Sustainable energy transition and its demand for scarce resources: Insights into the German Energiewende through a new risk assessment framework

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A B S T R A C T

In this study, a new framework to analyze resource-demanding projects in regard to their risk of resource scarcity is proposed and exemplary applied on the German energy transition (Energiewende). With the interpretation of a commodity's price as an economic scarcity indicator, price thresholds are defined, which, once exceeded, determine a commodity to be scarce. The corresponding probability of scarcity is derived via a logistic regression model, given pre-selected price determinants. The combination of this probability of scarcity with the substitutability of a commodity, as well as the scaled demand per project, results in the commodity-specific expected loss due to scarcity, which, aggregated over all commodities, marks the final risk indicator, the expected loss due to scarcity per project. In a case study, the framework is applied to the resource requirements for eight transformation pathways of the German energy system, differing in the climate targets as well as the German societies acceptance for the required actions. The results highlight the general high demand in cobalt, mainly used for energy storage. In combination with a relatively high probability of scarcity, this reveals a potential bottleneck for the German Energiewende.

1. Introduction

In this study, a framework is developed to analyze resource-demanding projects in regard to their resource scarcity risk. Subsequently, the proposed framework is applied in the context of the German Energiewende. Following classical microeconomic theory, a good's price is derived from the supply–demand equilibrium. As the interaction between supply and demand also influences the price of metals, see [1], high metal prices are the result of high demand and/or low supply, and therefore, the price can be interpreted as a scarcity indicator. Moreover, prices are a superior measure of a commodity's availability, since the limiting factor for the availability of a commodity is the extraction, which is represented in the price, see [2].

Large scale projects like the German Energiewende require, due to the build-up of renewable energy technologies, an enormous amount of metal commodities in their realization, leading to a significant demand increase, see [3,4]. This increase could therefore, even under elastic supply conditions, increase commodity prices, resulting in uneconomical conditions for their application, which is equivalent to a shortage.

This effect is underrepresented in the literature, as the review study [5] on criticality assessment frameworks on a product, technology, company, country, region and a global level, shows. The main objectives of the reviewed studies are to raise the government's and industry's awareness of supply issues, to provide information to policy and consumers for the mitigation of criticality and to generate a broad information basis for further, in-depth studies. Other renowned commodity risk assessment approaches by [6–8], also focus on supply risks of single commodities, while [9] show the physical scarcity of commodities is unlikely to be the limiting factor in the energy transition, again indicating economic risks are underrepresented in the literature. Among the few studies analyzing financial instead of supply risk, [10] show a more resilient structure of renewable investments compared to fossil fuel-based energy assets.

In the proposed framework, a commodity's price is interpreted as a measure of its scarcity, where a high price represents a situation of comparably little supply paired with a high demand. To start, price thresholds, above which a commodity is regarded scarce, are defined and commodity-specific price influencing factors are determined by

Abbreviations: ISI, Fraunhofer-Institut für System- und Innovationsforschung; REMod, Regenerative Energien Modell of Fraunhofer ISE; GDP, Gross domestic product; BIC, Bayesian information criterion; EL, Expected Loss; LGD, Loss given default; PD, Probability of default; ES, Expected scarcity; EAS, Exposure at scarcity; LGS, Loss given scarcity; PS, Probability of scarcity; Ag, Silver; Co, Cobalt; Dy, Dysprosium; In, Indium; Li, Lithium; Nd, Neodymium; Ni, Nickel; Pt, Platinum

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a two-step model selection. Through logistic regression models and appropriate scenarios for the input variables, the economic measure of a commodity's probability to become scarce, the probability of scarcity, inspired by the probability of default from credit risk models in the banking industry, is derived. Combining the probability of scarcity with a substitutability score and the scaled demand of the commodity for a specific project leads to the final commodity-specific risk indicator. The aggregation of this indicator over all commodities required results in the project-level risk measure, the expected loss due to scarcity, in analogy to the expected loss on portfolio level, which enables the comparison of different project alternatives.

For an exemplary, empirical application of the proposed framework, the German Energiewende is analyzed in regard to its resource demand, given eight pre-defined transformation pathways, according to [11, 12]. Hereby, the German Energiewende marks the transition process from the current, fossil energy source based system, to a renewable energy source based system, which relies on wind and solar power (PV) for the energy production. However, this transition process is resource demanding, as the new technologies require large amounts of non-renewable, metal commodities, in the build-up phase.

This study analyzes eight transformation pathways which differ in the underlying climate targets, as well as the hypothesized acceptance of the required actions within the German society, resulting in different technology mixes and ultimately in different resource demands, which are analyzed from a scarcity perspective within this study. Overall, the four ISI pathways, modeled by [12] under the 80% CO_2 reduction goal, outperform the four $REMod$ pathways, modeled by [11] under the respective 95% reduction goal, since higher climate targets ultimately lead to a larger amount of commodities required. Among the four $REMod$ pathways, the sufficiency path $REMod - SUF$, which hypothesizes full support for the transition phase within the German society, outperforms the other paths. From a commodity-specific perspective, cobalt, mainly used in energy storage solutions, as well as indium, mainly allocated to PV technologies, show the highest risks of scarcity.

We contribute to the literature by an alternative framework, based on a different definition of resource scarcity, motivated by demand increases, in addition to supply shortages. Further, this framework allows the comparison of several projects, including different technologies, based on their required amount as well as their substitutability.

The remainder of this paper is structured as follows: In Section 2 the framework for the assessment of the commodity scarcity risk is derived on individual as well as project level. The empirical application as well as the results are described in Section 3, while Section 4 concludes.

2. Framework

The objective of this study is the analysis of resource-demanding projects, such as the German Energiewende, with regard to their resource scarcity risks. Therefore, a new framework is developed, which explicitly accounts for the additional resource demand caused by the investigated project. Hereby, the framework supports in the assessment of whether and why projects are at risk from a commodity scarcity perspective. This is accomplished via a two-stage process. First, the individual probability of scarcity for each commodity of the project is calculated via a logistic regression model, by interpreting a commodity's price as a scarcity indicator. Second, the commodity-specific risk indicator is calculated by combining the individual probability of scarcity with a commodity-specific substitutability score and the scaled demand of the commodity for a specific project. Finally, the commodity risk scores are aggregated on project level, to enable the comparison of the scarcity risk of several project alternatives. Hereby, a high value indicates a high risk of scarcity for the resource-demanding project under consideration.

2.1. Probability of scarcity

The first stage of the framework uses a logistic regression model to calculate the individual probability of scarcity per commodity. To start, an appropriate price threshold is defined, which, once exceeded, determines the commodity to be scarce, whereby, scarcity is associated with situations of extremely high prices, following [2] as well as [13]. Subsequently, a logistic regression model is estimated on preselected, commodity-specific price determinants and the predefined price threshold. Finally, the estimated logistic regression model is used to calculate the probability of scarcity per commodity, considering different scenarios of the price determinants.

