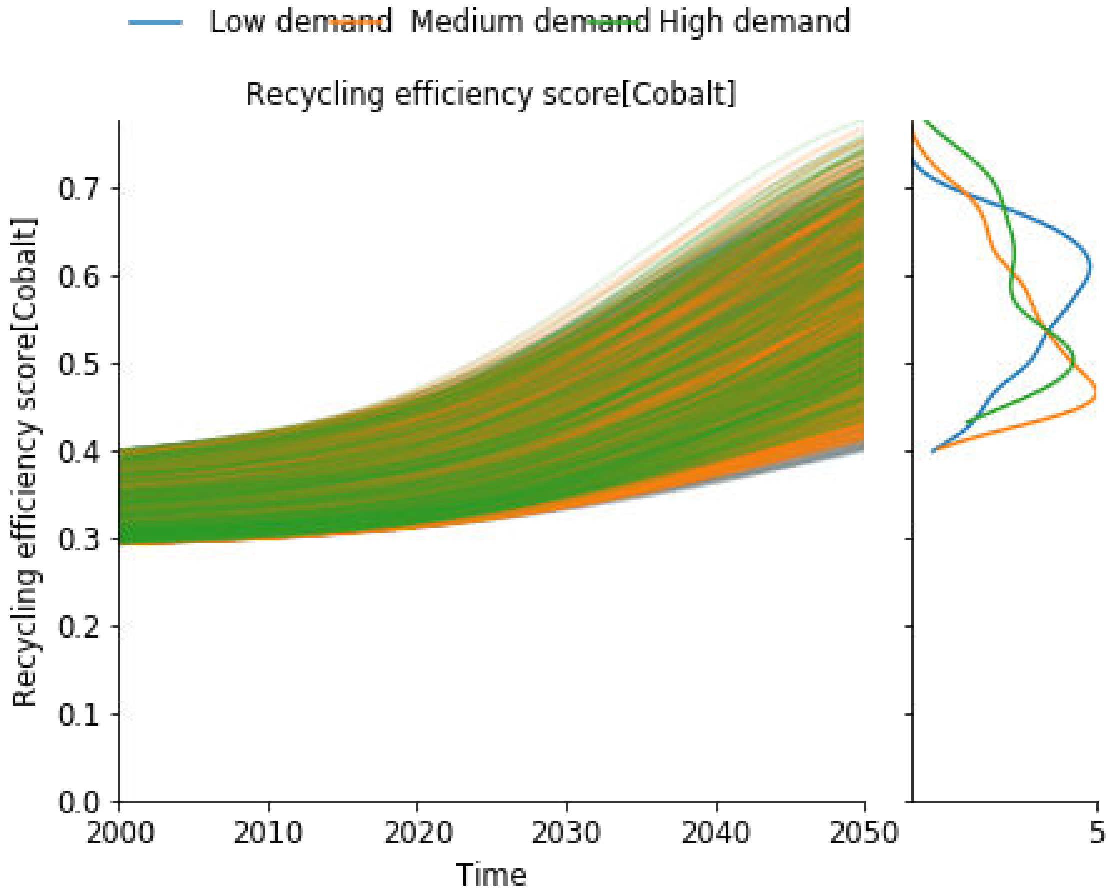

Low demand
Medium demand
High demand
Resources[Cobalt]
1e11
1.0
0.8
0.6
0.4
0.2
0.0
Resources[Cobalt]
2000
2010
2020
2030
2040
2050
Time
1e11
4.1e-11

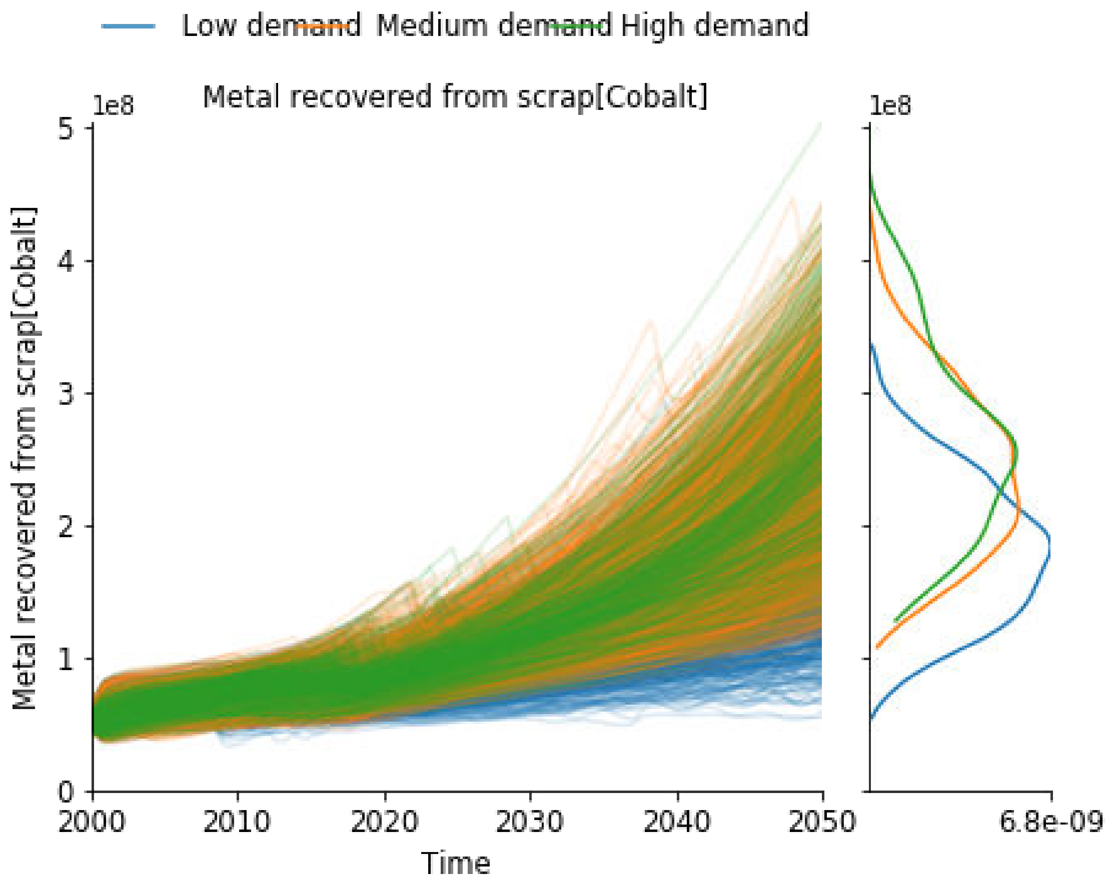


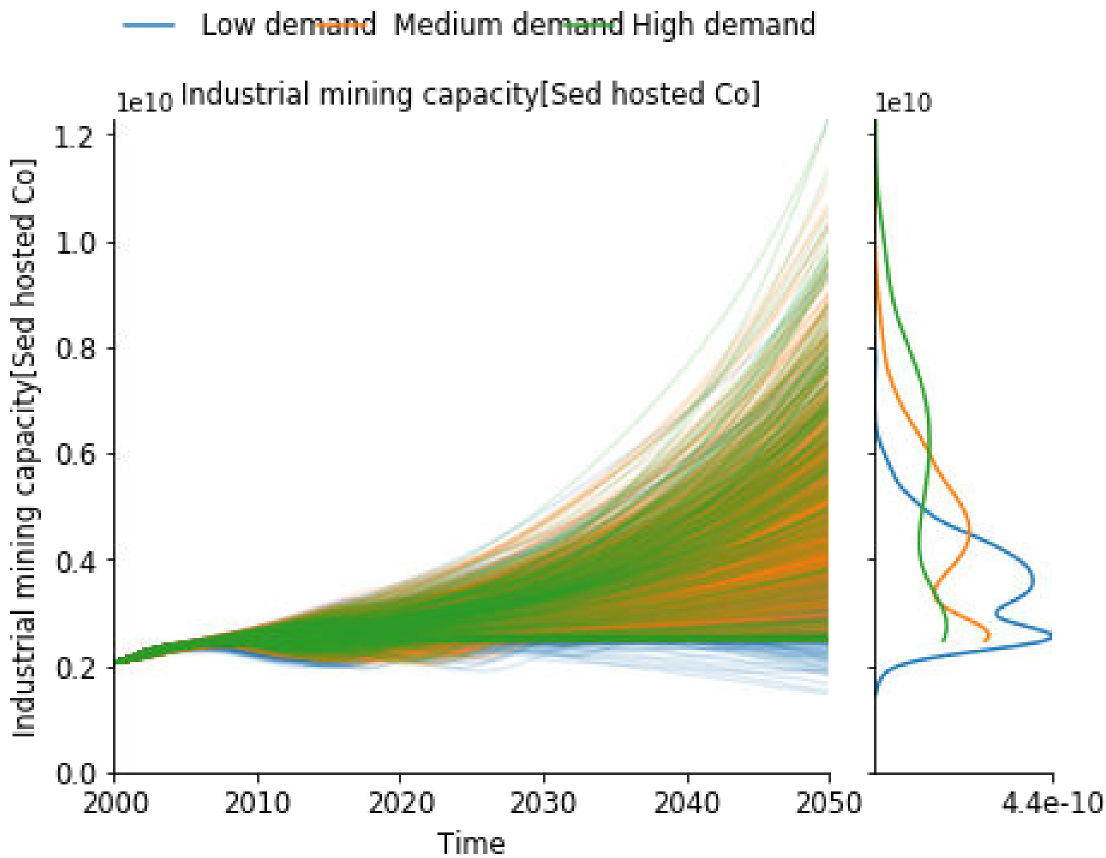
Low demand
Medium demand
High demand
Reserves[Cobalt]
1e11
2.5
2.0
1.5
1.0
0.5
0.0
Reserves[Cobalt]
2000
2010
2020
2030
2040
2050
Time
1e11
2.4e-11



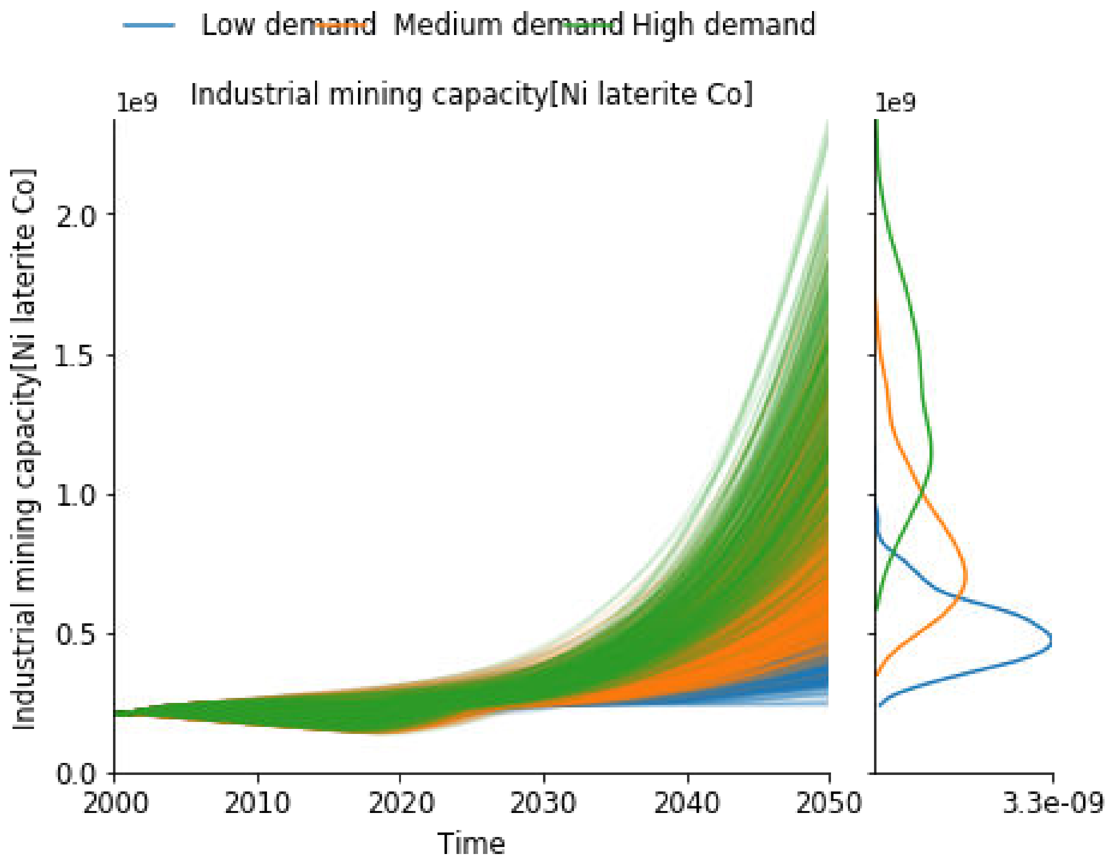
Low demand
Medium demand
High demand
Recycling input rate[Cobalt]
Recycling input rate[Cobalt]
0.0
0.1
0.2
0.3
0.4
0.5
0.6
2000
2010
2020
2030
2040
2050
Time
9.8

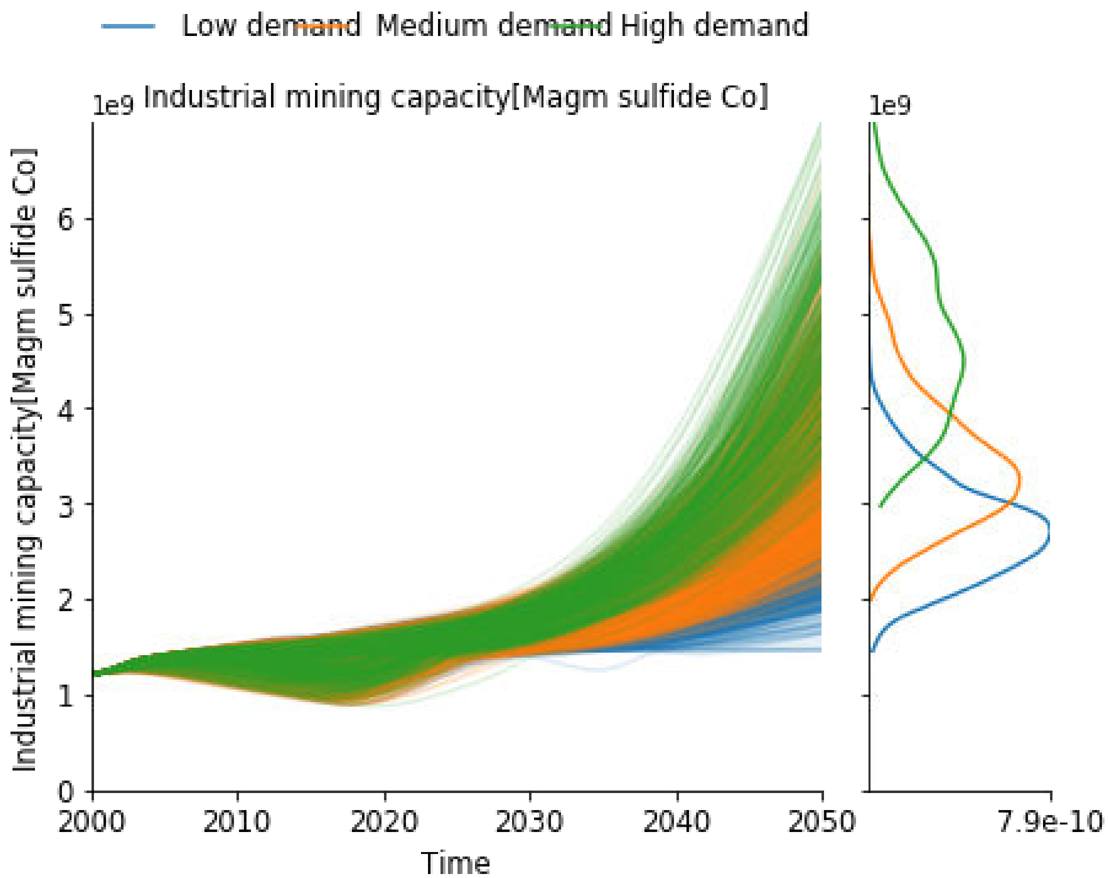

Low demand
Medium demand
High demand
Recycling efficiency score[Cobalt]
Recycling efficiency score[Cobalt]
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
2000
2010
2020
2030
2040
2050
Time
5

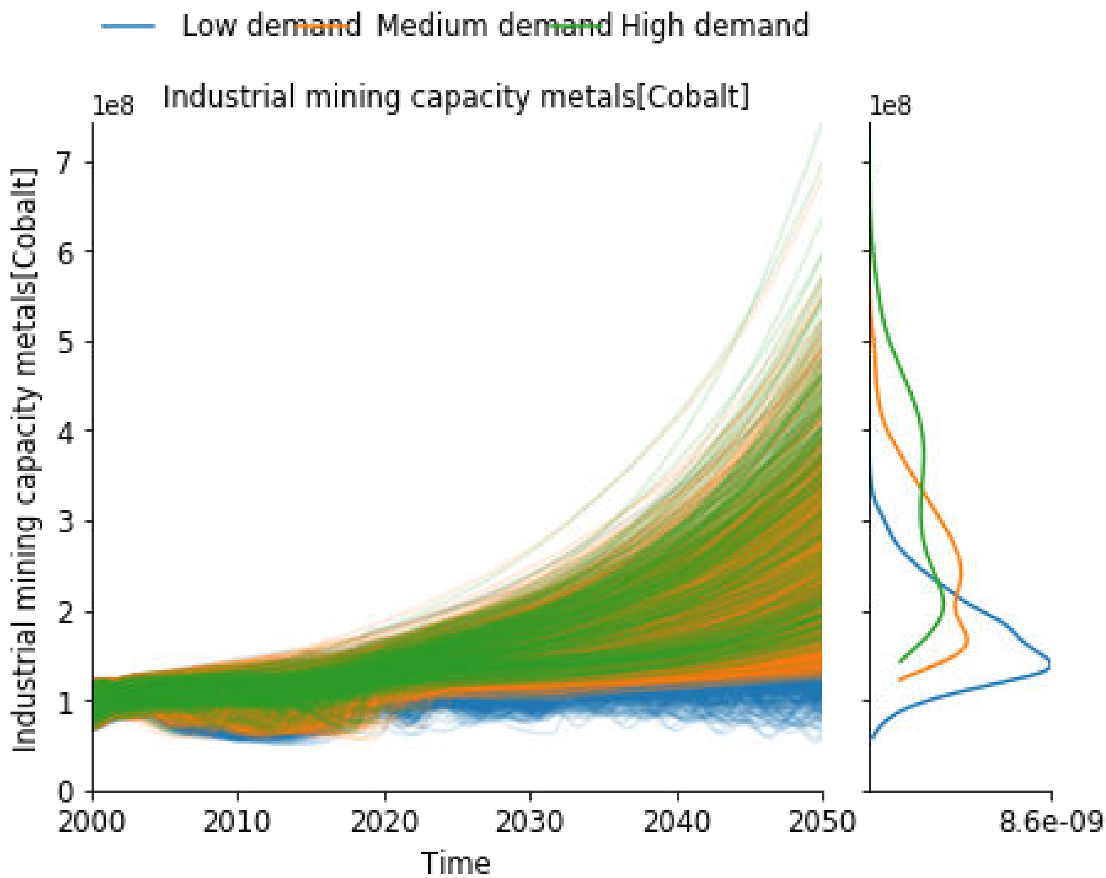

Low demand
Medium demand
High demand
Metal recovered from scrap[Cobalt]
1e8
Metal recovered from scrap[Cobalt]
0
1
2
3
4
5
2000
2010
2020
2030
2040
2050
Time
1e8
6.8e-09