As the scarcity of a commodity is not observable, a commodity's price is interpreted as scarcity indicator, following [2] as well as [13]. In this context, the commodities are classified into scarce or non-scarce states, based on a predefined threshold price θ_i for each commodity $i = 1, \dots, N$. Therefore, the commodity-specific, binary latent variable $scarce_{i,t}$ is defined within this framework, for all commodities i and times $t = 1, \dots, T$, with value 1 if the commodity price exceeds the threshold, indicating scarcity of the commodity, and value 0 else:

$$scarce_{i,t} = \begin{cases} 1, \ price_{i,t} > \theta_i \\ 0, \ price_{i,t} \leq \theta_i. \end{cases} \tag{1}$$

Two approaches for setting this price threshold are proposed. First, it may be based on expert knowledge of the respective commodity markets. As the commodities under consideration are included in the profitability calculation of a project, experts may determine the price above which the utilization of a commodity becomes uneconomic, leading to infeasible projects. Second, the threshold price may be derived statistically based on volatility measures or quantiles of historical data. In this study, we suggest to use the one-sigma approach, see [14], as this leads to approximately $100\% - 68,27\% = 31,73\%$ observations being classified as scarce for normally distributed random variables, which in turn enables a statistically valid analysis:

$$\theta_i = \mu_{price_i} + \sigma_{price_i}, \tag{2}$$

with μ_{price_i} denoting the historical mean of the price of commodity i and σ_{price_i} being the corresponding standard deviation.[1]

Subsequently, the dependencies between various price determinants and the variable $scarce_{i,t}$, defined in Eq. (1) via the threshold, are modeled to calculate the probability of scarcity per commodity. Hereby, possible price influential factors can be classified into the five dimensions: Macroeconomic, demographic, capital market driven as well as supply-sided and demand-sided variables, see Section 3.1. Subsequently, a two-step model selection is applied on each commodity, see Appendix A for more details, to identify the K_i determining variables $\mathbf{x}_{i,t} = (x_{1,i,t}, \dots, x_{K_i,i,t})'$.[2]

Thereafter, a standard logistic regression model is estimated, see [15], to calculate the probability of scarcity per commodity. Therefore, the commodity-specific price determinants $\mathbf{x}_{i,t} = (x_{1,i,t}, \dots, x_{K_i,i,t})'$ are regressed on the binary, dependent variable $scarce_{i,t}$, defined in Eq. (1) by the threshold θ_i:

$$P(scarce_{i,t} = 1 | \mathbf{X} = \mathbf{x}_{i,t}) = \frac{1}{1 + \exp(-z_{i,t})} \in [0, 1], \tag{3}$$

with the logit $z_{i,t}$:

$$z_{i,t} = \beta_0 + \beta_1 x_{1,i,t} + \beta_2 x_{2,i,t} + \dots + \beta_{K_i} x_{K_i,i,t} + \varepsilon_{i,t}, \tag{4}$$

[1] Instead of the historical mean and standard deviation over a predefined time period, a rolling window approach could be used to determine a time-varying price threshold.

[2] For the application of the risk assessment framework to other projects, one might alternatively use a set of fixed, predefined covariates or other model selection procedures.

in which β_0 denotes the intercept, $\beta_1, \dots, \beta_{K_i}$ are the coefficients corresponding to the K_i covariates $x_{1,i,t}, \dots, x_{K_i,i,t}$ for commodity i at time t and $\varepsilon_{i,t}$ represents the error term. Hereby, we follow the standard in literature, see [15], and obtain the estimated parameters $\hat{\beta}_0, \dots, \hat{\beta}_{K_i}$ of Eq. (3) via the Maximum-Likelihood approach. Finally, the estimated logistic regression model per commodity enables the calculation of the commodity-specific probability of scarcity. However, the probability of a commodity becoming scarce depends on the values of the covariates. We propose a scenario-based risk assessment and therefore, we investigate several scenarios for the covariates.

In the following, we focus on the scenarios $\zeta \in \{1, \dots, Z\}$ for the covariates, namely a mean scenario, a shock scenario, an extreme value scenario and a focus scenario. While the mean scenario considers the probability of scarcity under normal circumstances, the extreme scenario analyzes the probability of scarcity in periods when the variables take on extremer values. In addition, the focus scenario investigates the sensitivity of the probability of scarcity to one specific covariate.

In the mean scenario $\zeta = 1$, the covariates $k_i = 1, \dots, K_i$ for commodity i follow the sample average:

$$x_{k_i,i,1} = \frac{1}{T}\sum_{t=1}^{T} x_{k_i,i,t} = \mu_{k_i,i}. \tag{5}$$

In the shock scenario $\zeta = 2$, each covariate follows the one-sigma approach:

$$x_{k_i,i,2} = \mu_{k_i,i} + sgn(\beta_{k_i})\sigma_{k_i,i}, \tag{6}$$

in which $\mu_{k_i,i}$ denotes the sample mean, $\sigma_{k_i,i}$ is the standard deviation of the sample and $sgn(\beta_{k_i})$ is the signum function of the estimated coefficient in Eq. (4). In the extreme scenario $\zeta = 3$, each covariate follows the two-sigma approach:

$$x_{k_i,i,3} = \mu_{k_i,i} + 2sgn(\beta_{k_i})\sigma_{k_i,i}. \tag{7}$$

In the focus scenario $\zeta = 4_j$, the jth covariate follows the extreme scenario, whereas the remaining variables follow the mean scenario:

$$\begin{aligned} x_{k_i,i,4_j} &= \mu_{k_i,i} && \forall k_i \in \{1, \dots, K_i\} \setminus j \\ x_{j,i,4_j} &= \mu_{j,i} + 2sgn(\beta_{k_i})\sigma_{j,i}. \end{aligned} \tag{8}$$

Using the scenario values of the covariates $x_{1,i,\zeta}, \dots, x_{K_i,i,\zeta}$ and the corresponding estimated logistic regression model of Eq. (3), the probability of scarcity per commodity and scenario is calculated. On the one hand, the scenario-specific comparison between multiple commodities may be used to decide between possible substitute materials from a risk perspective, while on the other hand, the commodity-specific comparison between the scenarios may be used as a sensitivity analysis.

2.2. Expected scarcity on commodity and project level

The main objective of the framework is the comparison of several resource demanding projects, with respect to the economic scarcity risk of the required commodities. Hereby, these projects may differ in the selection and quantity of the commodities included. Given a certain scenario and project, the required amount of each commodity is given in the project's context, while the probability of scarcity is derived according to Section 2.1. The aggregation of this commodity-specific information to a project level risk measure is performed in accordance to the combination of multiple credit contracts into a portfolio-based risk measure.

Within credit risk modeling, portfolios may be compared by the expected loss (EL), defined as:

$$EL = \sum_{cred \in pf} EL_{cred} = \sum_{cred \in pf} EAD_{cred} \cdot LGD_{cred} \cdot PD_{cred}, \tag{9}$$

in which EL_{cred} denotes the expected loss of credit $cred$ in the portfolio pf, PD_{cred} the respective probability of default, LGD_{cred} the loss given default and EAD_{cred} the corresponding exposure at default, see [16]. While the probability of default (PD) and the probability of scarcity (PS) may be regarded equivalently, the adoption of the expected loss (EL) to the expected loss due to scarcity (ES) of commodity markets requires adjustments on the loss given default (LGD) and the exposure at default (EAD).

The loss given default normally represents the loss a bank realizes in case a borrower defaults. The respective measure of our framework, the loss given scarcity (LGS), is linked to the substitutability rate (SR), representing a normalized indicator for the substitutability of commodity i, by:

$$LGS_i = 1 - SR_i \in [0, 1]. \tag{10}$$

Hereby, a LGS_i of 0 indicates the commodity i is perfectly substitutable by other commodities, hence its scarcity is irrelevant in a project context. In contrast, a LGS_i of 1 indicates no substitute for the commodity i is available and the project is unfeasible in case of scarcity.

Additionally, the exposure at default is converted to the exposure at scarcity, under the assumption the entire amount of the specific commodity is inaccessible in case of scarcity, independent of the project's state $p = 1, \dots, P$ at which the scarcity occurs. For a project comparison, the required amount of each commodity, measured in metric tons, is scaled by the world production S_i of the respective commodity i, measured in metric tons, resulting in the project and commodity-specific exposure at scarcity:

$$EAS_{p,i} = \frac{q_{p,i}}{S_i}, \tag{11}$$

in which $q_{p,i}$ denotes the required amount of commodity i for the project p. Using these adjusted parameters, the expected loss due to scarcity ($ES_{p,i,\zeta}$) for project p, commodity i and scenario ζ is calculated according to:

$$ES_{p,i,\zeta} = EAS_{p,i} \cdot LGS_i \cdot PS_{i,\zeta}. \tag{12}$$

Subsequently, the commodity-specific measures of expected loss due to scarcity are aggregated on project level[3] in analogy to credit risk modeling.

$$ES_{p,\zeta} = \sum_{i=1}^{N} ES_{p,i,\zeta} = \sum_{i=1}^{N} EAS_{p,i} \cdot LGS_i \cdot PS_{i,\zeta}. \tag{13}$$

3. Empirical analysis of resource requirements for the German Energiewende

In the following, the proposed risk assessment framework is in a case study applied on the resource requirements of eight possible, predefined transformation pathways of the German energy system. Hereby, each transformation pathway represents a resource demanding project, as it requires, due to the build-up of renewable energy technologies, an enormous amount of commodities in their realization. First, these eight different transformation pathways and their commodity requirements are analyzed, followed by the description of possible commodity price determinants. Second, the presented data is used to assess the scarcity risk of the German Energiewende.