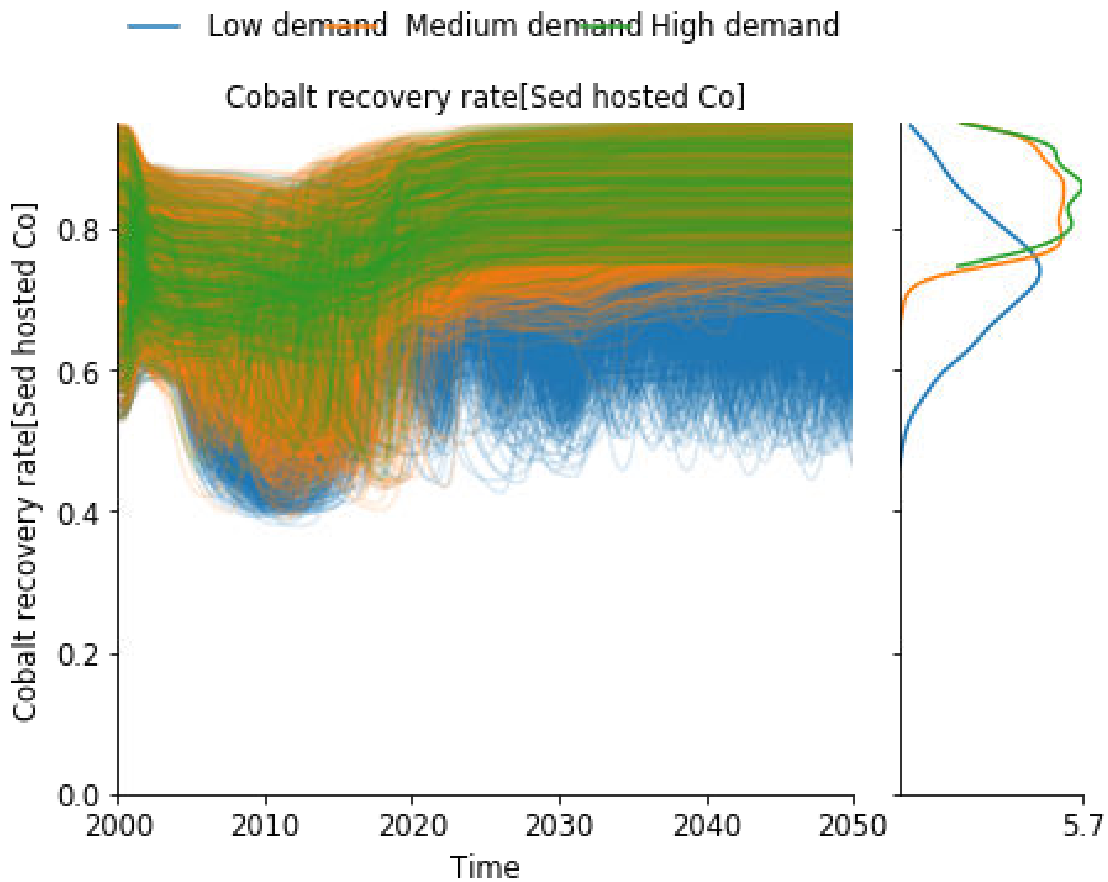


Low demand
Medium demand
High demand
Industrial mining capacity[Sed hosted Co]
1e10
1.2
1.0
0.8
0.6
0.4
0.2
0.0
Industrial mining capacity[Sed hosted Co]
2000
2010
2020
2030
2040
2050
Time
1e10
4.4e-10

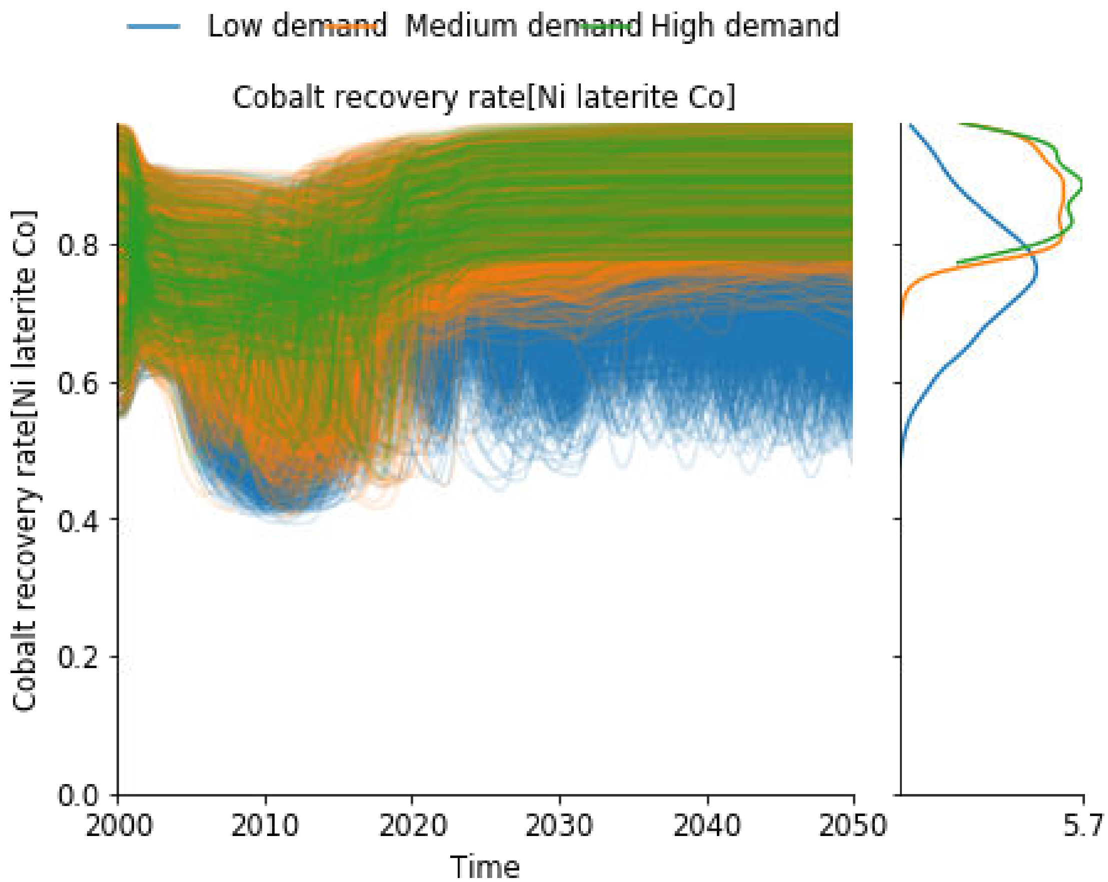

Low demand
Medium demand
High demand
Industrial mining capacity[Ni laterite Co]
1e9
Industrial mining capacity[Ni laterite Co]
2.0
1.5
1.0
0.5
0.0
2000
2010
2020
2030
2040
2050
Time
1e9
3.3e-09

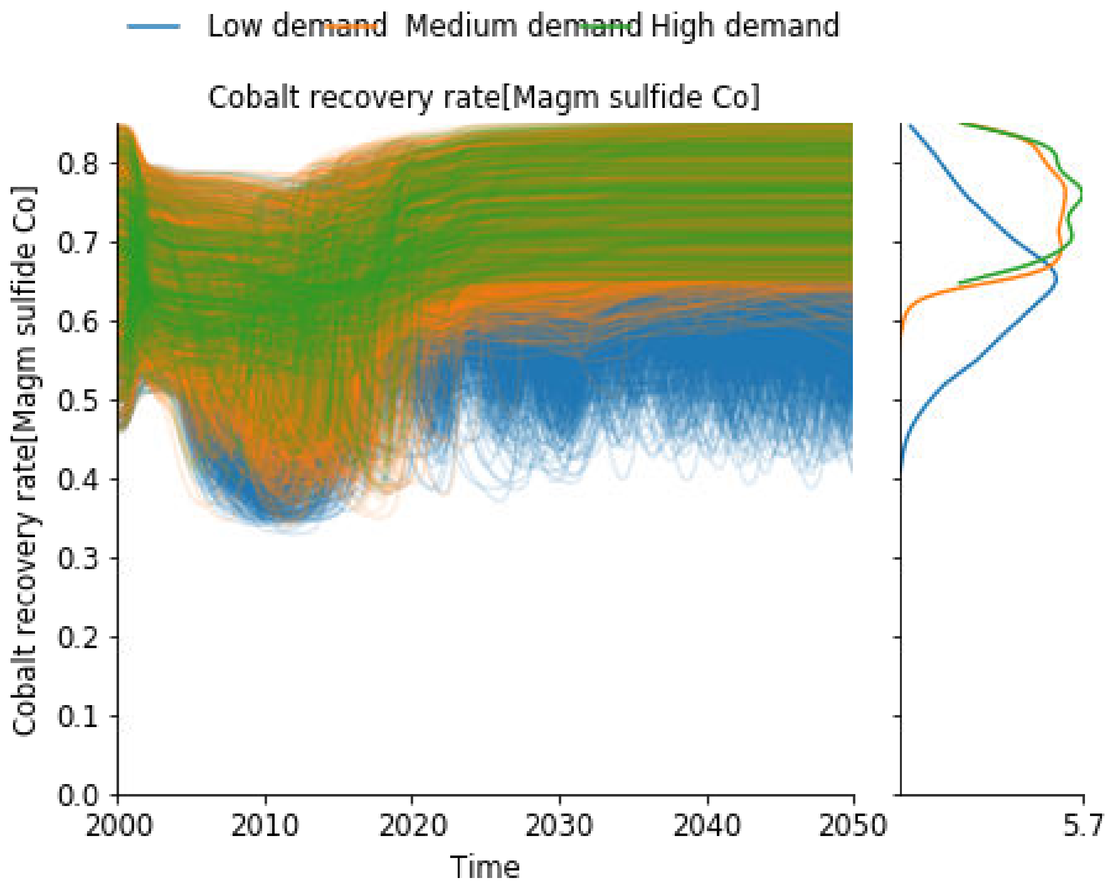

Low demand
Medium demand
High demand
Industrial mining capacity[Magm sulfide Co]
1e9
Industrial mining capacity[Magm sulfide Co]
0
1
2
3
4
5
6
2000
2010
2020
2030
2040
2050
Time
1e9
7.9e-10


Low demand
Medium demand
High demand
Industrial mining capacity metals[Cobalt]
1e8
Industrial mining capacity metals[Cobalt]
0
1
2
3
4
5
6
7
2000
2010
2020
2030
2040
2050
Time
1e8
8.6e-09

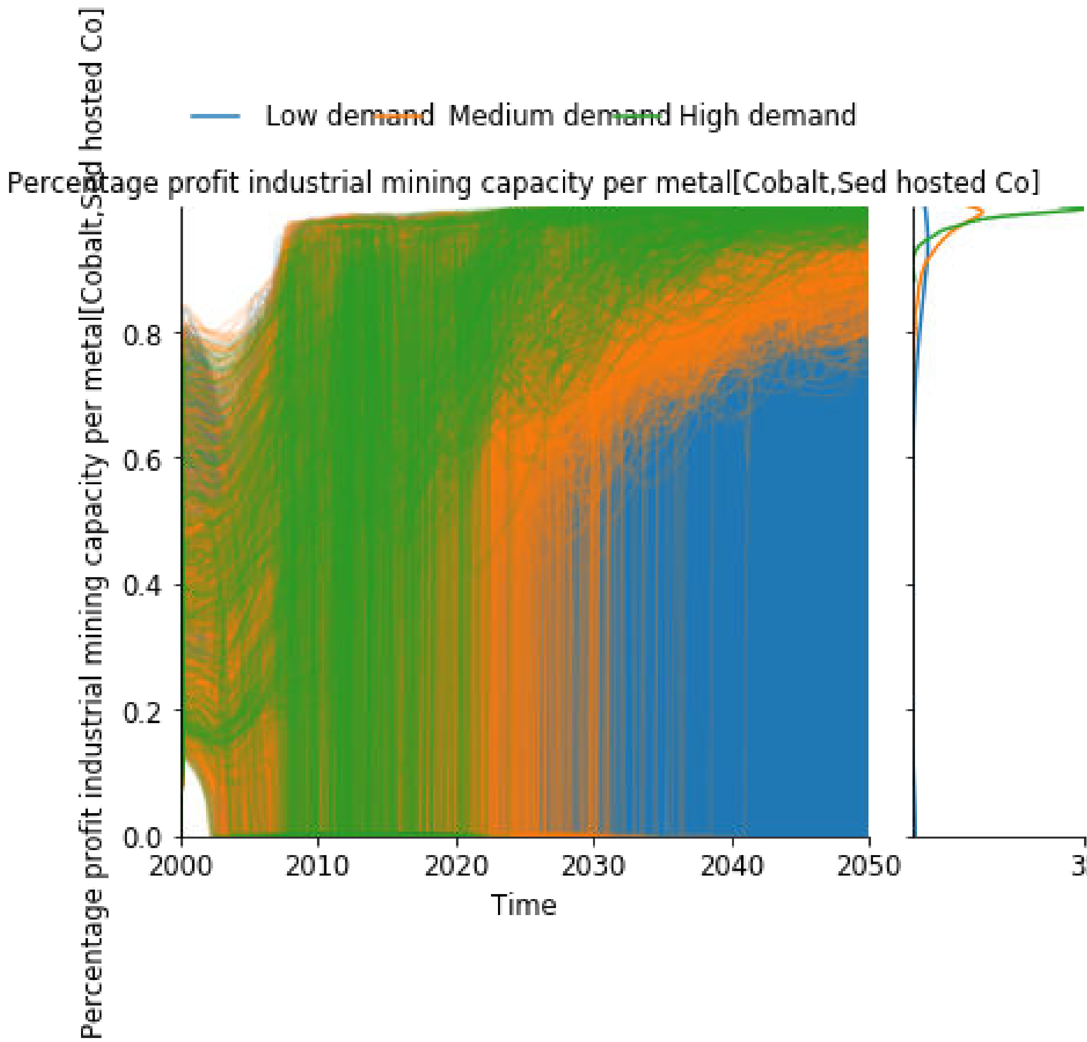


Low demand
Medium demand
High demand
Cobalt recovery rate[Sed hosted Co]
Cobalt recovery rate[Sed hosted Co]
0.0
0.2
0.4
0.6
0.8
2000
2010
2020
2030
2040
2050
Time
5.7

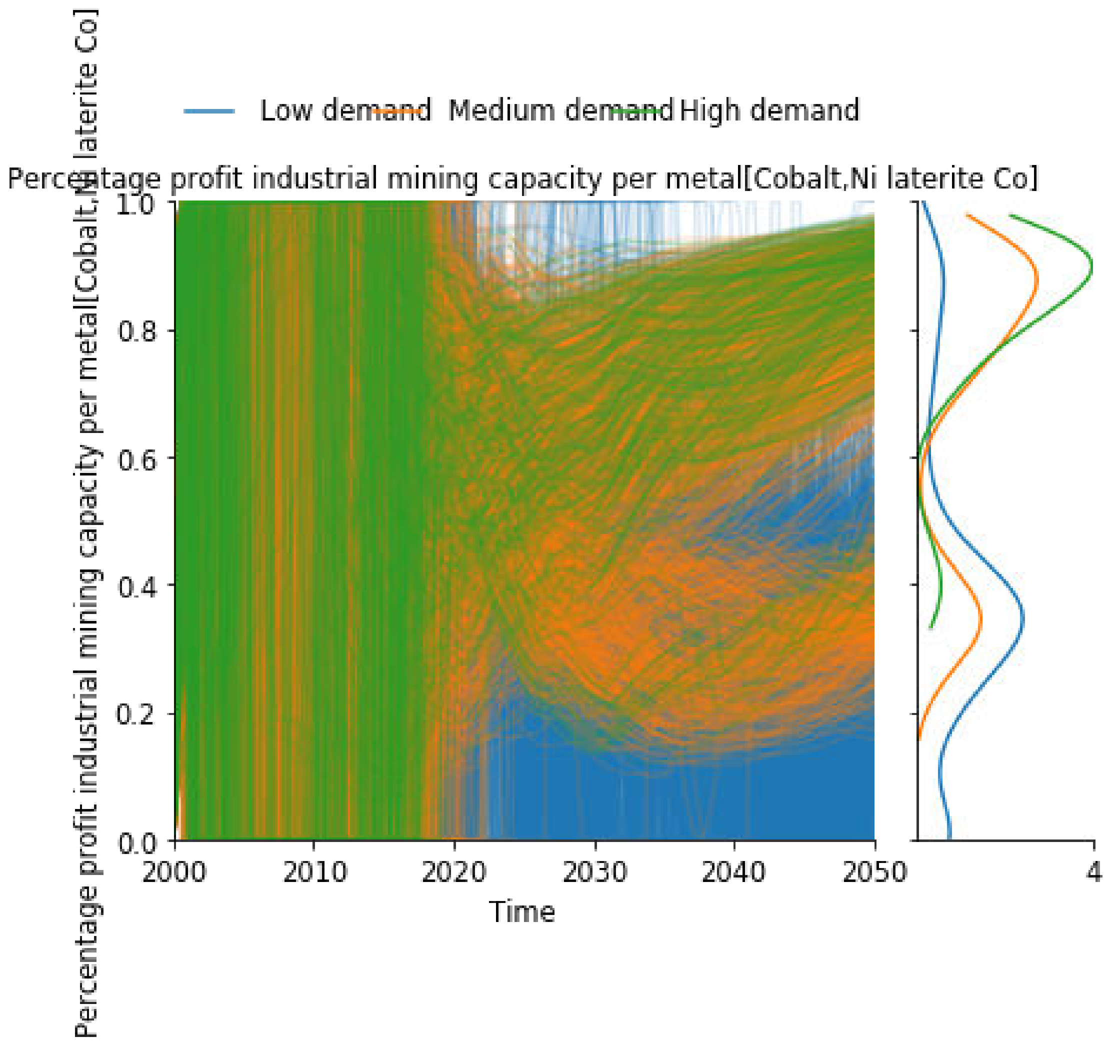

Low demand
Medium demand
High demand
Cobalt recovery rate[Ni laterite Co]
Cobalt recovery rate[Ni laterite Co]
0.0
0.2
0.4
0.6
0.8
2000
2010
2020
2030
2040
2050
Time
5.7