3.1. Data

The eight transformation pathways of the German energy system, called $REMod$ and ISI paths, which originate from the studies of [11, 12], are generated under the restriction of a 95% or 80% CO_2 reduction until 2050, compared to Germany's emissions in 1990. The $REMod$

[3] The assumption of independence between the commodities allows for the additivity of the expected loss due to scarcity values, as potential dependencies between commodities may be reflected in the probability of scarcity via the macroeconomic determinants already.

Table 1
Energy system pathways — Demand and installed capacities.

	$REMod-REF$	$REMod-SUF$	$REMod-PER$	$REMod-UNA$	$ISI-REF$	$ISI-LIN$	$ISI-RED$	$ISI-LRE$
CO_2 reduction goal	95%	95%	95%	95%	80%	80%	80%	80%
Total energy demand in 2050 [in TWh]	1447	1068	1464	1282	612	646	611	686
Limits for installed capacity [in GW]								
Photovoltaic	530	530	530	800	69	88	69	49
Wind Onshore	230	230	230	80	75	100	82	101
Wind Offshore	80	80	80	40	15	15	15	7
Electricity import [in TWh]	40	40	40	20	105	24	106	31

Description of the demand and installed capacities in the examined energy system pathways, according to [11] and [12].

Table 2
Energy system pathways — Consumption development.

Name Abbreviation	Reference $REMod-REF$	Sufficiency $REMod-SUF$	Persistence $REMod-PER$	Unacceptance $REMod-UNA$
Classic power applications	constant	decreasing	constant	constant
Traffic performance	increasing	decreasing	increasing	increasing
Heated building area	increasing	decreasing	increasing	increasing
Process heat	slightly	decreasing	slightly	slightly

Description of central boundary conditions in the examined energy system pathways, according to [11].

pathways further differentiate by the underlying assumptions of the German society's acceptance for actions to fulfill these reduction goals. While the initial transformation pathways of the energy system are modeled according to [11,12], a translation of these pathways into annual resource demands from 2020 to 2050 is performed via a life-cycle assessment, as well as a system dynamics model,[4] see [17,18]. A general overview of the pathways is displayed in Table 1.

Within the $REMod$ reference path, which marks the baseline scenario, denoted as $REMod-REF$, the energy system is modeled at optimal costs, without further boundary constraints that promote or aggravate the achievement of the 95% CO_2 reduction goal. In contrast, a substantial change in the behavior of the German population towards a decrease in the energy consumption, i.e. by tripling the maximum renovation rate for buildings, is modeled in the $REMod-SUF$ path, resulting in the least energy requirements of all $REMod$ pathways. However, reservations of the population against new technologies in the private sector could cause a substantial time delay for the spreading and usage of renewable energy technologies, as well as a continuous high demand of conventional energy technologies, represented in the $REMod-PER$ path. In addition, local protests against big infrastructural plans, such as wind energy parks or power grid expansions, are modeled in the $REMod-UNA$ path. To reach Germany's climate goals under these restraints, the demand for photovoltaic as well as storage technologies increases drastically, as does the demand for the corresponding commodities (see Table 2).

In contrast to the $REMod$ pathways, the ISI paths assume a 80% reduction until 2050. In addition, the overall required energy demand in 2050 is significantly lower, see Table 1. Hereby, the basis path, denoted as $ISI-REF$, represents a cost optimized system regarding actions towards the 80% CO_2 reduction goal, which is established under three major constraints for solar power stations, offshore wind parks and carbon capture and storage technologies, see [12] for more details. While a reduced expansion of the transmission networks, causing a different power distribution in Germany, is modeled in the $ISI-LIN$ path, the $ISI-RED$ path differs from the $ISI-REF$ path mainly in the location of onshore wind turbine parks, reflecting an alternative regional distribution of renewable energy technologies. Within the $ISI-LRE$ path, the three major restrictions of the $ISI-REF$ path are still included, but in a relaxed form.

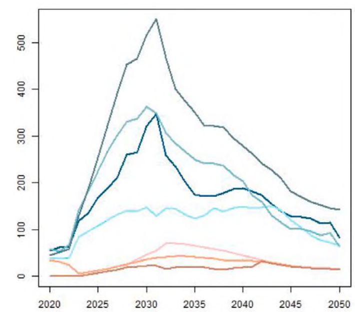
Table 3
Main uses in the context of the energy transition of the metals.

	Ag	Co	Cu	Dy	In	Li	Nd	Ni	Pt
Photovoltaic systems	x				x			x	
Wind turbines			x	x			x		
Lithium-ion batteries	x	x				x		x	
Redox flow storage									
Solar thermal power plant	x								
Magnets		x		x			x		
Alloys		x							
Catalysts		x							x
Electric traction motors			x						
Batteries	x	x			x	x			x
Smart Grid (display)					x				
Micro Energy Harvesting				x			x		

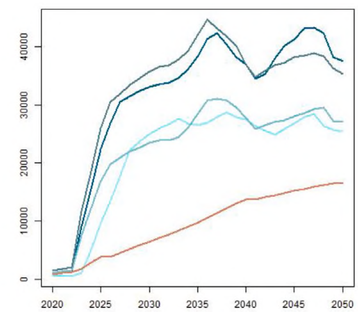
The main uses in the context of energy technologies of the metals silver (Ag), cobalt (Co), copper (Cu), dysprosium (Dy), indium (In), lithium (Li), neodymium (Nd), nickel (Ni), and platinum (Pt), according to [19].

The annual resource requirements of 36 metals are calculated for each of these pathways from 2020 to 2050 within the project InteRessE, Grant-Nr: 03ET4065B, supported by the German Federal Ministry for Economic Affairs and Climate Action, see [18]. In this study, we focus on the nine commodities silver (Ag), cobalt (Co), copper (Cu), dysprosium (Dy), indium (In), lithium (Li), neodymium (Nd), nickel (Ni) and platinum (Pt), which are key resources for the German Energiewende, according to [20]. The main uses of these metals in the context of the energy transition are described in Table 3, according to [19]. Hereby, silver, indium and platinum are mainly utilized for the installation of photovoltaic systems, while copper as well as the rare earth metals dysprosium and neodymium are used for wind turbines. Moreover, the metals silver, cobalt, indium, lithium, nickel, and platinum are required for energy storage within lithium-ion batteries, redox flow storage or general batteries.

[4] These calculations are generated within the project InteRessE, Grant-Nr: 03ET4065B, supported by the German Federal Ministry for Economic Affairs and Climate Action, which aims to analyze the resource demand of the German Energiewende from various perspectives. As the project is still ongoing, the specific data for the technologies considered as well as the resource requirement are not yet published.



(a) Ag



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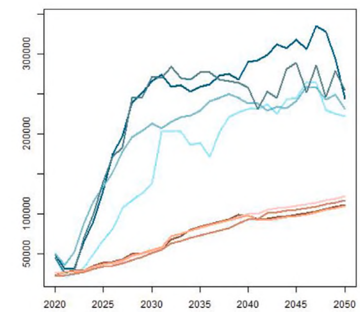
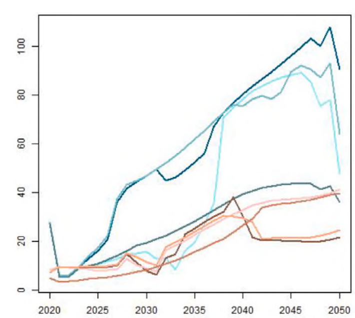
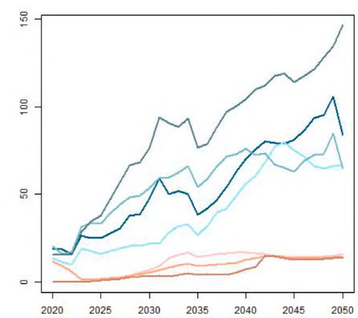


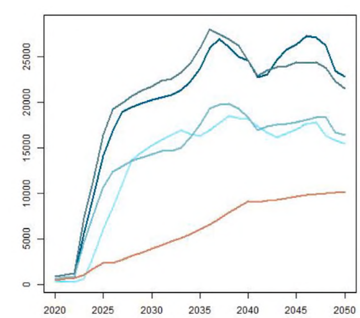
(c) Cu



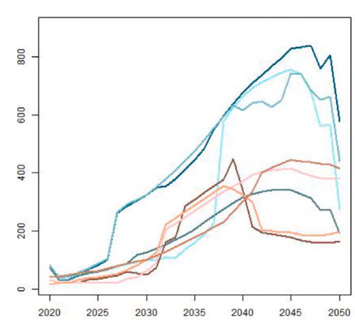
(d) Dy



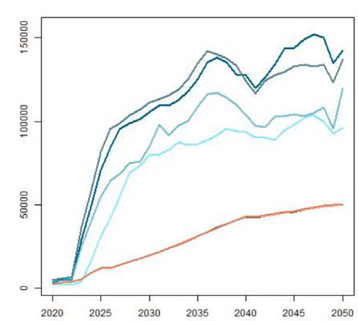
(e) In



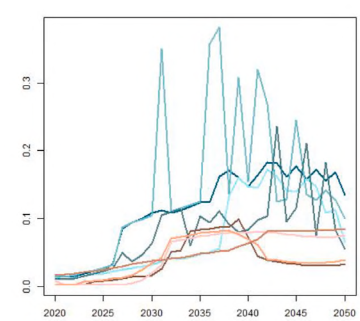
(f) Li



(g) Nd



(h) Ni



(i) Pt

Fig. 1. Required amount per commodity, in the period from 2020 to 2050, for the eight considered transformation pathways $REMod-REF$, $REMod-SUF$, $REMod-PER$, $REMod-UNA$, $ISI-REF$, $ISI-LIN$, $ISI-RED$, $ISI-LRE$.

The commodity requirements of the four $REMod$, as well as the four ISI transformation pathways for the German Energiewende in the period from 2020 to 2050 are graphically displayed in Fig. 1 of Appendix B. The corresponding descriptive statistics, the total amount over time as well as the average annual world production from 2010 to 2019, are given in Table 9 in Appendix B. Overall, the demand for the commodities will increase over time, except for silver and platinum, indicating more renewable energy technologies will be built up at the end of the considered time period. In addition, the total demand of the German Energiewende for cobalt is outstandingly high, compared to the average annual world production of the previous decade, whereas the requirements for platinum are almost neglectable.

Comparing the commodity demands for the eight different transformation pathways, the ISI paths generally require less metals than the $REMod$ paths, which can be explained by the different model assumptions. The ISI pathways model a cost optimized system regarding actions towards the 80% CO_2 reduction goal, in contrast to the 95% CO_2 objective of the $REMod$ pathways. In addition, the ISI pathways assume more energy imports combined with a lower, assumed total energy demand in 2050, implying less new renewable energy technologies have to be built up in Germany.

The main difference between the $ISI-RED$ and $ISI-REF$ paths is the location of onshore wind parks, resulting in almost equal resource demands, however, the $ISI-REF$ path requires slightly less commodities. Due to the reduced expansion of the transmission grids and the associated different energy distribution, the commodity amounts are highest for the $ISI-LIN$ path.

Regarding the $REMod$ pathways, the sufficiency path $REMod-SUF$ requires the least amount of metals, except for the rare earths dysprosium and neodymium. In particular, the least demand for dysprosium and neodymium in the unacceptance path $REMod-UNA$

can be attributed to the modeled resistance with respect to large infrastructural plans. Hereby, less wind parks will be installed, resulting in a reduced demand for the rare earth metals. However, in order to be able to achieve the energy targets despite the few wind parks, more photovoltaic systems and storage technologies must be set up, which is why the required amount for silver, cobalt, indium, lithium and nickel is comparably high in the unacceptance path $REMod - UNA$.

To obtain the expected loss due to scarcity for each transformation path described above, the commodity-specific probabilities of scarcity are calculated via logistic regression models, according to Section 2.1. Hereby, 18 initial input factors derived from the literature are considered, which are expected to have a direct or indirect price influence, as the most relevant factors are subsequently selected by the two-step model selection, to avoid data limitation issues.

The determinants originate from macroeconomic and demographic dimensions, as well as from capital market driven risk factors, additional to the classical supply and demand factors. A detailed overview of the factors,[5] their sources and previous considerations in the literature are given in Table 10 of Appendix B.

In general, commodities, especially industrial metals, are industrial goods in real economies. In this context, the classical fundamental theory states a good's price is the result of its supply and demand equilibrium, see [21–23]. Therefore, the impact of the commodity-specific supply and demand on commodity prices is investigated. Hereby, the commodity-specific supply variable is represented by the worldwide primary production per commodity, reported by [24]. Following the idea of Fernandez (2015) [25], the global commodity-specific demand is approximated by the global apparent consumption. Therefore, the commodity-specific U.S. apparent consumption, as provided by [24], is adjusted by the ratio of the reported U.S. Gross Domestic Product and the World Gross Domestic Product, drawn from [26,27].

The impact of global demand on commodity prices is represented by the gross domestic product and the industrial production, approximating economic activity, in accordance with [28–31]. Hereby, the World Gross Domestic Product (GDP) is drawn from [27], while the U.S. Industrial Production (IP),[6] is drawn from [32]. In addition, the U.S. Consumer Price Index (CPI), drawn from [33], accounts for the inflation rate in the model, see [28].

Theoretically, lower interest rates should increase the demand for commodities, due to reduced carrying costs, while simultaneously decreasing the supply, due to a less profitable extraction, see [28]. Therefore, the short-term interest rate, approximated by the 3-Month U.S. Treasury Rate (SIR), drawn from [34], as well as the long-term interest rate, measured by the 10-Year U.S. Treasury Rate (LIR), drawn from [35], are included. Since commodities are traded worldwide, a raise in the dollar exchange rate should be accompanied by lower commodity prices, due to the law of one price, according to [28], which is why the U.S. Dollar Index (FX), drawn from [36], is included in the analysis.

The study of Aksoy et al. (2019) [37] detects a significant impact of the demographic structure on the macroeconomy, in particular, on output growth, investment, savings, hours worked per capita, real interest rates, and inflation. In this study, the U.S. Employment (EMP), drawn from [38], as well as the World Population (POP), drawn from [39], are considered as potential demographic determinants.

Due to the financialization of commodity markets, financial institutions, such as hedge funds and commodity index funds, play an important role in commodity futures markets, as commodities represent an alternative asset class for investors, see [40]. Therefore, the MSCI World (MSC), drawn from [41], as well as the Standard & Poor's 500 Index (SPX), drawn from [42], are included as capital market driven determinants.

According to the studies Arendt et al. (2020) [43] and Graedel et al. (2012) [6], the Herfindal–Hirschman Index (HHI), see [44], capturing the global supply concentration of raw materials, is regarded as scarcity indicator. Therefore, this index is considered as a further potential determinant of the supply side. It is defined for commodity $i = 1, \dots, N$ at time $t = 1, \dots, T$ as:

$$HHI_{i,t} = 10000 \cdot \sum_{r=1}^{R} \left(\frac{prod_{i,t,r}}{\sum_{r=1}^{R} prod_{i,t,r}} \right)^2, \tag{14}$$

in which $prod_{i,t} = \sum_{r=1}^{R} prod_{i,t,r}$ represents the production for commodity i at time t, for all production countries $r = 1, \dots, R$, whereby the production data is the per country breakdown of the commodity-specific worldwide production, provided by [24].