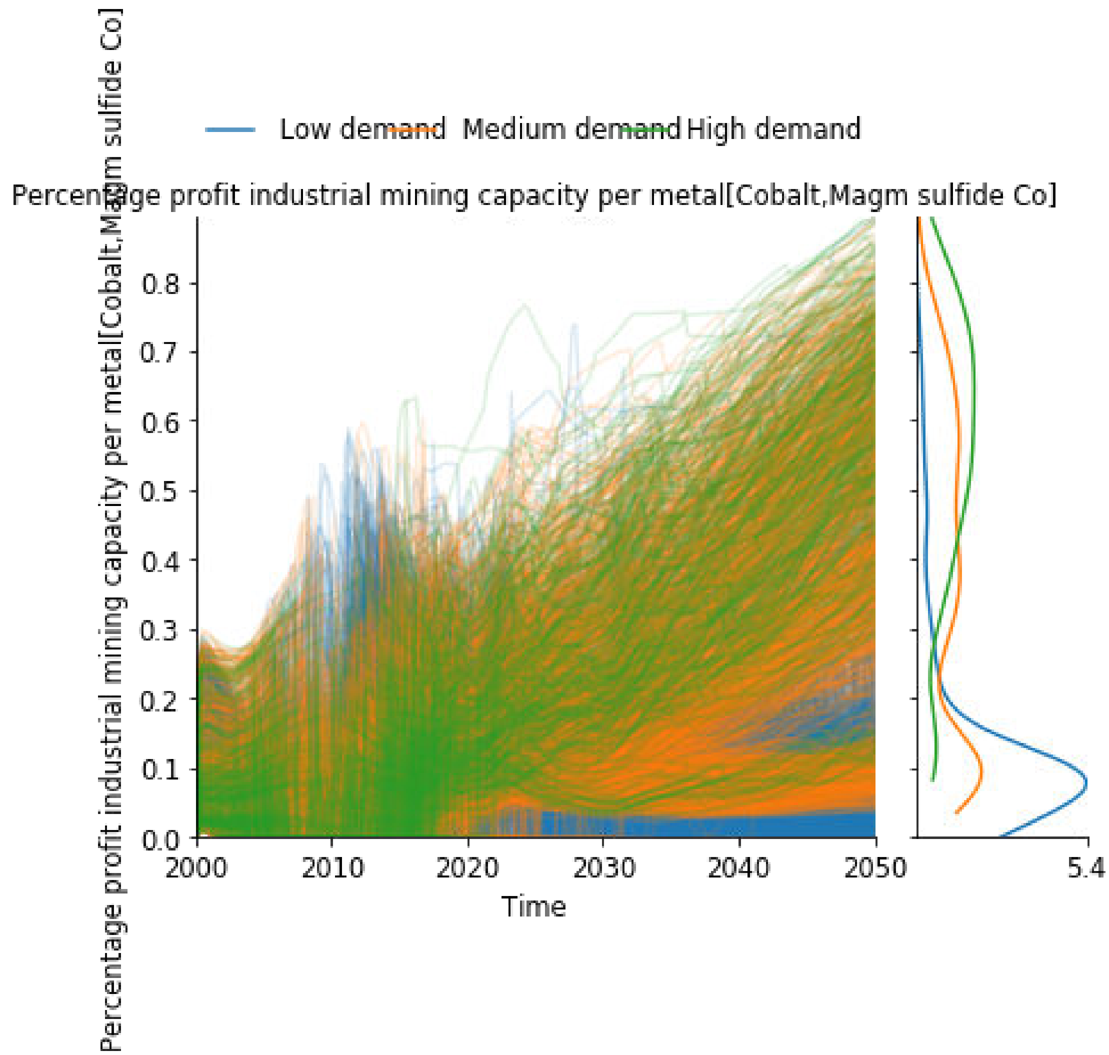
Low demand
Medium demand
High demand
Cobalt recovery rate[Magm sulfide Co]
Cobalt recovery rate[Magm sulfide Co]
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
2000
2010
2020
2030
2040
2050
Time
5.7

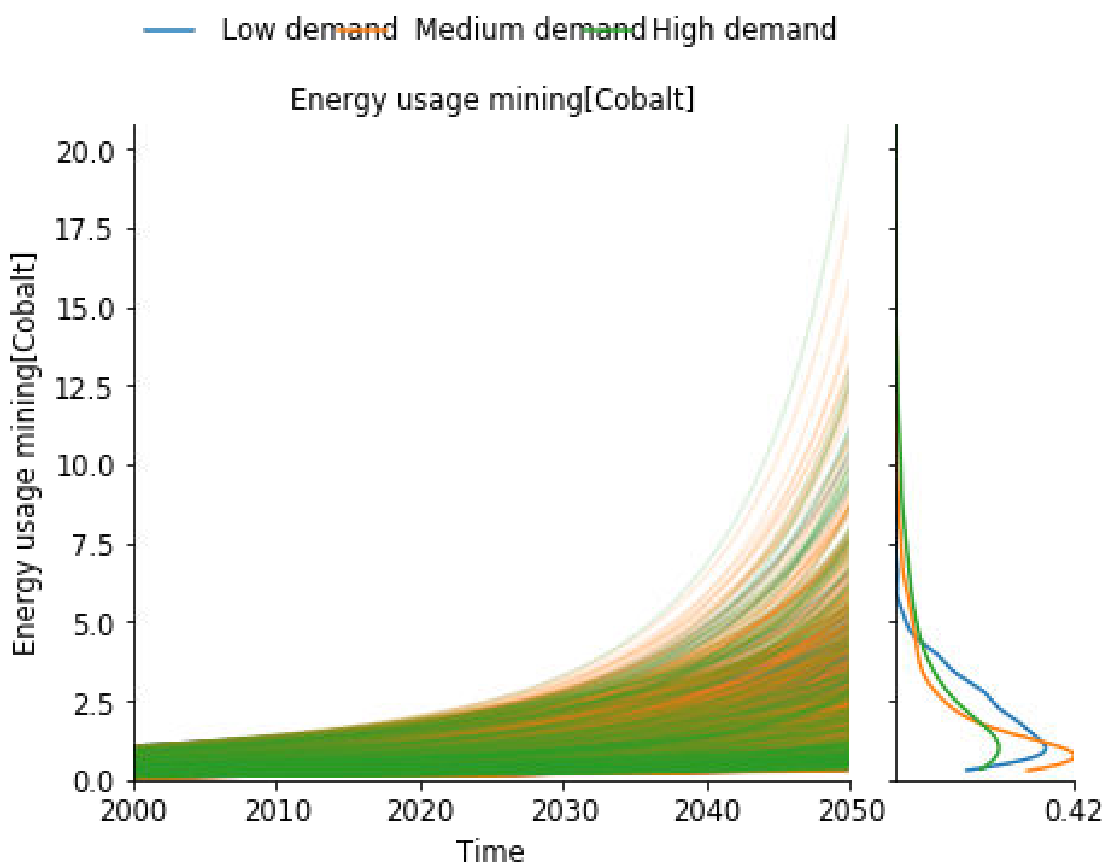


Low demand
Medium demand
High demand
Percentage profit industrial mining capacity per metal[Cobalt,Sed hosted Co]
Percentage profit industrial mining capacity per metal[Cobalt,Sed hosted Co]
0.0
0.2
0.4
0.6
0.8
2000
2010
2020
2030
2040
2050
Time
35

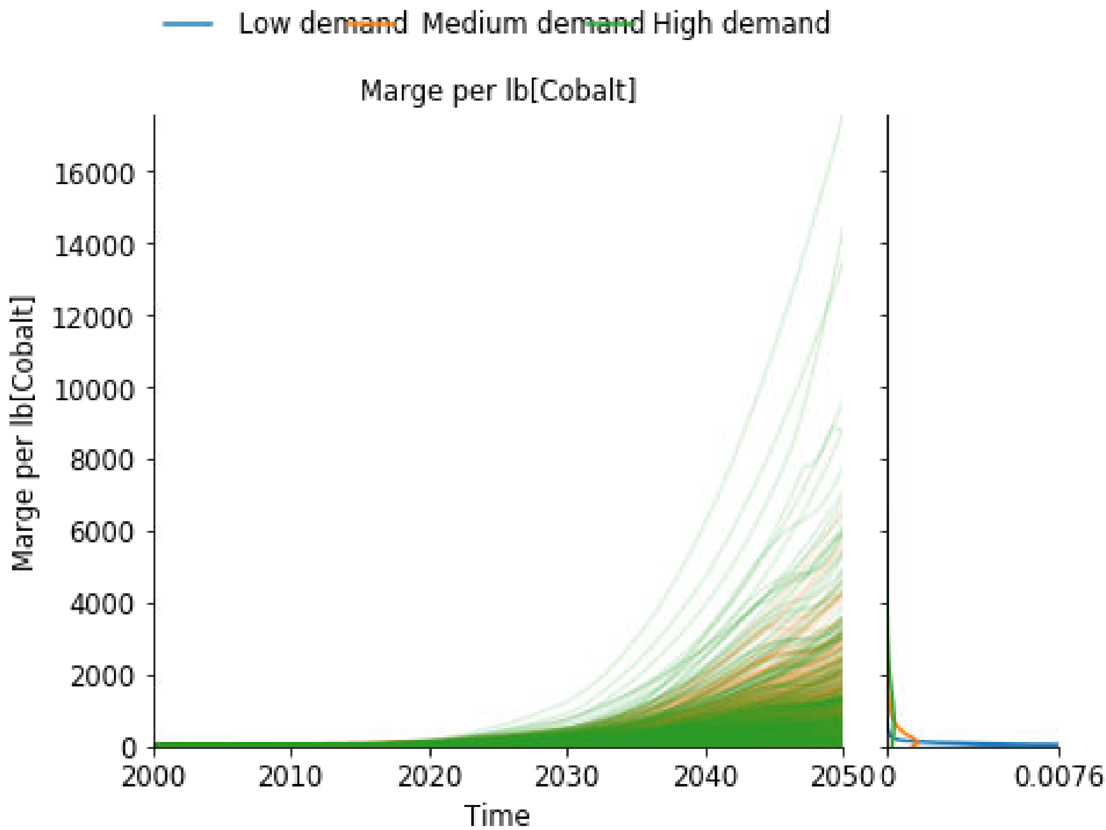


Low demand
Medium demand
High demand
Percentage profit industrial mining capacity per metal[Cobalt,Ni laterite Co]
Percentage profit industrial mining capacity per metal[Cobalt,Ni laterite Co]
0.0
0.2
0.4
0.6
0.8
1.0
2000
2010
2020
2030
2040
2050
Time
4

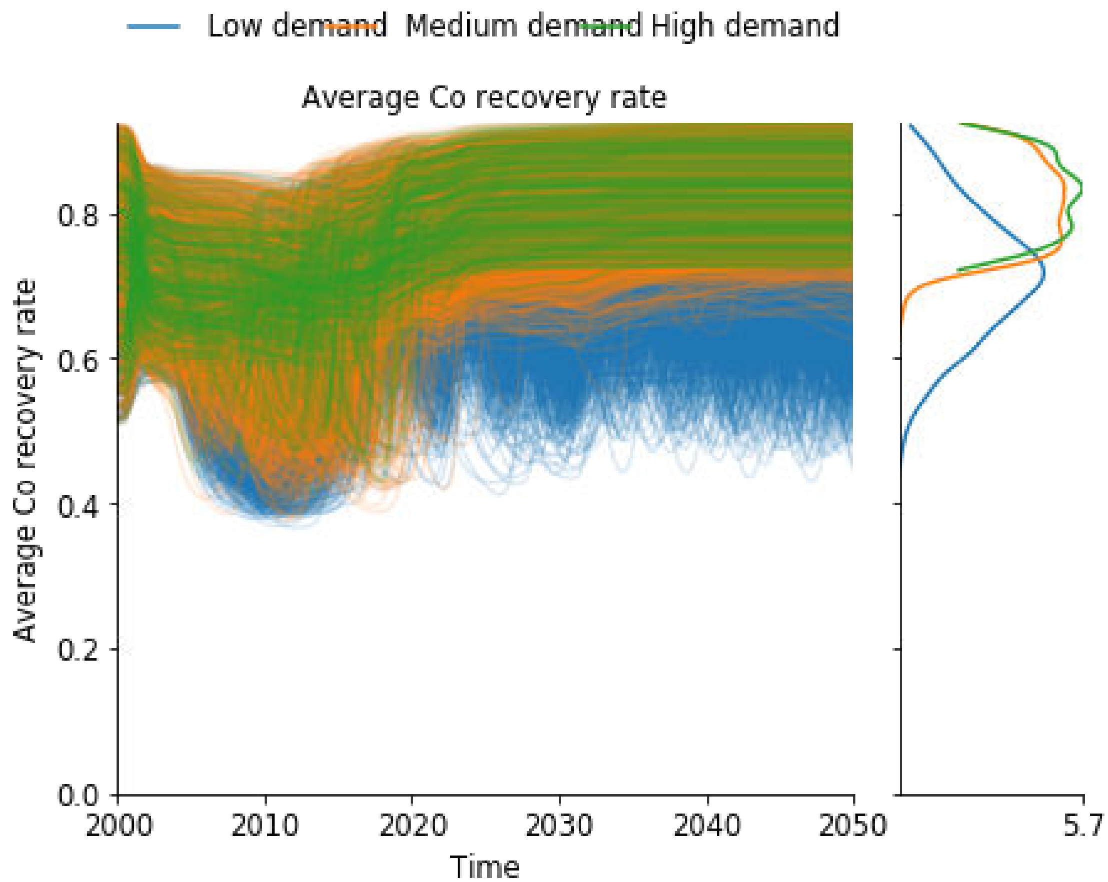

Low demand
Medium demand
High demand
Percentage profit industrial mining capacity per metal[Cobalt,Magm sulfide Co]
Percentage profit industrial mining capacity per metal[Cobalt,Magm sulfide Co]
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
2000
2010
2020
2030
2040
2050
Time
5.4



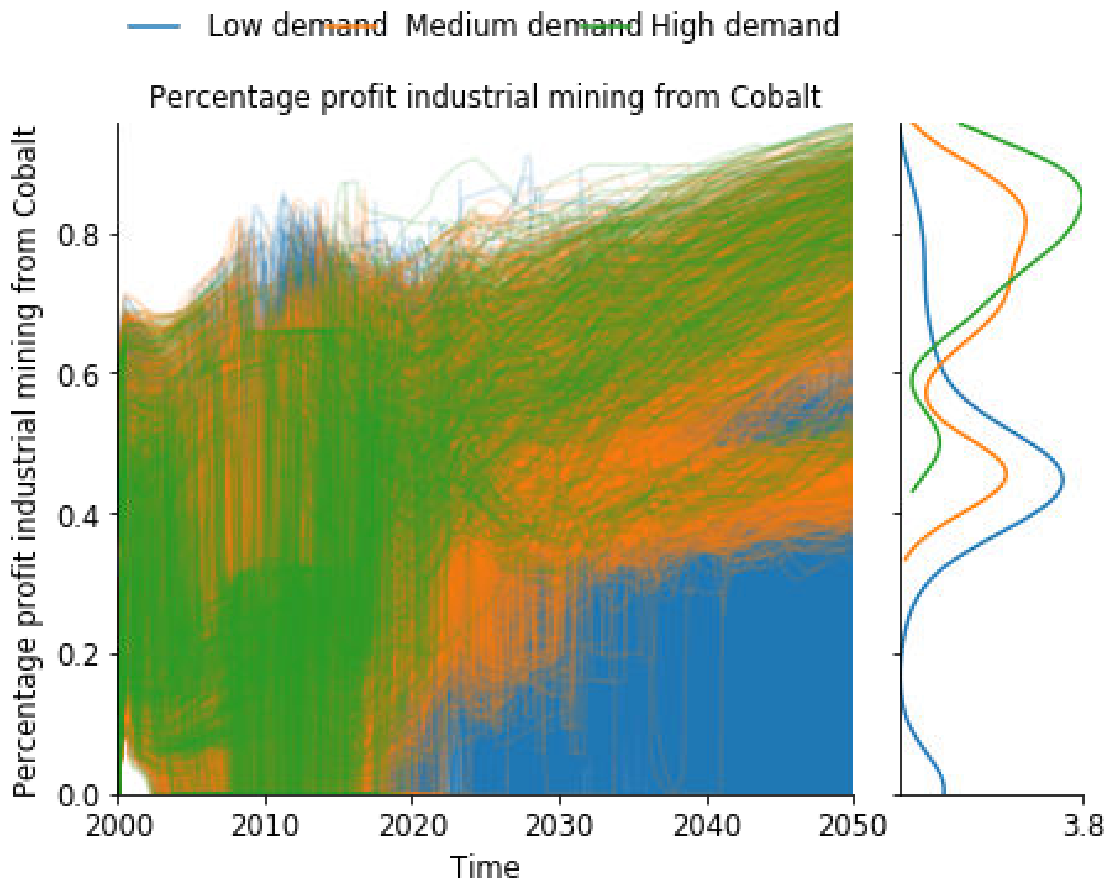
Low demand
Medium demand
High demand
Energy usage mining[Cobalt]
Energy usage mining[Cobalt]
20.0
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
2000
2010
2020
2030
2040
2050
Time
0.42