In addition, the Global Natural Disasters Index (ND), drawn from [45] and the KOF Globalization Index (KOF), drawn from [46], measuring the trade activity and political relations, are included as proxies for the supply-side of markets. Further, the WTI crude oil price (OIL), drawn from [47], is included as important determinant of cash costs in the mining industry, following [48].

Moreover, additional demand proxies are considered. Hereby, the U.S. Monetary Base (MB), drawn from [49], which is interpreted as a liquidity measure, according to [50],[7] as well as the World Gross Domestic Product per Capita (GDPc), drawn from [51], which is expected to shift the demand curve over time, see [52,53], are included.

The objective of the empirical part of this study is the analysis and comparison of the resource requirements of several transformation pathways for the German Energiewende, from 2020 until 2050, in regard to their availability, respectively their scarcity. This study is a long-term commodity scarcity risk analysis, and therefore, based on annual data in the period from 1970 to 2019. Information on the descriptive statistics of the commodity-specific as well as macroeconomic and demographic factors is provided in Table 11 of Appendix B, where higher-frequency data is aggregated by the annual average.

The augmented Dickey–Fuller test controls for stationarity of the variables. In case of non-stationary variables, logarithmic returns are calculated.[8] Finally, to guarantee comparability and interpretability between commodities and paths, the data is standardized.

3.2. Results

In this section, the individual probabilities of scarcity per commodity are analyzed, followed by the comparison of the resulting expected loss due to scarcity of the transformation pathways of the German energy system. Via the definition of appropriate price thresholds, the commodities are classified in scarce and non-scarce states. In this study, the thresholds are only derived statistically, using the one-sigma approach displayed in Eq. (2), while they may be based on individual expert knowledge for other applications. The resulting, statistically derived threshold values per commodity are displayed in Table 4.

[5] As commodities are globally traded, prices are the result of their supply and demand equilibrium. Although this study investigates the risk of several German energy transformation pathways, global factors are considered as potential price influential factors, instead of their German counterpart. This is based on the assumption global factors would affect the commodity prices more than changes in the German economy. As some variables are not available on a global scope for the considered time period from 1970 to 2019, the global behavior is then approximated by U.S. based data.

[6] As data for the world industrial production is only available since 1990, we use the U.S. Industrial Production.

[7] As "an increase in liquidity will, in general, have a positive impact on demand for minerals and should, therefore, also have a positive effect on commodity prices" [50], we include the liquidity measure as a demand indicator, instead of a capital market indicator.

[8] In case of the U.S. CPI, returns are calculated, instead of logarithmic returns. Further, we have to calculate returns twice for KOF as well as Population to obtain stationary variables.

Table 4
Commodity price threshold.

	Ag	Co	Cu	Dy	In	Li	Nd	Ni	Pt
$\$/t$	901638	53318	7951	608299	647207	111979	81920	19813	50831971

Price threshold per commodity in $U.S.\$/t$, derived from the statistical one-sigma approach, based on price data from 2010 to 2019.

Table 5
Logistic regression parameters.

	Ag	Co	Cu	Dy	In	Li	Nd	Ni	Pt
FX				−0.59			−0.59		
LIR		0.66				8.19		−0.30	
SIR				0.23			0.23		
CPI						3.07			
GDP				−1.20			−1.20		
IP			0.35						
EMP		0.22							
S								1.42	
ND		−0.76							
OIL	0.16		0.19						
GDPc	−0.12	0.59	−0.22		0.37				0.48

Estimated coefficients for the U.S. Dollar Index (FX), the 10 Year U.S. Treasury Rate (LIR), the 3 Month U.S. Treasury Rate (SIR), the U.S. Consumer Price Index (CPI), the World Gross Domestic Product (GDP), the U.S. Industrial Production, the U.S. Employment (EMP), the Commodity World Production (S), the Global Natural Disasters (ND), the WTI Spot Crude Oil Price (OIL) and the World Gross Domestic Product per Capita (GDPc) of the logistic regression model per commodity.

Table 6
PS, LGS and EAS values.

	Ag	Co	Cu	Dy	In	Li	Nd	Ni	Pt
PS Mean	0.04	0.10	0.04	0.02	0.09	0.00	0.02	0.10	0.02
PS Shock	0.05	0.53	0.07	0.10	0.11	1.00	0.10	0.57	0.03
PS Extreme	0.07	0.92	0.11	0.37	0.15	1.00	0.37	0.94	0.04
LGS	0.59	0.63	0.75	1.00	0.62	0.56	0.47	0.62	0.67
EAS REMod - REF	0.21	5.64	0.39	1.42	2.20	0.62	0.45	1.41	0.01
EAS REMod - SUF	0.14	3.79	0.28	1.01	1.61	0.41	0.32	0.95	0.01
EAS REMod - PER	0.24	4.06	0.33	1.36	2.25	0.44	0.42	1.11	0.01
EAS REMod - UNA	0.33	5.77	0.37	0.68	3.36	0.63	0.19	1.41	0.01
EAS ISI - REF	0.03	1.69	0.12	0.43	0.38	0.19	0.16	0.39	0.00
EAS ISI - LIN	0.04	1.69	0.13	0.55	0.46	0.19	0.22	0.39	0.00
EAS ISI - RED	0.03	1.69	0.12	0.45	0.38	0.19	0.17	0.39	0.00
EAS ISI - LRE	0.02	1.69	0.12	0.46	0.25	0.19	0.22	0.39	0.00

Probability of scarcity for the three scenarios mean (PS Mean), shock (PS Shock) and extreme (PS Extreme), the loss given scarcity (LGS) and the exposure at scarcity for each of the 8 paths analyzed, for all commodities.

Subsequently, the two step model selection identifies the most influencing determinants per commodity. The estimated coefficients of the logistic regression models, corresponding to the commodity-specific determinants, are displayed in Table 5, whereby we focus on the most important factors. Hereby, the world gross domestic product per capita is the determining factor for five of the nine commodities.[9] Overall, the long-term interest rate has the highest influence of the determinants, especially on lithium, indicating a high interest rate leads to a high probability of scarcity. This is counter-intuitive, as interest rates raise the costs of capital, which is supposed to result in lower demand and a probably reduced risk of scarcity. However, our findings may reflect the reverse causality, as central banks raise interest rates in response to high commodity prices.

The commodity-specific probability of scarcity is based on different scenarios of the input variables. The initial mean scenario, proposed in Eq. (5), leads to moderate results, displayed in the row PS Mean of Table 6. Hereby, the commodities' sensitivities to the scenarios are heterogeneous. While lithium's risk increases to an extremely high value for the shock and extreme scenario, the probability of scarcity of silver and platinum remain comparably low, even under the extreme scenario. In addition, indium and copper show remarkably low risks in all scenarios. Cobalt as well as the rare earth metals bear a moderate risk of scarcity in the mean scenario, which raises to 92% and 37%, respectively, for the extreme scenario. Overall, cobalt, as well as lithium and nickel, will be the key commodities for the German Energiewende, regarding their probability of scarcity, in particular, in the extreme scenario.

The loss given scarcity, an indicator describing the substitutability of commodities, is calculated based on information about the metals' applications with primary substitutes and substitute performance from Table S1 from the supporting information of [54]. Hereby, the aggregation over all applications per metal results in the final loss given scarcity. For other applications of the framework, where a metal is used in a specific application, one may apply technology-specific parameters for the substitutability of the commodities. Table 6 displays the final loss given scarcities per commodity, highlighting the inability to substitute dysprosium, indicated by a loss given scarcity of 1. In contrast, lithium as well as neodymium have adequate substitutes, resulting in a score of approximately 50%. Thereby, the comparably low loss given scarcity of neodymium is caused by the possibility to substitute it by dysprosium within its major application, neodymium magnets. However, as dysprosium bears a high scarcity risk itself, this

[9] Due to data limitation issues, the model selection could not be performed for dysprosium and neodymium. Instead, the U.S. Dollar Index, the short-term interest rate as well as the world GDP are pre-selected for their logistic regression models. As dysprosium and neodymium are classified as scarce at identical points in time, their results are equal in the framework.