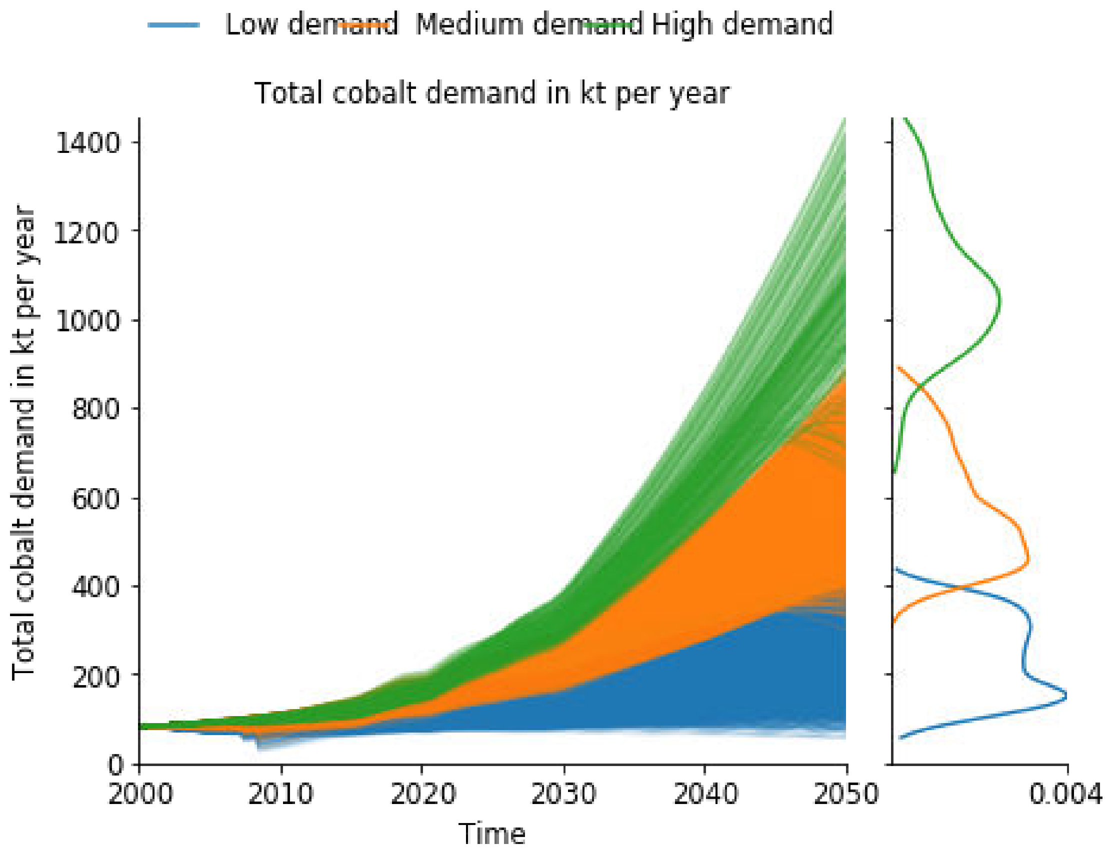


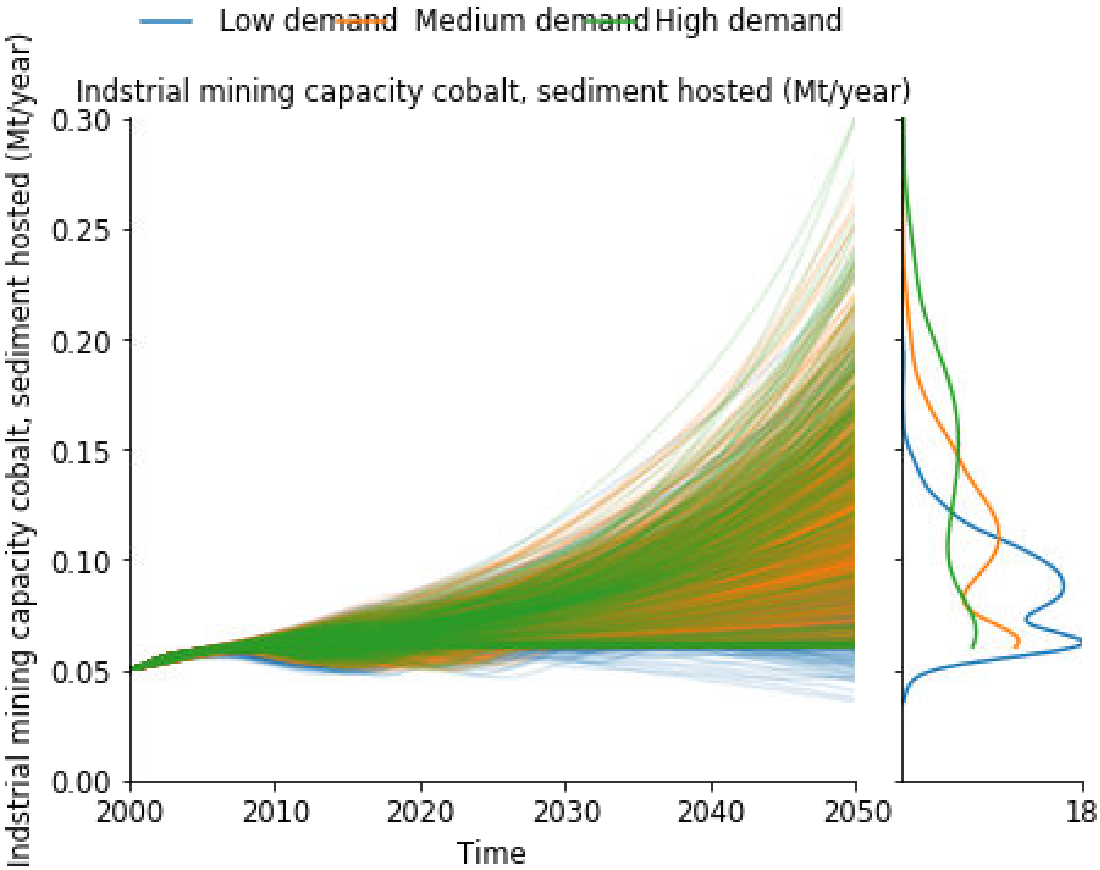
Low demand
Medium demand
High demand
Marge per lb[Cobalt]
16000
14000
12000
10000
8000
6000
4000
2000
0
2000
2010
2020
2030
2040
2050
0
0.0076
Time

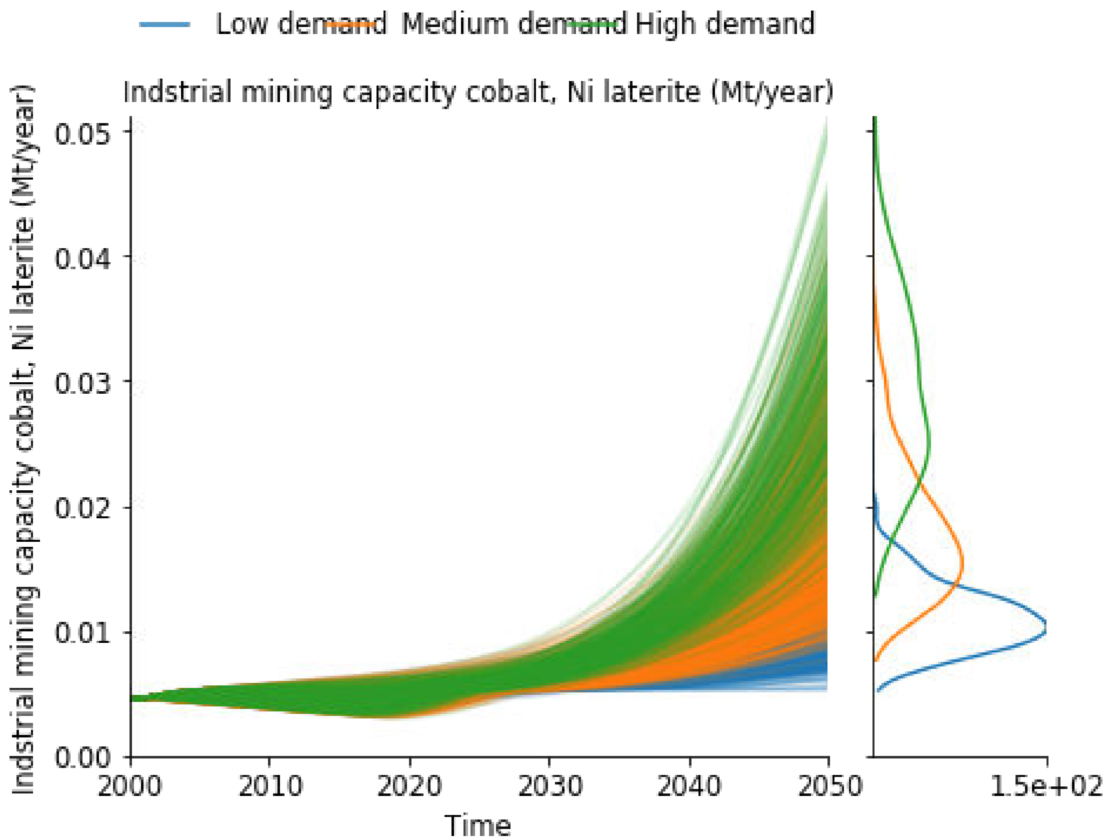


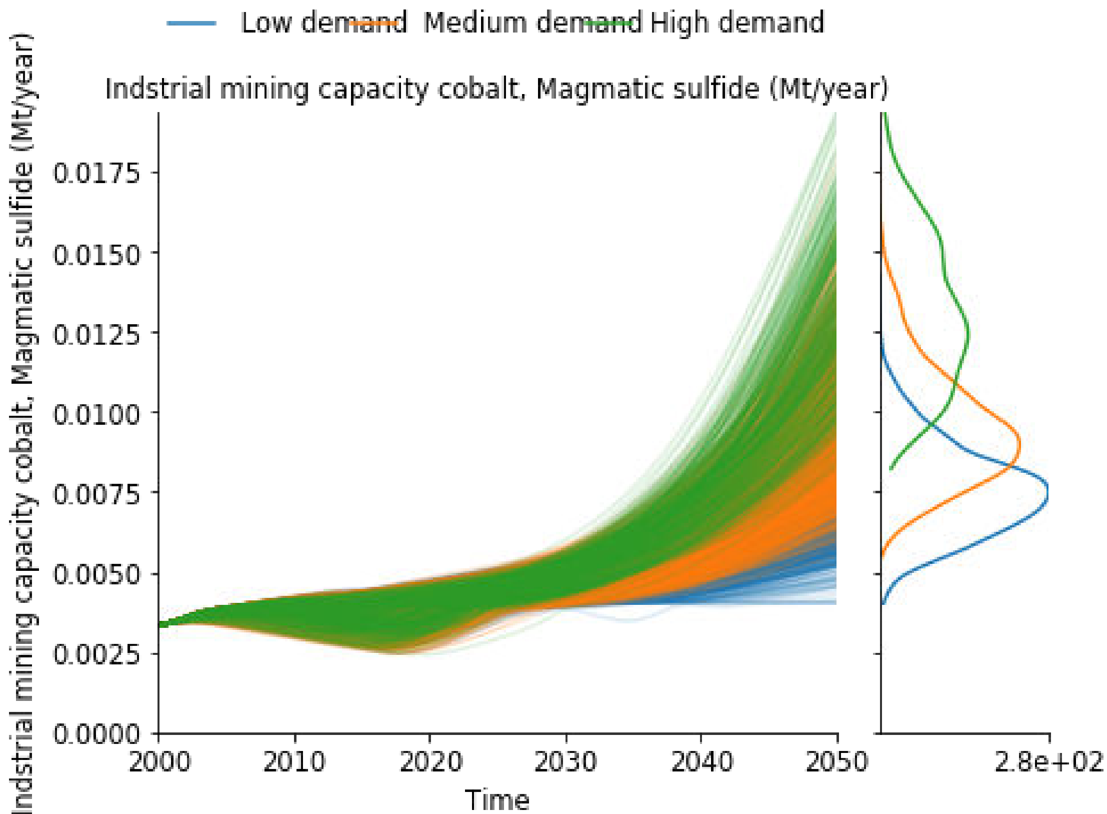
Low demand
Medium demand
High demand
Average Co recovery rate
Average Co recovery rate
0.0
0.2
0.4
0.6
0.8
2000
2010
2020
2030
2040
2050
Time
5.7

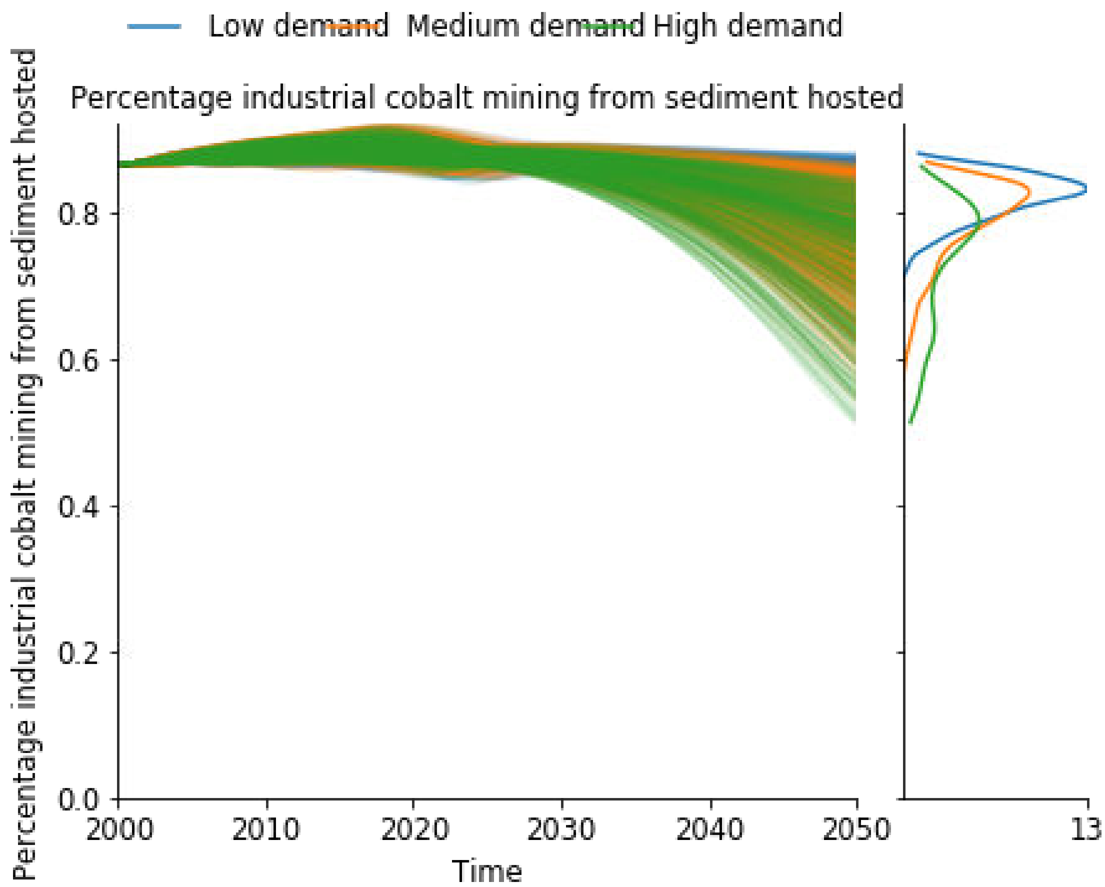

Low demand
Medium demand
High demand
Percentage profit industrial mining from Cobalt
Percentage profit industrial mining from Cobalt
0.0
0.2
0.4
0.6
0.8
2000
2010
2020
2030
2040
2050
Time
3.8

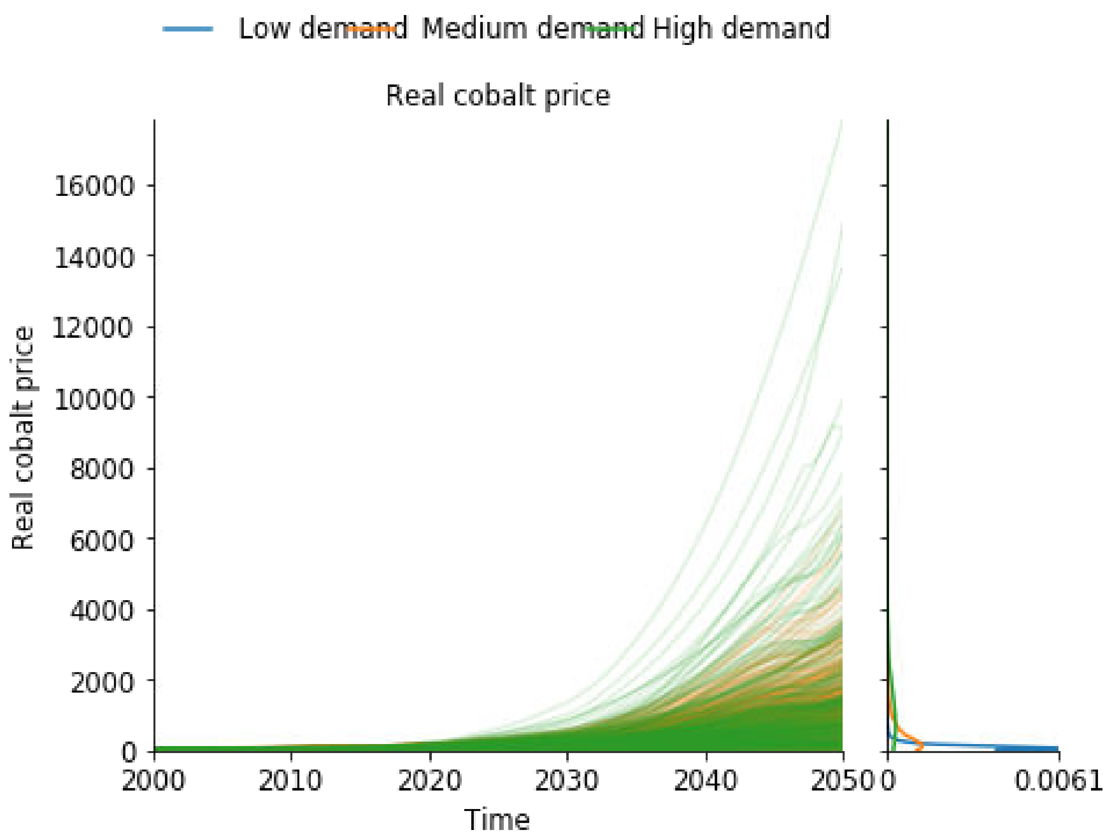

Low demand
Medium demand
High demand
Total cobalt demand in kt per year
Total cobalt demand in kt per year
1400
1200
1000
800
600
400
200
0
2000
2010
2020
2030
2040
2050
Time
0.004


Low demand
Medium demand
High demand
Indstrial mining capacity cobalt, sediment hosted (Mt/year)
Indstrial mining capacity cobalt, sediment hosted (Mt/year)
0.30
0.25
0.20
0.15
0.10
0.05
0.00
2000
2010
2020
2030
2040
2050
Time
18

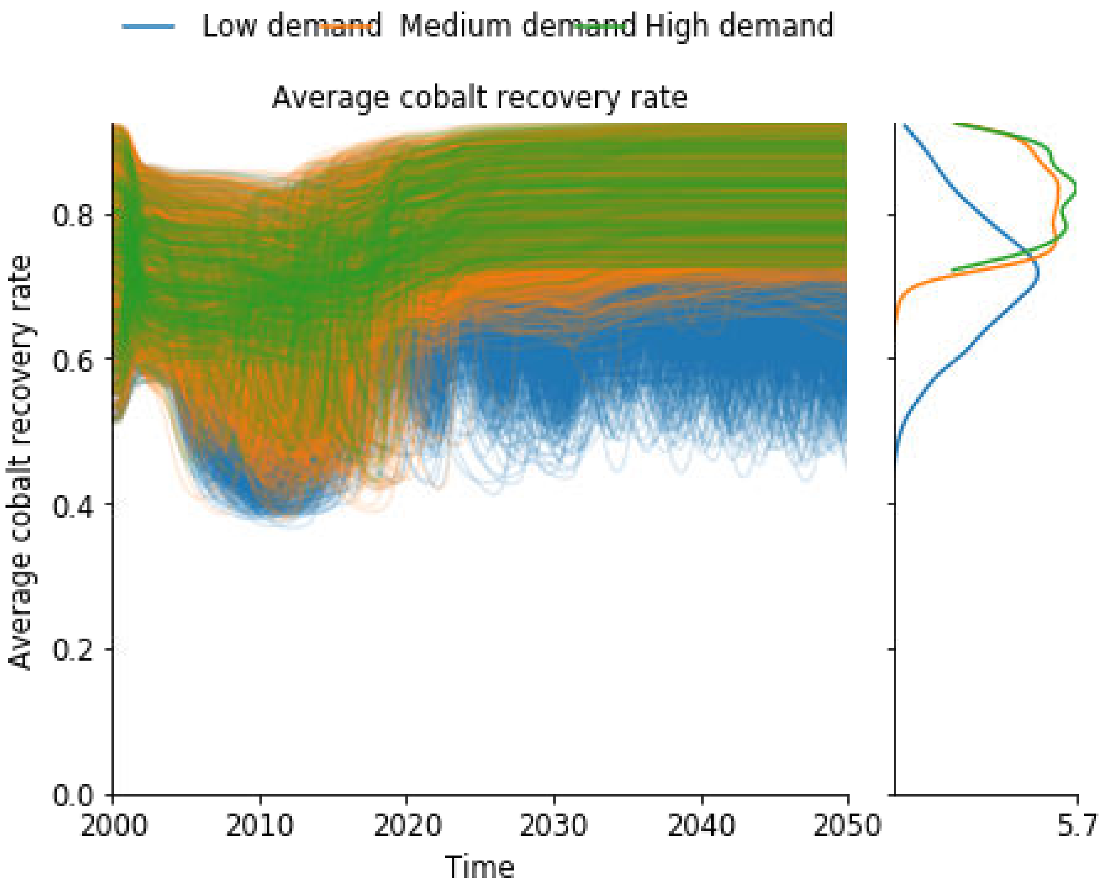

Low demand
Medium demand
High demand
Indstrial mining capacity cobalt, Ni laterite (Mt/year)
Indstrial mining capacity cobalt, Ni laterite (Mt/year)
0.05
0.04
0.03
0.02
0.01
0.00
2000
2010
2020
2030
2040
2050
Time
1.5e+02


Low demand
Medium demand
High demand
Indstrial mining capacity cobalt, Magmatic sulfide (Mt/year)
Indstrial mining capacity cobalt, Magmatic sulfide (Mt/year)
0.0000
0.0025
0.0050
0.0075
0.0100
0.0125
0.0150
0.0175
2000
2010
2020
2030
2040
2050
Time
2.8e+02

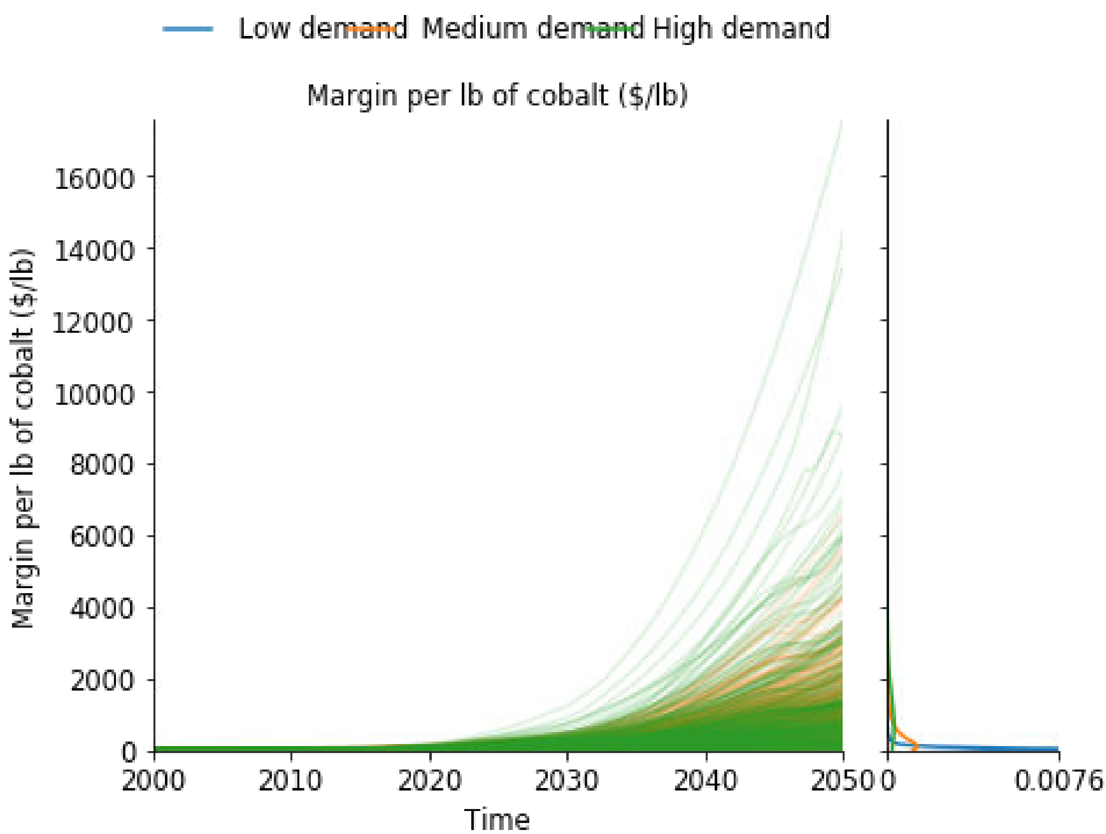

Low demand
Medium demand
High demand
Percentage industrial cobalt mining from sediment hosted
Percentage industrial cobalt mining from sediment hosted
0.0
0.2
0.4
0.6
0.8
2000
2010
2020
2030
2040
2050
Time
13



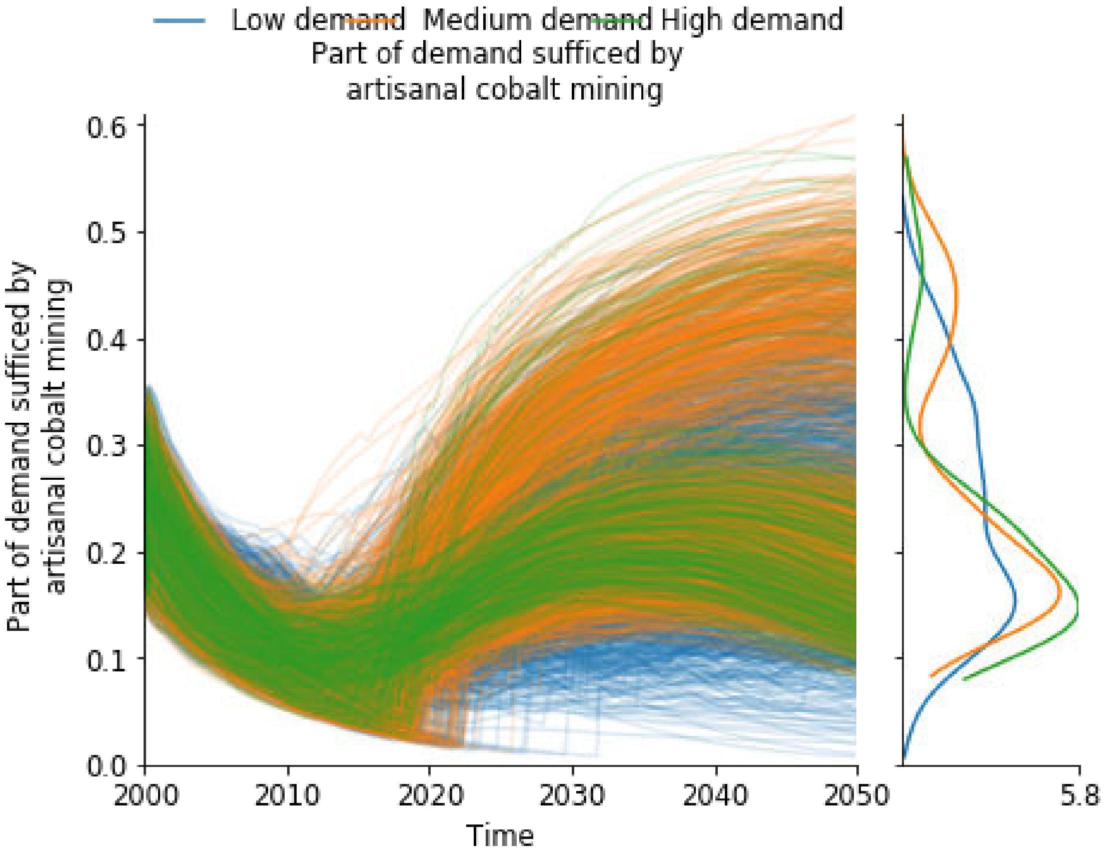
Low demand
Medium demand
High demand
Real cobalt price
Real cobalt price
16000
14000
12000
10000
8000
6000
4000
2000
0
2000
2010
2020
2030
2040
2050
Time
0
0.0061

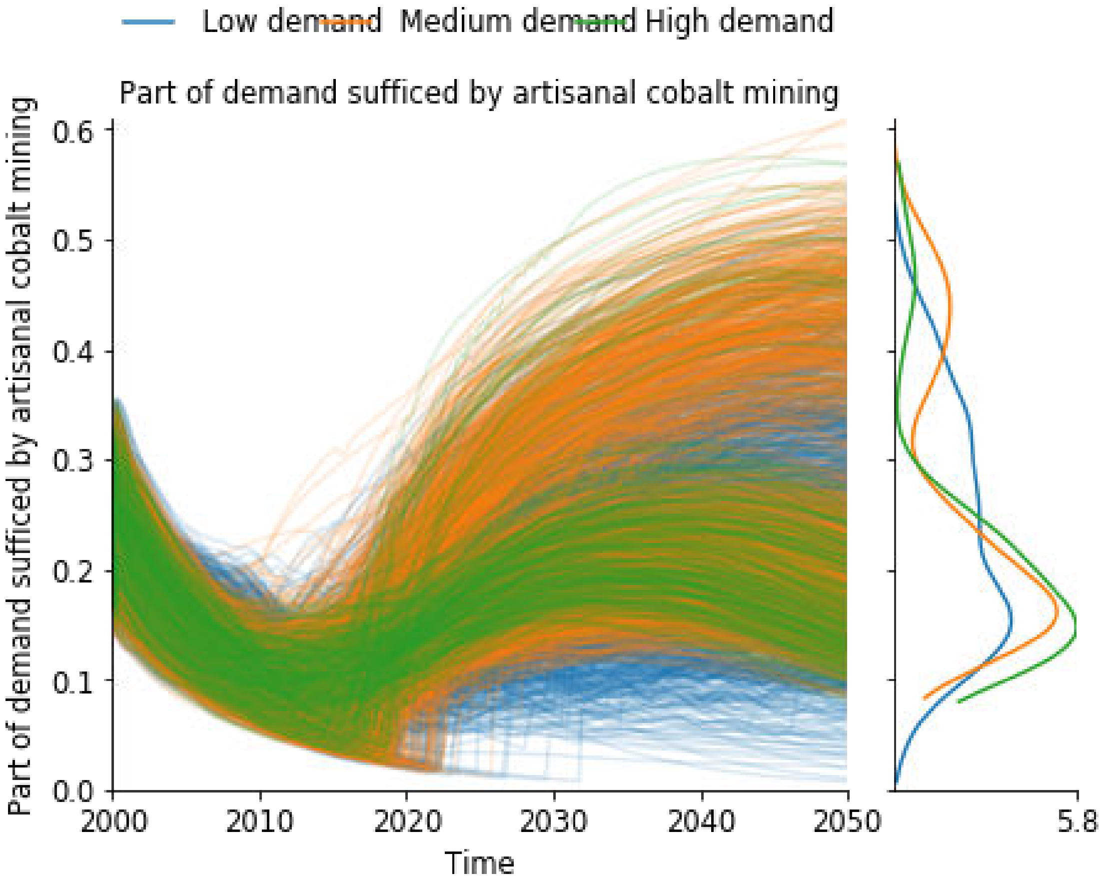


Low demand
Medium demand
High demand
Average cobalt recovery rate
Average cobalt recovery rate
0.0
0.2
0.4
0.6
0.8
2000
2010
2020
2030
2040
2050
Time
5.7

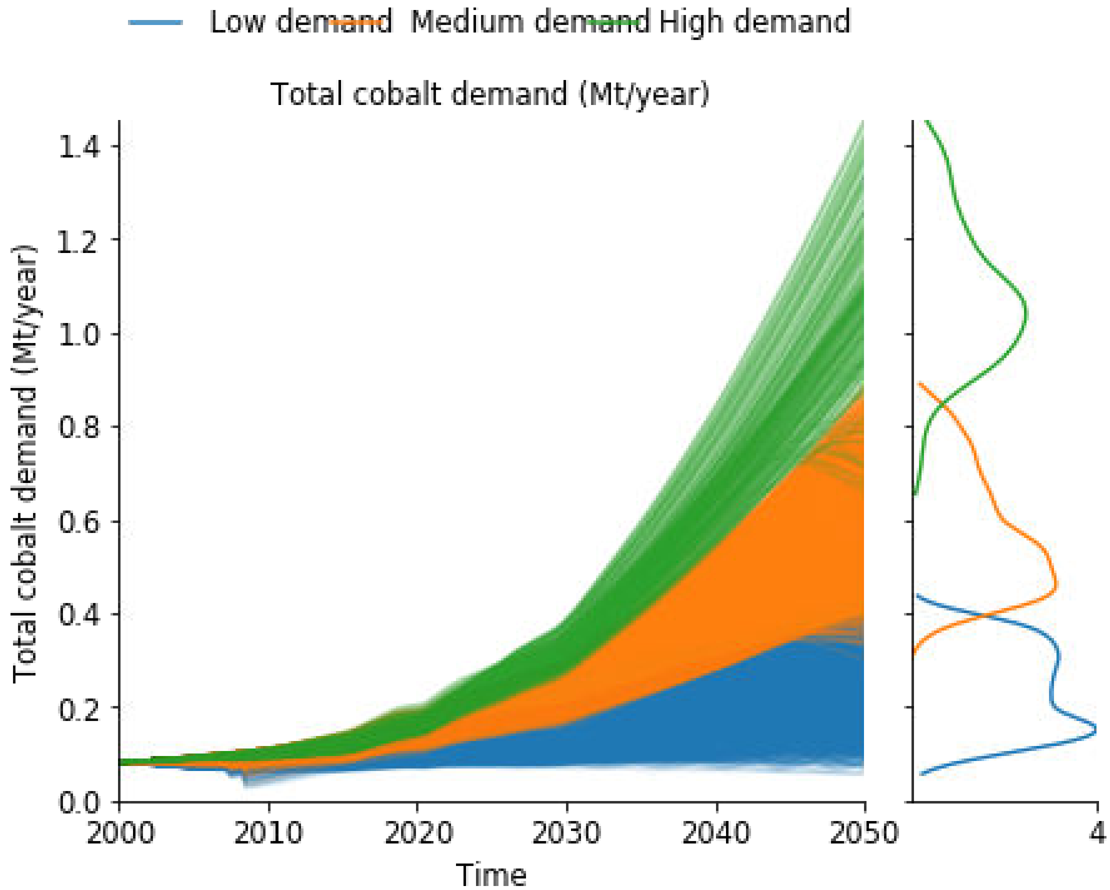


Low demand
Medium demand
High demand
Margin per lb of cobalt ($/lb)
16000
14000
12000
10000
8000
6000
4000
2000
0
Margin per lb of cobalt ($/lb)
2000
2010
2020
2030
2040
2050
Time
0
0.0076