Table 7
Commodity-specific expected loss due to scarcity — Mean.

	Ag	Co	Cu	Dy	In	Li	Nd	Ni	Pt
REMod - REF	0.01	0.36	0.01	0.03	0.12	0.00	0.00	0.08	0.00
REMod - SUF	0.00	0.24	0.01	0.02	0.09	0.00	0.00	0.06	0.00
REMod - PER	0.01	0.26	0.01	0.03	0.12	0.00	0.00	0.07	0.00
REMod - UNA	0.01	0.37	0.01	0.02	0.18	0.00	0.00	0.08	0.00
ISI - REF	0.00	0.11	0.00	0.01	0.02	0.00	0.00	0.02	0.00
ISI - LIN	0.00	0.11	0.00	0.01	0.02	0.00	0.00	0.02	0.00
ISI - RED	0.00	0.11	0.00	0.01	0.02	0.00	0.00	0.02	0.00
ISI - LRE	0.00	0.11	0.00	0.01	0.01	0.00	0.00	0.02	0.00

Expected scarcities based on the mean scenario for all transformation paths per commodity.

example shows the substitutability score neglects the scarcity risks of the substitutes.[10]

The exposure at scarcity represents the required amount of each commodity per pathway, scaled by the average annual world production of the last decade, see Table 6. While the required amounts of the precious metals platinum and silver are relatively low in each path, the required amount of cobalt is outstandingly high, compared to its annual world production. Overall, we clearly notice a reduced exposure at scarcity of all commodities for the ISI paths, compared to the $REMod$ ones, caused by the 80% reduction goals modeled in ISI, in contrast to the 95% goals of $REMod$, which require less build-up of renewables and ultimately fewer commodities. While the differences in the ISI pathways are only minor, the $REMod$ paths differ substantially. Hereby, the $REMod-SUF$ path shows the lowest exposure at scarcity for all commodities, except for the rare earth metals, indicating the acceptance of society also determines the resource requirements.

The low requirements of dysprosium and neodymium in the unacceptance path $REMod - UNA$ can be attributed to the modeled resistance of the society with respect to large infrastructural plans. Hereby, less wind energy parks will be installed, resulting in a reduced demand for the rare earth metals. However, in order to achieve the energy targets, despite the few wind parks, more photovoltaic systems and storage technologies must be set up, which is why the required amounts for silver, cobalt, indium, lithium as well as nickel are comparably high in the unacceptance path $REMod-UNA$. This results in cobalt requirements being as high as five times of the average annual world production, allocated only for the German Energiewende. Overall, cobalt, as well as indium and nickel, will be the key commodities for the German Energiewende, regarding their required amounts.

Finally, the probability of scarcity, the loss given scarcity and the exposure at scarcity are aggregated to the expected loss due to scarcity per commodity, scenario and path, following Eq. (12). The commodity- and path-specific expected loss due to scarcity values of the mean scenario are displayed in Table 7. Due to the low probability of scarcity for most of the commodities in the mean scenario, the expected loss due to scarcity values are near zero. However, cobalt, as well as indium and nickel, will be the key commodities for the German Energiewende, regarding their expected loss due to scarcity.

Aggregating these commodity-specific expected loss due to scarcity values on path level, the expected loss due to scarcity $ES_{p,\zeta}$ per path and scenario is derived according to Eq. (13), see Table 8. The expected loss due to scarcity values for the four ISI paths are similar, independent of the scenario considered, due to the similar required amounts of the commodities. In line with the results of the exposure at scarcity and the expected loss due to scarcity values on commodity level, the aggregated expected loss due to scarcity measure is significantly lower for the ISI pathways, compared to the $REMod$ ones, mainly caused by the 15% difference in the CO_2 reduction goals as well as the different assumptions on energy imports for the pathways of ISI and $REMod$.

Table 8
Project-specific expected loss due to scarcity.

	Mean	Shock	Extreme
REMod - REF	0.62	3.08	5.26
REMod - SUF	0.43	2.09	3.58
REMod - PER	0.50	2.35	4.06
REMod - UNA	0.67	3.12	5.14
ISI - REF	0.17	0.89	1.54
ISI - LIN	0.18	0.92	1.60
ISI - RED	0.17	0.90	1.55
ISI - LRE	0.16	0.89	1.55

Expected scarcities on path level for all transformation paths and scenarios.

Comparing the four $REMod$ pathways, the sufficiency path $REMod-SUF$ bears the lowest scarcity risk, due to the least required amount of commodities. In contrast, the $REMod - UNA$ path shows the highest expected loss due to scarcity values of all pathways, in the mean and shock scenario, due to the high demand in cobalt, caused by the large required amount of battery storage in this path, where its expected loss due to scarcity values are closely followed by those of the $REMod - REF$ path. The lower values for the $REMod - PER$ path, compared to the $REMod - REF$, are mainly determined by the comparably low exposure at scarcity of cobalt. Overall, the analysis suggests higher climate goals accompanied by fewer energy imports, lead to a increased build up of renewable technologies, and ultimately, higher scarcity risks of commodities. However, if the 95% reduction target is considered, the $REMod-SUF$ path should be accomplished, as a substantial change in the behavior of the German population towards a decrease in the energy consumption leads to fewer commodity requirements.

This study contributes to the literature by the development of a new framework to assess the scarcity risk of resource-demanding projects under the consideration of the substitutability of commodities, the future required amounts of the project as well as the historical information available. In contrast to around 80% of publications, which analyze the energy transition on global level, see [3], the focus of the empirical part of this study is on national level.

The study of Viebahn et al. (2015) [4] also concentrates on the German energy transition and detects, based on a meta-analysis, the sub-technologies wind power plants, using neodymium and dysprosium, thin-film CIGS photovoltaic cells, using indium and selenium, and large-scale redox flow batteries, using vanadium, are critical with regard to potential supply risks. While their analysis focuses on the availability of the resources for constructed transformation paths based on a meta-analysis, this study proposes a framework to compare several transformation paths with regard to their scarcity risks. Moreover, Viebahn et al. (2015) assume manganese will substitute cobalt in the future, which is why cobalt is not regarded as critical in their study, in contrast to the findings of this study, where cobalt and indium bear the highest scarcity risks.

[10] We thank an anonymous reviewer for the hint, substitute materials may be equally or even more scarce than the current material. In addition, the study of [54], analyzing the substitutability of 62 metals and metalloids in their major uses, reveals several metals have no substitute or the product performance will suffer from substitution. Therefore, the robustness analysis in Appendix D.1 investigates how the results change if neither commodity is regarded substitutable. Hence, the LGS of each commodity is set to one, however, the findings are similar.

Similar to the study of Viebahn et al. (2015) [4], Valero et al. (2018) [55] compares future required material demand with global reserves. However, they aim to detect bottlenecks in the future global demand for green technologies until 2050 under the consideration of estimates for demand of the remaining sectors. Overall, they identify the commodities cadmium, chromium, cobalt, copper, gallium, indium, lithium, manganese, nickel, silver, tellurium, tin and zinc with the highest supply risks. In addition, the study of Manberger and Stenqvist (2018) [56] on global level analyzes the material demand for global climate mitigation scenarios up to 2060. Hereby, the lithium demand exceeds the global reserves, which is why Manberger and Stenqvist (2018) regard this commodity as the most critical commodity, while Gruber et al. (2011) [57] state lithium resources are sufficient to support demand. In their study, they analyze up to 100 deposits regarding the lithium resources and conclude the lithium resources exceed even the highest demand scenario for lithium until 2100. In this study, lithium has a high probability of scarcity, however, due to the comparably small required amount of lithium for the German Energiewende the overall supply risk is moderately.

While most studies focus on the criticality of individual commodities or technologies used in the energy transition, this study provides a scarcity analysis and comparison of different transformation paths of the German Energiewende, hereby simultaneously taking into account the future demands of various technologies and multiple commodities. Overall, the acceptance of the German society for the energy transition is the main determinant for the resulting resource requirements. The so established, less constrained power system has to satisfy lower power consumption, which ultimately leads to a reduced scarcity risk.