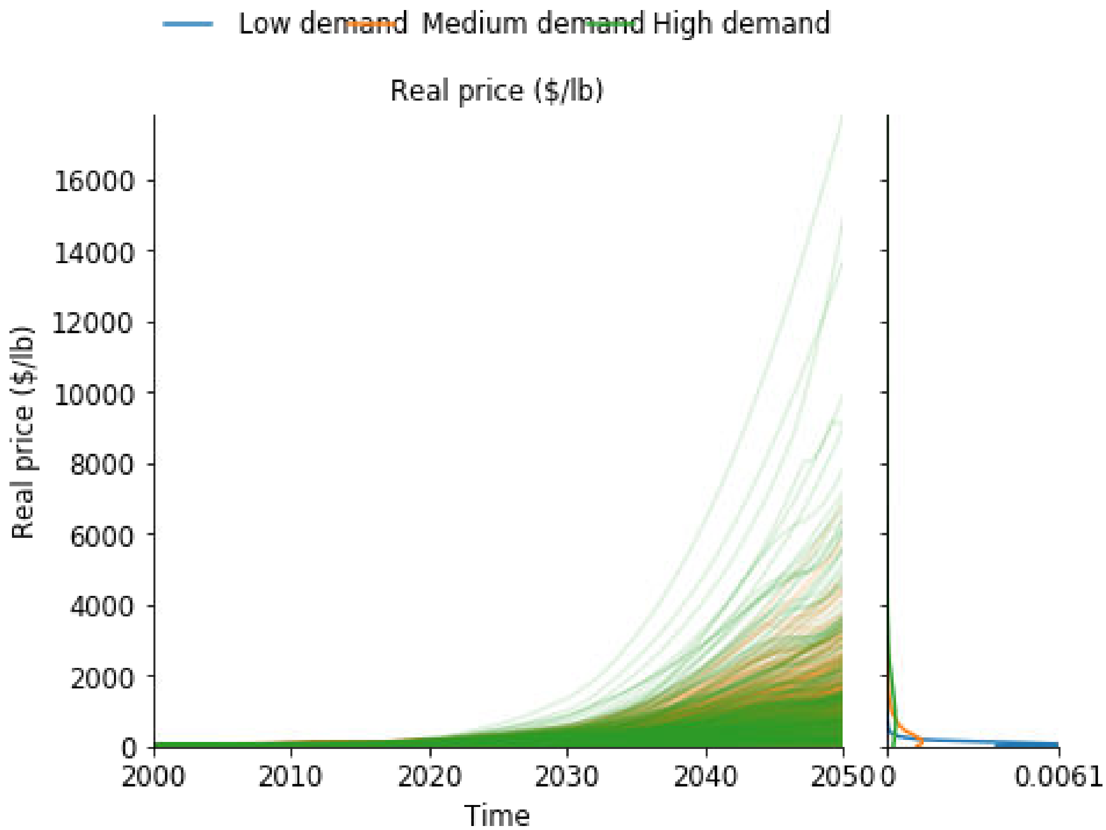

Low demand
Medium demand
High demand
Part of demand sufficed by
artisanal cobalt mining
Part of demand sufficed by
artisanal cobalt mining
0.6
0.5
0.4
0.3
0.2
0.1
0.0
2000
2010
2020
2030
2040
2050
Time
5.8



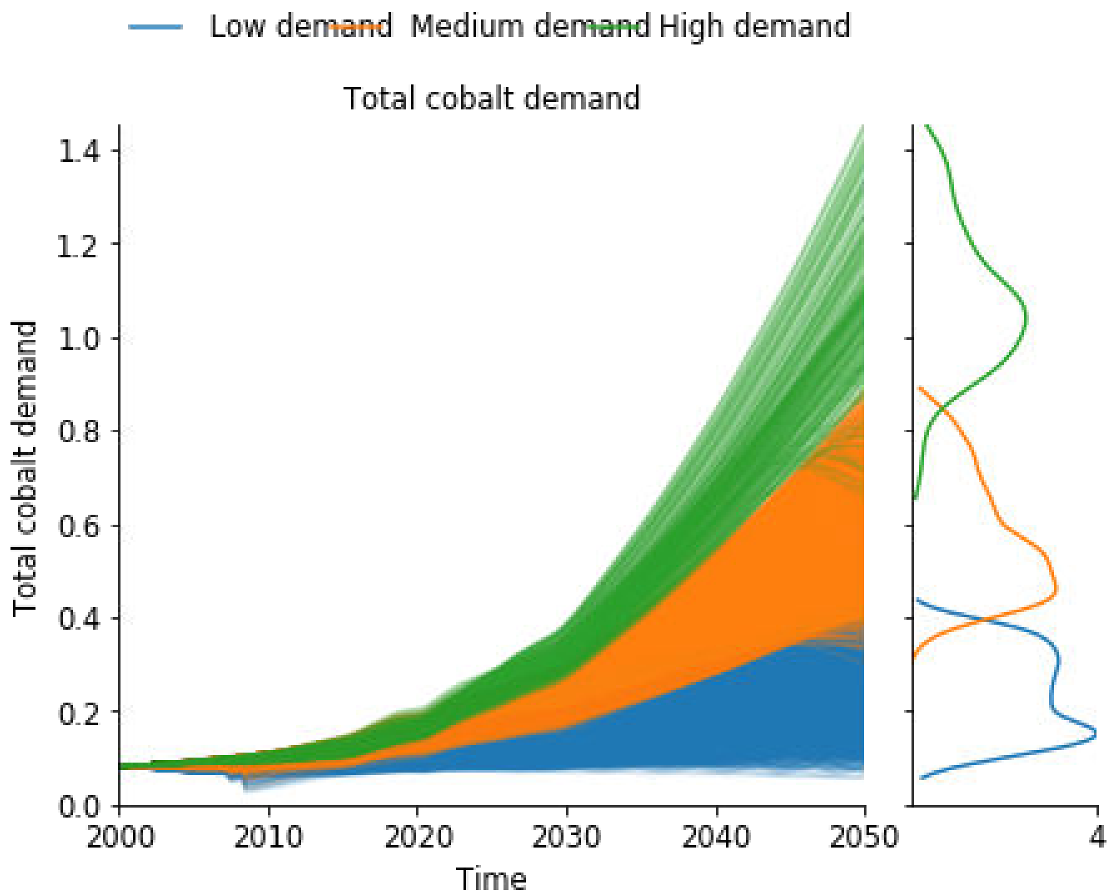
Low demand
Medium demand
High demand
Part of demand sufficed by artisanal cobalt mining
Part of demand sufficed by artisanal cobalt mining
0.0
0.1
0.2
0.3
0.4
0.5
0.6
2000
2010
2020
2030
2040
2050
Time
5.8

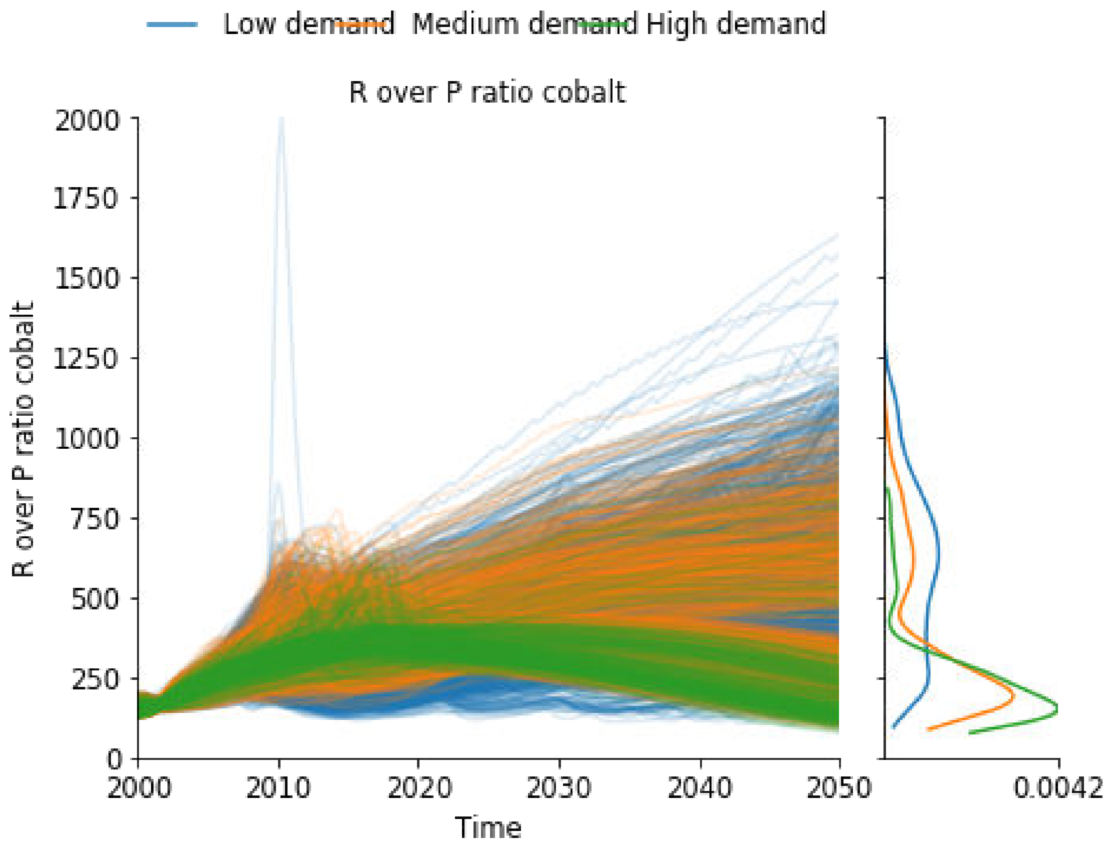


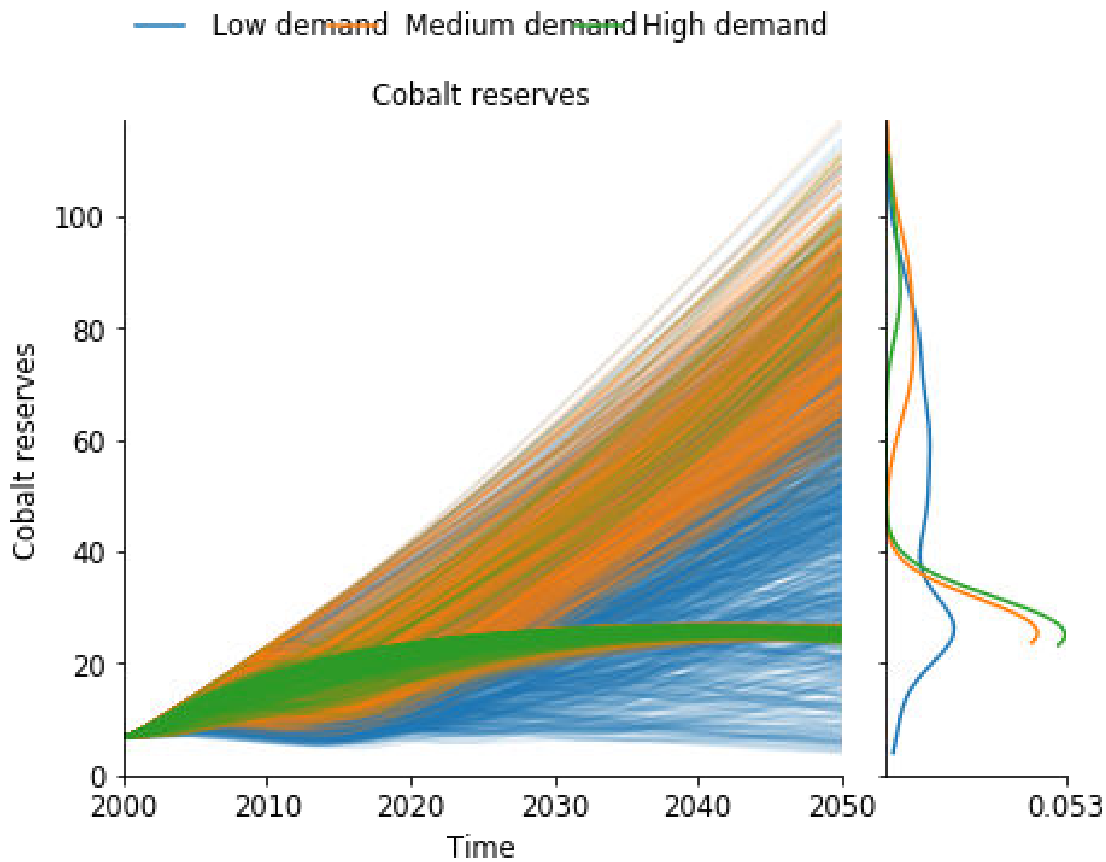
Low demand
Medium demand
High demand
Total cobalt demand (Mt/year)
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
Total cobalt demand (Mt/year)
2000
2010
2020
2030
2040
2050
Time
4

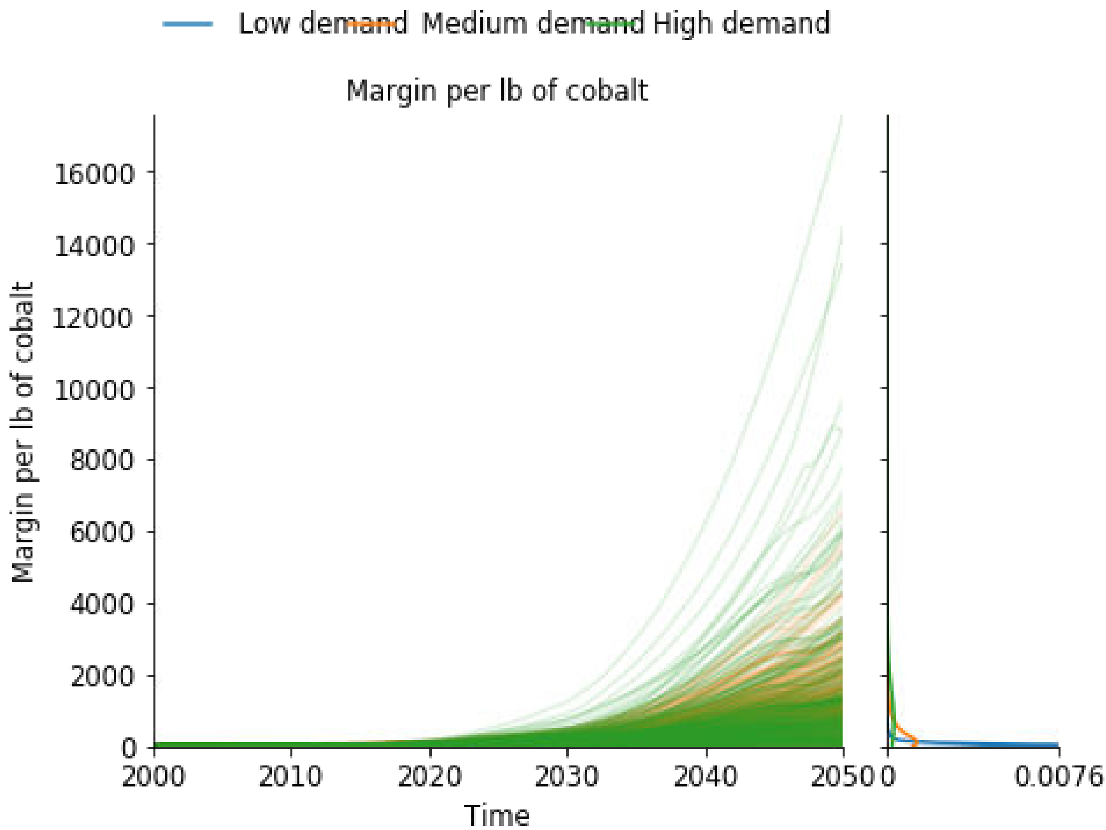


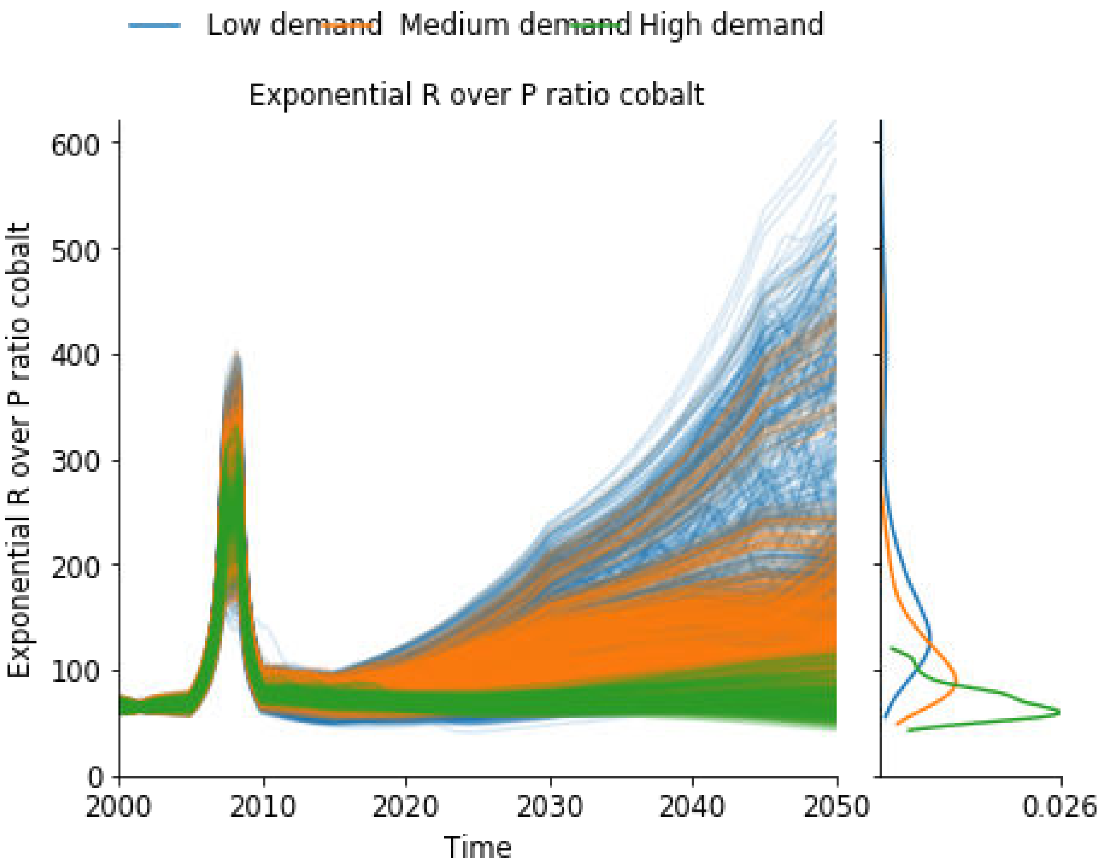
Low demand
Medium demand
High demand
Real price ($/lb)
Real price ($/lb)
16000
14000
12000
10000
8000
6000
4000
2000
0
2000
2010
2020
2030
2040
2050
Time
0
0.0061