4. Conclusion and policy implications

In this study, a new framework is developed to analyze resource-demanding projects in regard to their economic risk of resource scarcity. Subsequently, the framework is applied to eight energy transformation pathways for the German Energiewende in an exemplary manner. With the assumption of the commodity price being the result of the supply and demand equilibrium, the price is regarded as a reliable economic indicator of commodity scarcity.

Methodologically, the framework is a two-stage process: First, commodity-specific probabilities of scarcity are calculated via logistic regressions, based on pre-selected determinants and an appropriate price threshold. Second, this probability of scarcity is combined with a substitutability rate as well as the required amount per commodity and project to a commodity-specific risk indicator. Subsequently, the commodity-specific risk indicators are aggregated to the final measure, the expected loss due to scarcity, on project level.

In a case study, the framework is applied on eight transformation pathways of the German energy system, focusing on the nine commodities silver, cobalt, copper, dysprosium, indium, lithium, neodymium, nickel and platinum, which are regarded as key resources for the German Energiewende, see [20]. The pathways considered differ in the underlying climate targets, the assumption of Germany's overall energy demand, as well as the acceptance of the required actions within the German society. This leads to varying technology mixes, with corresponding resource requirements and in turn different scarcity risks for the commodities considered. Hereby, cobalt and indium, mainly allocated to energy storage and solar PV technologies, bear the highest risks, while lithium demonstrates a high probability of scarcity for the extreme scenario. Overall, the sufficiency scenario $REMod-SUF$, which models the transformation of the German energy system with full support by the society, shows the lowest expected loss due to scarcity among the paths aiming for the 95% CO_2 reduction goals.

This study reveals the economic scarcity risk of commodities highly depends on the required amounts. In the context of the German Energiewende, we recommend to take measures leading to a lower power consumption and an optimized power system, without any constraints, in order to significantly reduce the scarcity risk of the commodities. Policy should therefore raise the awareness in the German population to save electricity and stand behind the necessary infrastructure projects so the energy system can be set up optimally.

Further research could include time-varying parameters in the framework. Moreover, the expected loss due to scarcity is based on the sum of the required commodity amounts over the entire period from 2020 to 2050. However, a time-varying analysis might reveal which transformation pathway bears the highest scarcity risk throughout the considered time period. Additionally, the proposed risk assessment could be extended to a risk prognosis by exchanging the scenarios with forecasted values for the price determinants.

CRediT authorship contribution statement

A. Schischke: Methodology, Software, Formal analysis, Writing – original draft, Visualization, Project administration. **P. Papenfuß:** Validation, Data curation, Writing – original draft. **M. Brem:** Methodology, Writing – original draft. **P. Kurz:** Software, Data curation. **A.W. Rathgeber:** Conceptualization, Writing – review & editing, Supervision, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Two-step model selection

In general, commodity prices are affected by various influencing variables. However, the inclusion of all variables in an analysis is unfeasible from the statistical point of view, due to data limitations. Therefore, a two-step model selection is applied for each commodity to identify the commodity-specific price determining factors, which will be included in the calculation of the probability of scarcity. First, all factors which do have a significant impact on the commodity price are extracted from a broad list of potential variables. Subsequently, a bidirectional stepwise model selection is performed based on these factors to identify the most important ones.

In the first step, factors which do have a significant impact on the commodity price are identified from the entire set of potential

Table 9
Descriptive statistics of the commodity- and transformation path-specific demand.