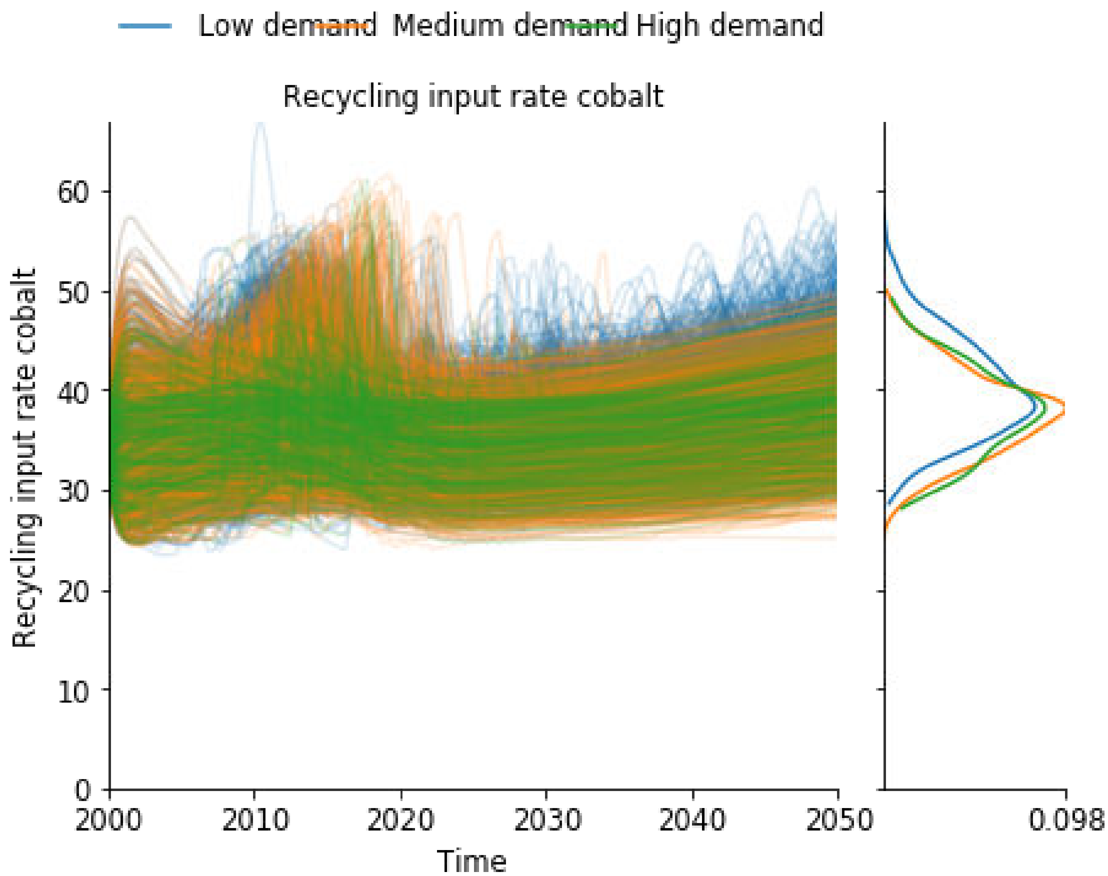

Low demand
Medium demand
High demand
Total cobalt demand
Total cobalt demand
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
2000
2010
2020
2030
2040
2050
Time
4

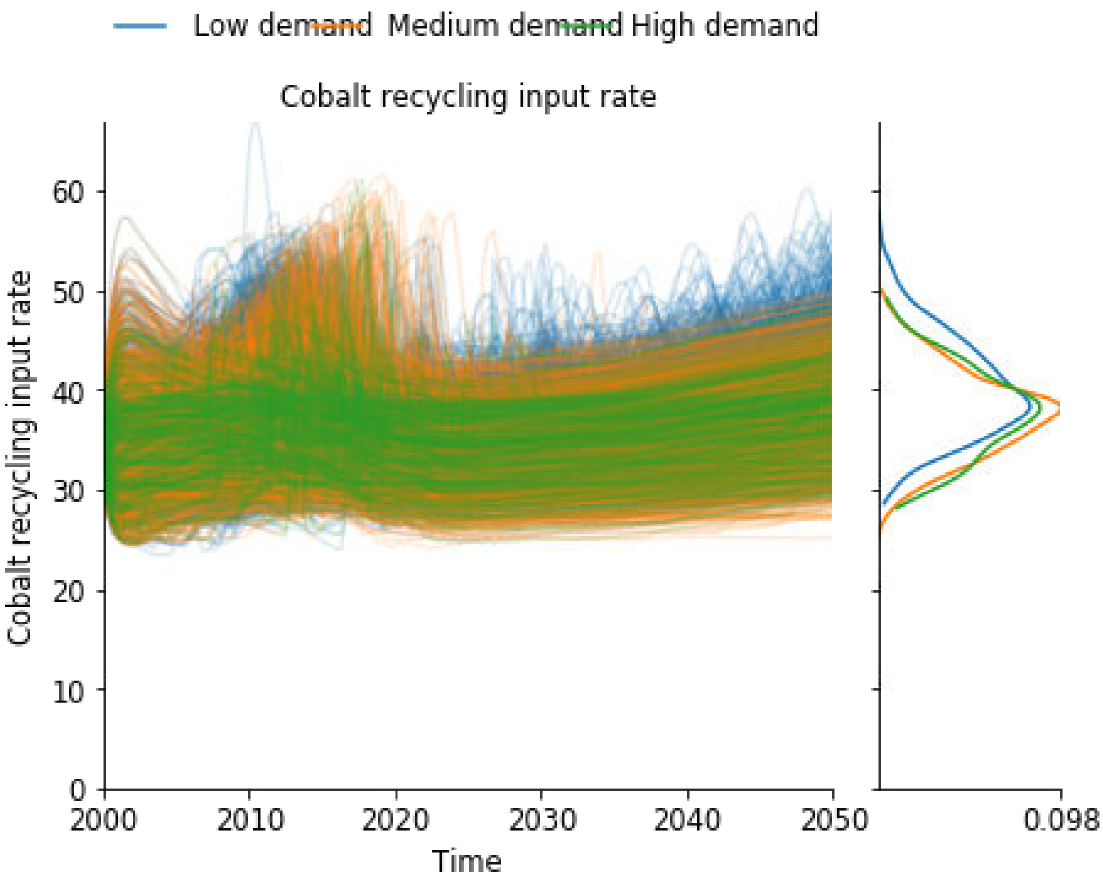

Low demand
Medium demand
High demand
R over P ratio cobalt
R over P ratio cobalt
2000
1750
1500
1250
1000
750
500
250
0
2000
2010
2020
2030
2040
2050
Time
0.0042


Low demand
Medium demand
High demand
Cobalt reserves
Cobalt reserves
0
20
40
60
80
100
2000
2010
2020
2030
2040
2050
Time
0.053


Low demand
Medium demand
High demand
Margin per lb of cobalt
Margin per lb of cobalt
16000
14000
12000
10000
8000
6000
4000
2000
0
2000
2010
2020
2030
2040
2050
Time
0
0.0076


Low demand
Medium demand
High demand
Exponential R over P ratio cobalt
Exponential R over P ratio cobalt
0
100
200
300
400
500
600
2000
2010
2020
2030
2040
2050
Time
0.026


Low demand
Medium demand
High demand
Recycling input rate cobalt
Recycling input rate cobalt
0
10
20
30
40
50
60
2000
2010
2020
2030
2040
2050
Time
0.098


Low demand
Medium demand
High demand
Cobalt recycling input rate
Cobalt recycling input rate
0
10
20
30
40
50
60
2000
2010
2020
2030
2040
2050
Time
0.098

Extra trees feature scoring

January 9, 2020

1 Extra trees feature scoring

1.1 Import pacakages

[1]:
```
from __future__ import (absolute_import, print_function, division, ␣
↪unicode_literals)
from ema_workbench import (Model, RealParameter, ScalarOutcome, Constant,␣
↪Policy, perform_experiments, ema_logging,
                           TimeSeriesOutcome, perform_experiments,␣
↪save_results, load_results)
from ema_workbench.analysis import (feature_scoring)
from ema_workbench.analysis.pairs_plotting import (pairs_lines, pairs_scatter,␣
↪pairs_density)
from ema_workbench.connectors.vensim import (VensimModel) #LookupUncertainty,␣
↪VensimModel, VensimModelStructureInterface)
from ema_workbench.em_framework import CategoricalParameter
from ema_workbench.em_framework.evaluators import LHS, SOBOL, MORRIS
from ema_workbench.analysis.plotting import lines, envelopes
from ema_workbench.analysis import clusterer, plotting, Density

from Figures import plot_lines_with_envelopes
from plotting_util import group_results, filter_scalar_outcomes,make_grid,␣
↪make_legend
TIME_LABEL = 'Time'
from ema_workbench.analysis.plotting_util import prepare_data, COLOR_LIST,␣
↪simple_kde, group_density,\
                                                 plot_envelope, simple_density,␣
↪do_titles,\
                                                 do_ylabels, TIME
import ema_workbench.analysis.plotting_util as plt_util
from ema_workbench.analysis.plotting import group_by_envelopes,␣
↪single_envelope, plot_lines_with_envelopes
from ema_workbench.analysis.pairs_plotting import pairs_scatter, pairs_density
from ema_workbench.analysis import pairs_plotting
from ema_workbench.analysis import (get_ex_feature_scores,
                                    RuleInductionType)
```

```
C:\ProgramData\Anaconda3_32bits\lib\site-
packages\ema_workbench\em_framework\optimization.py:48: ImportWarning: platypus
based optimization not available
  warnings.warn("platypus based optimization not available", ImportWarning)
C:\ProgramData\Anaconda3_32bits\lib\site-
packages\ema_workbench\analysis\prim.py:31: ImportWarning: altair based
interactive inspection not available
  "inspection not available"), ImportWarning)
C:\ProgramData\Anaconda3_32bits\lib\site-packages\sklearn\externals\six.py:31:
DeprecationWarning: The module is deprecated in version 0.21 and will be removed
in version 0.23 since we've dropped support for Python 2.7. Please rely on the
official version of six (https://pypi.org/project/six/).
  "(https://pypi.org/project/six/).", DeprecationWarning)
C:\ProgramData\Anaconda3_32bits\lib\site-
packages\ema_workbench\connectors\__init__.py:27: ImportWarning: netlogo
connector not available
  warnings.warn("netlogo connector not available", ImportWarning)
```

[2]:
```python
import numpy as np
import seaborn as sns #; sns.set(style="ticks", color_codes=True)
import pandas as pd
import matplotlib.pyplot as plt

import itertools
import copy
from copy import deepcopy

import numpy as np
import datetime
import math
import matplotlib.gridspec as gridspec

import scipy.stats.kde as kde
from matplotlib.colors import ColorConverter
from matplotlib.collections import PolyCollection, PathCollection
import matplotlib.pyplot as plt
from matplotlib.pyplot import pie
from matplotlib.ticker import FormatStrFormatter, FuncFormatter
from matplotlib.patches import ConnectionPatch
import matplotlib.font_manager as fm
import matplotlib as mpl
```

1.2 Set WD

[3]:
```python
wd = 'C:/Users/erika/Desktop/EMA_runs/'
ema_logging.log_to_stderr(ema_logging.INFO)
```

[3]:
```
<Logger EMA (DEBUG)>
```

1.3 create or load results

[ ]:
```
Cobalt_model.uncertainties = [
#     Switches
        CategoricalParameter('Switch opportunity cost fixed stock',(1,2),pff =␣
 ↪True ),
        CategoricalParameter('Switch SSP', (1,2,3,4,5) ),
        CategoricalParameter('Switch carbon policy',(0,1) ),
        CategoricalParameter('Switch energy price growth scenario', (1,2,3) ),
        CategoricalParameter('Switch real price', (1,2)),
#     Assumptions metal stocks
        RealParameter('Percentage lost during artisanal mining',0.4 ,0.6 ),
        RealParameter('Part artisanal mining from classified reserves',0.1 ,0.3␣
 ↪),
        RealParameter('Administration time',10 ,20 ),
        RealParameter('Average time mining until refining',0.09 ,0.11 ),
        RealParameter('Average time scrap to recycling',0.38 ,0.42 ),
        RealParameter('Maximum recycling efficiency score',0.8 ,0.99 ),
        RealParameter('Yearly increase recyclying efficiency score', 0.03, 0.07␣
 ↪),
        RealParameter('Recycling efficiency score in 2018', 0.4,0.6),
        RealParameter('Percentage of primary scrap',0.25 ,0.4 ),
        RealParameter('Average lifetime of metal in use',5 ,15 ),
        RealParameter('Collection rate metal products',0.4 ,0.8 ),
        RealParameter('Short forecasting period', 0.5,2 ),
        CategoricalParameter('Delay order consumption forecast',(1,3,5) ),
        RealParameter('Minimum usage mining capacity', 0.7,0.9),
        RealParameter('Minimum usage smelting and refining capacity', 0.7,0.9),
        RealParameter('Percentage lost during operations', 0.04, 0.08),
#     Assumptions industrial and artisanal mining capacity
        RealParameter('Mining usage investment cap',0 ,0.95 ),
        CategoricalParameter('Delay order production capacity',(1,3,5) ),
        RealParameter('Average permit term', 5 , 15 ),
        RealParameter('Smelter and refiner usage investment cap', 0, 0.95),
        RealParameter('Percentage of profit from refined cobalt for artisanal␣
 ↪miners', 0.04, 0.1),
        RealParameter('Productivity of artisanal mining', 800, 1600),
        RealParameter('Minimum cost of artisanal mining', 800, 1300),
        RealParameter('Maximum increase recovery rate', 0.05, 0.25),
#     Assumptions Demand
        RealParameter('Ni per dollar GDP', 0.000004, 0.000008 ),
        RealParameter('Co per dollar GDP', 0.000001, 0.0000015 ),
        RealParameter('Cu per dollar GDP', 0.000025, 0.000035 ),
        RealParameter('Period for long term effect on demand', 5,15),
        RealParameter('Copper substitution threshold', 3,5),
        RealParameter('Nickel substitution threshold', 5,9),
        RealParameter('Cobalt substitution threshold', 5,7),
```

```
        RealParameter('Long term substitution strength',0.1, 0.15),
        RealParameter('Short term substitution strength', 0.02, 0.06),
        RealParameter('Substitution strength battery compared to traditional',␣
 ↪0.01,0.05),
#     Assumptions Battery transition
        RealParameter('Increase in demand stationary storage', 0.2 , 0.4),
        RealParameter('Slowing of increase in demand stationary storage', 0.88␣
 ↪, 0.96),
        RealParameter('Battery capacity PHEV', 8 , 17),
        RealParameter('Battery capacity BEV', 20 , 40),
        RealParameter('Number of cars per dollar GDP', 1.369e-006, 2.369e-006),
        RealParameter('Battery capacity Ebus',150, 220 ),
        RealParameter('Number of buses per person',0.001, 0.002),
        RealParameter('Battery capacity Etruck', 60, 100),
#     Assumptions Economics
        RealParameter('Percentage cost on top of marginal cost', 0.05 , 0.25 ),
        RealParameter('Price elasticity long term', 0.1 , 0.25),
        RealParameter('Price elasticity short term', 0.02, 0.08),
        RealParameter('Price amplifying factor', 0.5 , 3),
        RealParameter('Cobalt taxes in DRC', 0.3, 0.8),
        RealParameter('Marginal cost bottom price relationship copper', 0.01, 0.
 ↪015),
        RealParameter('Marginal cost bottom price relationship nickel', 0.08, 0.
 ↪12),
        RealParameter('Marginal cost bottom price relationship cobalt', 0.05,0.
 ↪075),
        RealParameter('Exponent copper price curve',-1.6, -1.4),
        RealParameter('Exponent nickel price curve',-0.95, -0.85),
        RealParameter('Exponent cobalt price curve',-1.3, -1.1),
        RealParameter('Innovation in mining sector', 0.8 ,1 ),
        RealParameter('Relation ore grade energy usage copper',-1.05,-0.95 ),
        RealParameter('Relation ore grade energy usage nickel',-0.77, -0.67 ),
        RealParameter('Relation ore grade energy usage cobalt',-3.1, -2.9 ),
        RealParameter('Base energy usage copper', 0.075,0.085),
        RealParameter('Base energy usage nickel', 0.09, 0.13),
        RealParameter('Base energy usage cobalt', 0.09, 0.11),
        RealParameter('Transport costs copper', 0.02, 0.06),
        RealParameter('Transport costs nickel', 0.1, 0.3),
        RealParameter('Transport costs cobalt', 0.1, 0.3),
        RealParameter('Price averaging period', 0.1, 0.4),
        RealParameter('Power for oregrades', 0.38, 0.42 ),
        RealParameter('Maximum increase production capacity', 0.1, 0.2),
        RealParameter('Maximum decrease production capacity', 0.02, 0.05),
]

Cobalt_model.outcomes =  [
#     General
```

```
        TimeSeriesOutcome('TIME'),
#         TimeSeriesOutcome('Total demand[Copper]'),
#         TimeSeriesOutcome('Total demand[Nickel]'),
#         TimeSeriesOutcome('Total demand[Cobalt]'),
#         TimeSeriesOutcome('Marginal cost[Copper]'),
#         TimeSeriesOutcome('Marginal cost[Nickel]'),
#         TimeSeriesOutcome('Marginal cost[Cobalt]'),
#     Fixed Stock metrics
#         TimeSeriesOutcome('R over P ratio[Copper]'),
#         TimeSeriesOutcome('R over P ratio[Nickel]'),
        TimeSeriesOutcome('R over P ratio[Cobalt]'),
#         TimeSeriesOutcome('Exponential index of depletion[Copper]'),
#         TimeSeriesOutcome('Exponential index of depletion[Nickel]'),
#         TimeSeriesOutcome('Exponential index of depletion[Cobalt]'),
#     Opportunity Cost metrics
#         TimeSeriesOutcome('Real price[Copper]'),
#         TimeSeriesOutcome('Real price[Nickel]'),
        TimeSeriesOutcome('Real price[Cobalt]'),
#     Relative parts types of mining
        TimeSeriesOutcome('Relative part artisanal mining[Cobalt]'),
#         TimeSeriesOutcome('Artisanal ore trade[Cobalt]'),
#         TimeSeriesOutcome('Industrial Ore mining[Copper]'),
#         TimeSeriesOutcome('Industrial Ore mining[Nickel]'),
        TimeSeriesOutcome('Industrial Ore mining[Cobalt]'),
#         TimeSeriesOutcome('Relative part industrial mining[Copper]'),
#         TimeSeriesOutcome('Relative part industrial mining[Nickel]'),
#         TimeSeriesOutcome('Relative part industrial mining[Cobalt]'),
#         TimeSeriesOutcome('Relative part recycled scrap[Copper]'),
#         TimeSeriesOutcome('Relative part recycled scrap[Nickel]'),
#         TimeSeriesOutcome('Relative part recycled scrap[Cobalt]'),
#     Metal stocks
#         TimeSeriesOutcome('Resources[Copper]'),
#         TimeSeriesOutcome('Resources[Nickel]'),
#         TimeSeriesOutcome('Resources[Cobalt]'),
#         TimeSeriesOutcome('Reserve base[Copper]'),
#         TimeSeriesOutcome('Reserve base[Nickel]'),
#         TimeSeriesOutcome('Reserve base[Cobalt]'),
#         TimeSeriesOutcome('Recycling input rate[Copper]'),
#         TimeSeriesOutcome('Recycling input rate[Nickel]'),
#         TimeSeriesOutcome('Recycling input rate[Cobalt]'),
#         TimeSeriesOutcome('Smelting and refining capacity utilisation␣
↪rate[Copper]'),
#         TimeSeriesOutcome('Smelting and refining capacity utilisation␣
↪rate[Nickel]'),
#         TimeSeriesOutcome('Smelting and refining capacity utilisation␣
↪rate[Cobalt]'),
#         TimeSeriesOutcome('Recycling efficiency score'),
```

```
# #     Industrial and artisanal mining capacity
#         TimeSeriesOutcome('Industrial mining capacity[Sed hosted Co]'),
#         TimeSeriesOutcome('Industrial mining capacity[Sed hosted]'),
#         TimeSeriesOutcome('Industrial mining capacity[Ni laterite Co]'),
#         TimeSeriesOutcome('Industrial mining capacity[Ni laterite]'),
#         TimeSeriesOutcome('Industrial mining capacity[Porphyry Cu]'),
#         TimeSeriesOutcome('Industrial mining capacity[Magm sulfide Co]'),
#         TimeSeriesOutcome('Industrial mining capacity[Magm sulfide]'),
#         TimeSeriesOutcome('Industrial mining capacity metals[Copper]'),
#         TimeSeriesOutcome('Industrial mining capacity metals[Nickel]'),
#         TimeSeriesOutcome('Industrial mining capacity metals[Cobalt]'),
#         TimeSeriesOutcome('Typical Co recovery rate[Sed hosted Co]'),
#         TimeSeriesOutcome('Typical Co recovery rate[Ni laterite Co]'),
#         TimeSeriesOutcome('Typical Co recovery rate[Magm sulfide Co]'),
#         TimeSeriesOutcome('Smelting and refining capacity[Copper]'),
#         TimeSeriesOutcome('Smelting and refining capacity[Nickel]'),
#         TimeSeriesOutcome('Smelting and refining capacity[Cobalt]'),
#         TimeSeriesOutcome('Population Katanga below poverty line'),
#         TimeSeriesOutcome('Percentage profit industrial mining capacity per␣
↪metal[Cobalt,Sed hosted Co]'),
#         TimeSeriesOutcome('Percentage profit industrial mining capacity per␣
↪metal[Copper,Sed hosted Co]'),
#         TimeSeriesOutcome('Percentage profit industrial mining capacity per␣
↪metal[Nickel,Ni laterite Co]'),
#         TimeSeriesOutcome('Percentage profit industrial mining capacity per␣
↪metal[Cobalt,Ni laterite Co]'),
#         TimeSeriesOutcome('Percentage profit industrial mining capacity per␣
↪metal[Copper,Magm sulfide Co]'),
#         TimeSeriesOutcome('Percentage profit industrial mining capacity per␣
↪metal[Nickel,Magm sulfide Co]'),
#         TimeSeriesOutcome('Percentage profit industrial mining capacity per␣
↪metal[Cobalt,Magm sulfide Co]'),
    #     Demand
#         TimeSeriesOutcome('Total substitution[Copper]'),
#         TimeSeriesOutcome('Total substitution[Nickel]'),
#         TimeSeriesOutcome('Total substitution[Cobalt]'),
#         TimeSeriesOutcome('Postponed demand[Copper]'),
#         TimeSeriesOutcome('Postponed demand[Nickel]'),
#         TimeSeriesOutcome('Postponed demand[Cobalt]'),
# #     Battery transition
#         TimeSeriesOutcome('Total battery capacity demand from cars'),
#         TimeSeriesOutcome('Battery capacity demand from Ebuses'),
#         TimeSeriesOutcome('Battery capacity demand from Etrucks'),
#         TimeSeriesOutcome('New consumer electronics capacity'),
#         TimeSeriesOutcome('Newly built stationary storage capacity'),
# #     Economics
```

```
#         TimeSeriesOutcome('Energy price'),
#         TimeSeriesOutcome('Energy costs mining[Copper]'),
#         TimeSeriesOutcome('Energy costs mining[Nickel]'),
#         TimeSeriesOutcome('Energy costs mining[Cobalt]'),
#         TimeSeriesOutcome('Normalised profit forecast[Copper]'),
#         TimeSeriesOutcome('Normalised profit forecast[Nickel]'),
#         TimeSeriesOutcome('Normalised profit forecast[Cobalt]'),
# #     SSPs
#         TimeSeriesOutcome('World population'),
#         TimeSeriesOutcome('Population growth'),
#         TimeSeriesOutcome('GDP per capita growth per year'),
#         TimeSeriesOutcome('World GDP growth per year'),
]
```

[4]:
```
results = load_results('C:/Users/erika/Desktop/EMA_runs/
 ↪30000runs_pff3_alloutcomes.tar.gz')
```

```
[MainProcess/INFO] results loaded succesfully from
C:\Users\erika\Desktop\EMA_runs\30000runs_pff3_alloutcomes.tar.gz
```

[5]:
```
experiments,outcomes = results
```

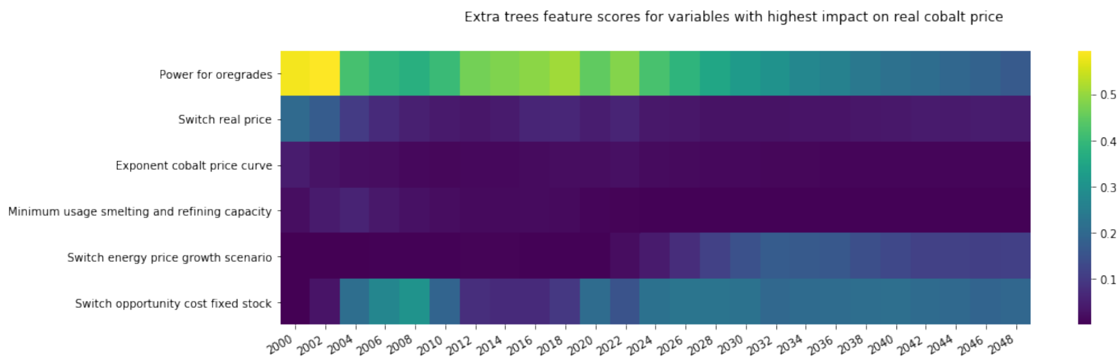
1.4 Define feature scoring functions

[61]:
```
def get_ex_feature_scores_topx (variable,top_nr):
    x= experiments.drop(['model', 'policy'], axis=1)
    y = outcomes[variable]
    all_scores = []
    top_x = set()
    for i in range(2, y.shape[1], 8):
        data = y[:, i]
        scores = get_ex_feature_scores(x, data,
                                       mode=RuleInductionType.REGRESSION)[0]
        top_x |= set(scores.nlargest(top_nr, 1).index.values)
        all_scores.append(scores)
    all_scores = pd.concat(all_scores, axis=1, sort=False)
    all_scores = all_scores.loc[top_x, :]
    all_scores.columns = np.arange(2000, 2050, 2)
    all_scores = all_scores.sort_values(by = [2000], ascending = False)
#     for i in all_scores.T:
#         if max(all_scores.T[i]) < 0.15:
#             all_scores_transposed = all_scores.T.drop[i]
    return (all_scores)
```

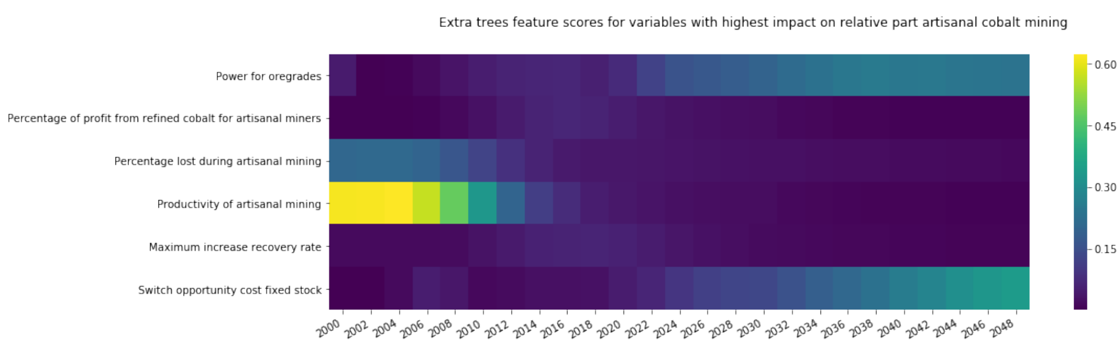
[54]:
```
def plot_heatmap_overtime (scores,title):
    sns.heatmap(scores, cmap='viridis')
    fig = plt.gcf()
    ax = fig.get_axes()
```

```
    ax[0].set_xticklabels(np.arange(2000, 2051, 2))
    fig.autofmt_xdate()
    fig.set_size_inches(15,5)
    fig.suptitle('Extra trees feature scores for variables with highest impact␣
↪on '+title)
    shorttitle = title.replace(" ","")
    fig.savefig(wd+shorttitle)
    plt.show()
```

[62]:
```
all_scores_price = get_ex_feature_scores_topx('Real price[Cobalt]',3)
plot_heatmap_overtime(all_scores_price,title =  'real cobalt price')
```

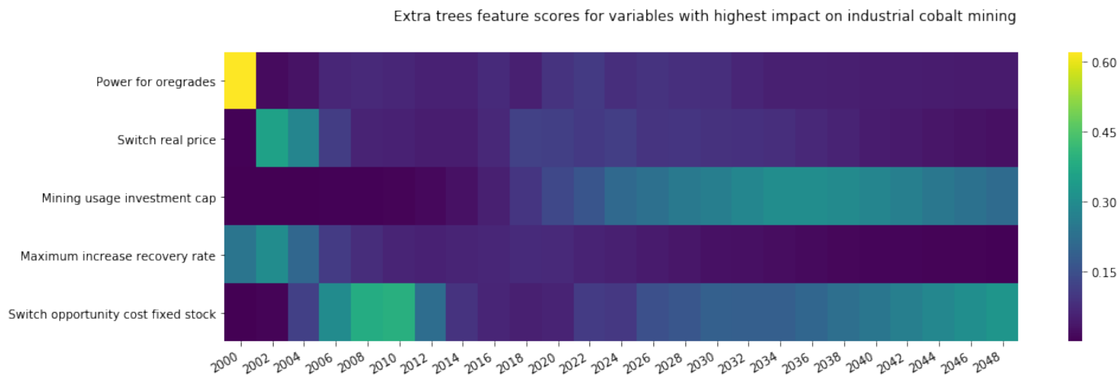


[51]:
```
all_scores_artisanal = get_ex_feature_scores_topx('Relative part artisanal␣
↪mining[Cobalt]',2).
plot_heatmap_overtime(all_scores_artisanal, title = 'relative part artisanal␣
↪cobalt mining')
plt.savefig(wd+'etfs_relativeartisanal')
```



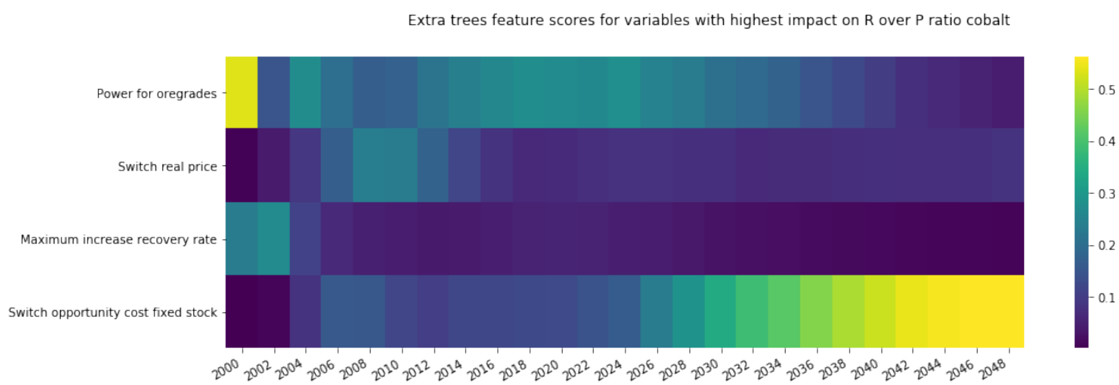

```
<Figure size 432x288 with 0 Axes>
```

[50]:
```
all_scores_mining = get_ex_feature_scores_topx('Industrial Ore␣
↪mining[Cobalt]',2)
plot_heatmap_overtime(all_scores_mining,title = 'industrial cobalt mining')
plt.savefig(wd+'etfs_industrialmining')
```



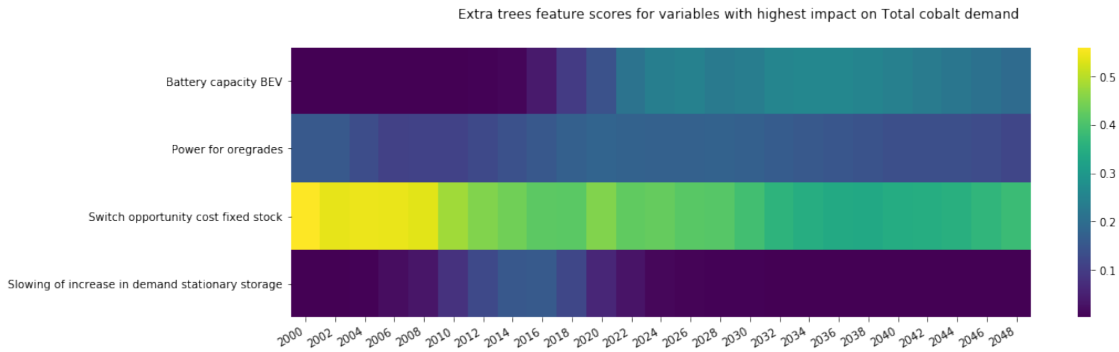
<Figure size 432x288 with 0 Axes>

[63]:
```
all_scores_RoverP = get_ex_feature_scores_topx('R over P ratio[Cobalt]',2)
plot_heatmap_overtime(all_scores_RoverP, title = 'R over P ratio cobalt')
plt.savefig(wd+'etfs_roverp')
```



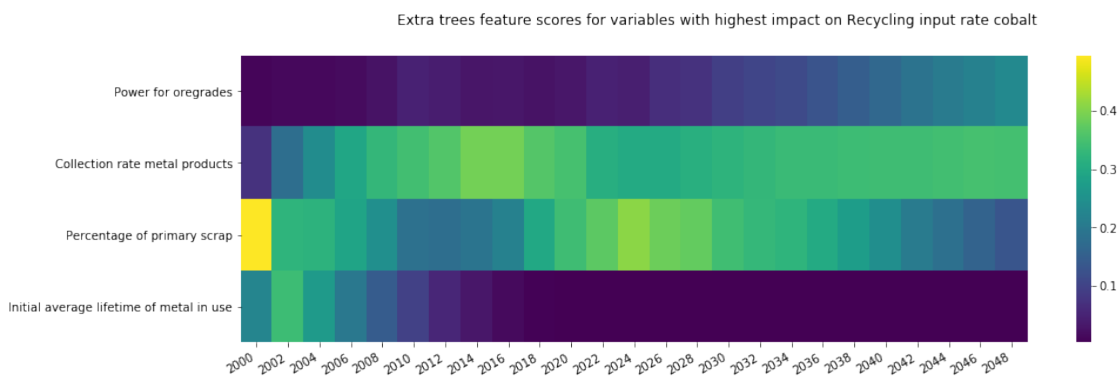
<Figure size 432x288 with 0 Axes>

[47]:
```
all_scores_totaldemand = get_ex_feature_scores_topx('Total demand[Cobalt]',2)
plot_heatmap_overtime(all_scores_totaldemand, title = 'Total cobalt demand')
plt.savefig(wd+'etfs_demand')
```



<Figure size 432x288 with 0 Axes>

[64]:
```
all_scores_recycling = get_ex_feature_scores_topx('Recycling input␣
↪rate[Cobalt]',2)
plot_heatmap_overtime(all_scores_recycling, title = 'Recycling input rate␣
↪cobalt')
plt.savefig(wd+'etfs_percentagefromrecycled')
```



<Figure size 432x288 with 0 Axes>