		Min.	5% Quantile	25% Quantile	Median	Mean	75% Quantile	95% Quantile	Max.	Av. annual supply	Total	St.Dev.
Ag [t]	$REMod-REF$	55.00	62.00	125.00	172.00	171.00	196.00	294.00	348.00	25440.00	5302.00	71.00
	$REMod-SUF$	37.00	39.00	91.00	131.00	115.00	145.00	149.00	150.00	25440.00	3579.00	36.00
	$REMod-PER$	53.00	61.00	101.00	204.00	195.00	267.00	343.00	362.00	25440.00	6039.00	97.00
	$REMod-UNA$	45.00	55.00	165.00	263.00	273.00	363.00	492.00	550.00	25440.00	8453.00	137.00
	$ISI-REF$	6.00	10.00	19.00	31.00	28.00	36.00	43.00	43.00	25440.00	859.00	11.00
	$ISI-LIN$	6.00	10.00	20.00	31.00	36.00	52.00	69.00	71.00	25440.00	1104.00	20.00
	$ISI-RED$	6.00	10.00	19.00	31.00	28.00	36.00	43.00	43.00	25440.00	860.00	11.00
	$ISI-LRE$	0.00	0.00	14.00	17.00	16.00	20.00	26.00	33.00	25440.00	492.00	8.00
Co [tsd. t]	$REMod-REF$	1.00	1.28	30.93	35.24	31.41	39.20	42.75	43.28	172.78	973.72	12.64
	$REMod-SUF$	0.46	0.51	19.95	25.84	21.12	26.85	28.18	28.65	172.78	654.64	9.71
	$REMod-PER$	1.10	1.37	21.45	26.11	22.64	28.16	30.77	31.08	172.78	701.94	8.83
	$REMod-UNA$	1.46	1.86	32.63	36.52	32.15	38.40	42.60	44.61	172.78	996.59	12.09
	$ISI-REF$	0.74	1.12	4.80	9.76	9.44	14.26	16.30	16.62	172.78	292.69	5.33
	$ISI-LIN$	0.74	1.12	4.80	9.76	9.44	14.26	16.30	16.62	172.78	292.70	5.33
	$ISI-RED$	0.74	1.12	4.80	9.76	9.44	14.26	16.30	16.62	172.78	292.69	5.33
	$ISI-LRE$	0.74	1.12	4.80	9.76	9.44	14.26	16.30	16.62	172.78	292.70	5.33
Cu [tsd. t]	$REMod-REF$	30.83	40.06	218.30	262.27	233.47	293.64	323.62	335.04	18580.00	7237.56	91.26
	$REMod-SUF$	22.02	28.17	111.78	202.90	168.75	228.69	254.96	265.56	18580.00	5231.27	78.56
	$REMod-PER$	35.65	50.14	187.31	228.67	198.30	240.76	254.03	259.54	18580.00	6147.16	65.62
	$REMod-UNA$	25.92	36.26	207.03	255.26	220.92	271.12	285.61	289.09	18580.00	6848.60	82.37
	$ISI-REF$	22.24	27.86	46.02	83.25	72.39	97.50	107.06	111.22	18580.00	2243.92	29.14
	$ISI-LIN$	25.46	26.88	43.14	81.77	75.27	105.62	117.81	121.77	18580.00	2333.48	33.09
	$ISI-RED$	21.33	26.67	44.61	82.25	71.66	94.95	105.65	109.72	18580.00	2221.37	28.81
	$ISI-LRE$	21.69	23.54	39.66	72.61	70.11	101.48	112.94	116.35	18580.00	2173.32	31.87
Dy [t]	$REMod-REF$	6.00	8.00	39.00	52.00	59.00	88.00	102.00	108.00	1280.00	1814.00	32.00
	$REMod-SUF$	5.00	7.00	13.00	27.00	42.00	78.00	88.00	89.00	1280.00	1297.00	33.00
	$REMod-PER$	6.00	8.00	40.00	62.00	56.00	78.00	91.00	93.00	1280.00	1747.00	28.00
	$REMod-UNA$	5.00	7.00	17.00	28.00	28.00	41.00	44.00	44.00	1280.00	865.00	13.00
	$ISI-REF$	6.00	7.00	9.00	20.00	18.00	22.00	31.00	38.00	1280.00	552.00	8.00
	$ISI-LIN$	8.00	8.00	9.00	23.00	23.00	36.00	39.00	41.00	1280.00	708.00	13.00
	$ISI-RED$	7.00	9.00	10.00	21.00	19.00	24.00	30.00	31.00	1280.00	578.00	7.00
	$ISI-LRE$	3.00	4.00	6.00	16.00	19.00	34.00	38.00	40.00	1280.00	587.00	13.00
In [t]	$REMod-REF$	16.00	19.00	34.00	50.00	55.00	79.00	94.00	106.00	774.00	1700.00	26.00
	$REMod-SUF$	10.00	12.00	20.00	32.00	40.00	65.00	76.00	80.00	774.00	1245.00	23.00
	$REMod-PER$	16.00	19.00	46.00	62.00	56.00	70.00	75.00	85.00	774.00	1742.00	18.00
	$REMod-UNA$	15.00	16.00	62.00	91.00	84.00	113.00	131.00	147.00	774.00	2597.00	37.00
	$ISI-REF$	1.00	2.00	6.00	10.00	9.00	14.00	15.00	15.00	774.00	290.00	5.00
	$ISI-LIN$	1.00	2.00	7.00	14.00	11.00	16.00	17.00	17.00	774.00	355.00	6.00
	$ISI-RED$	1.00	2.00	6.00	10.00	9.00	14.00	15.00	15.00	774.00	290.00	5.00
	$ISI-LRE$	0.00	0.00	2.00	4.00	6.00	13.00	14.00	15.00	774.00	193.00	5.00
Li [tsd. t]	$REMod-REF$	0.62	0.80	19.27	22.75	19.82	25.44	27.04	27.33	998.30	614.38	8.03
	$REMod-SUF$	0.28	0.32	12.42	16.38	13.32	17.04	18.26	18.50	998.30	413.04	6.16
	$REMod-PER$	0.68	0.85	13.36	16.46	14.29	17.96	19.58	19.83	998.30	443.06	5.64
	$REMod-UNA$	0.91	1.16	20.32	22.91	20.28	24.34	27.26	28.03	998.30	628.61	7.66
	$ISI-REF$	0.46	0.70	2.99	6.05	5.97	9.30	10.07	10.11	998.30	185.19	3.40
	$ISI-LIN$	0.46	0.70	2.99	6.05	5.97	9.30	10.07	10.11	998.30	185.19	3.40
	$ISI-RED$	0.46	0.70	2.99	6.05	5.97	9.30	10.07	10.11	998.30	185.19	3.40
	$ISI-LRE$	0.46	0.70	2.99	6.05	5.97	9.30	10.07	10.11	998.30	185.19	3.40
Nd [t]	$REMod-REF$	38.00	49.00	273.00	445.00	457.00	722.00	829.00	839.00	31400.00	14168.00	278.00
	$REMod-SUF$	31.00	42.00	81.00	159.00	325.00	642.00	742.00	756.00	31400.00	10077.00	287.00
	$REMod-PER$	38.00	49.00	277.00	441.00	423.00	637.00	712.00	743.00	31400.00	13115.00	236.00
	$REMod-UNA$	29.00	40.00	83.00	191.00	196.00	305.00	340.00	341.00	31400.00	6070.00	110.00
	$ISI-REF$	16.00	22.00	48.00	161.00	162.00	204.00	366.00	448.00	31400.00	5033.00	123.00
	$ISI-LIN$	22.00	22.00	33.00	270.00	225.00	380.00	410.00	414.00	31400.00	6990.00	163.00
	$ISI-RED$	16.00	22.00	59.00	189.00	173.00	255.00	339.00	354.00	31400.00	5367.00	110.00
	$ISI-LRE$	42.00	46.00	83.00	178.00	221.00	409.00	438.00	444.00	31400.00	6866.00	153.00
Ni [tsd. t]	$REMod-REF$	3.69	4.97	97.38	119.98	105.91	135.34	149.80	152.24	2330.00	3283.07	44.23
	$REMod-SUF$	1.94	2.35	62.28	87.11	71.58	93.79	100.99	103.85	2330.00	2219.09	33.72
	$REMod-PER$	3.97	5.50	71.83	97.46	83.78	104.61	116.71	120.14	2330.00	2597.08	34.41
	$REMod-UNA$	4.99	6.20	101.43	123.42	106.01	133.12	138.89	142.03	2330.00	3286.32	40.74
	$ISI-REF$	2.34	3.55	14.89	31.37	29.17	43.75	49.27	50.22	2330.00	904.24	16.21
	$ISI-LIN$	2.40	3.55	14.81	31.28	29.28	44.13	49.65	50.61	2330.00	907.60	16.34
	$ISI-RED$	2.34	3.55	14.91	31.32	29.20	43.76	49.31	50.28	2330.00	905.11	16.20
	$ISI-LRE$	2.41	3.59	14.95	31.04	29.25	44.11	49.69	50.63	2330.00	906.65	16.29

(*continued on next page*)

Table 9 (*continued*).

Pt [t]	$REMod-REF$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	436.00	4.00	0.00
	$REMod-SUF$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	436.00	2.00	0.00
	$REMod-PER$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	436.00	4.00	0.00
	$REMod-UNA$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	436.00	3.00	0.00
	$ISI-REF$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	436.00	1.00	0.00
	$ISI-LIN$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	436.00	2.00	0.00
	$ISI-RED$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	436.00	1.00	0.00
	$ISI-LRE$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	436.00	2.00	0.00

Descriptive statistics (Minimum (Min.), 5%, 25%, 75%, 95% quantiles, median, mean, maximum (Max.), standard deviation (St. Dev.) of the commodity-specific demand per transformation pathway of the German Energy System, combined with the average annual world production (Av. annual supply) and the total demand of the commodity per transformation pathway (Total).

Table 10
Description of input variables.

Abbr.	Factor	Freq.	Data per.	Literature source	Data source
FX	U.S. Dollar Index	Annually	1967–2021	[28], [58], [59]	[36]
LIR	10-Year U.S. Treasury Rate, in % per annum	Annually	1953–2021	[60], [61], [62]	[35]
SIR	3-Month U.S. Treasury Rate, in % per annum	Annually	1965–2021	[28],[29], [63]	[34]
CPI	U.S. Consumer Price Index, in percent, not seasonally adjusted	Annually	1960–2021	[28], [64], [61], [65]	[33]
GDP	World Gross Domestic Product, in current U.S. Dollar	Annually	1969–2021	[66], [23]	[27]
IP	U.S. Industrial Production, unadjusted, Index 2017=100	Annually	1935–2021	[30], [29] [31]	[32]
EMP	U.S. Employment, representing the % of working age population	Annually	1955–2020	[67], [68]	[38]
POP	World Population	Annually	1960–2021	[69], [52]	[39]
MSC	Annually Index Level of MSCI World, closing price in basis points	Daily	1969–2021	[40], [70], [71]	[41]
SPX	Standard & Poor's 500 Index	Annually	1963–2020	[72], [73]	[42]
S	World Production of each commodity	Annually	1969–2021	[22], [23]	[24]
HHI	Herfindahl–Hirschman Index (mining countries)	Annually	1970–2019	[43], [6]	[24]
ND	Global Natural Disasters	Annually	1970–2021		[45]
KOF	KOF Globalization Index	Annually	1970–2019		[46]
OIL	Spot Crude Oil Price: West Texas Intermediate (WTI), in U.S. Dollar per Barrel	Annually	1946–2021	[74], [48]	[47]
D	Estimated world apparent consumption per commodity, based on data of the U.S. apparent consumption as well as the ratio of reported U.S. GDP and World GDP	Annually	1969–2021	[25], [22], [75]	[24]
GDPc	World Gross Domestic Product per Capita, in current U.S. Dollar	Annually	1960–2021		[51]
MB	U.S. Monetary Base, in millions of U.S. Dollar	Monthly	1959–2020	[50], [76]	[49]
Ag	Average annual price of silver	Annually	1970–2020		[77] & [78]
Co	Average annual price of cobalt	Annually	1970–2020		[77] & [79]
Cu	Average annual price of copper	Annually	1970–2020		[80]
Dy	Average annual price of dysprosium	Annually	1970–2020		[81]
In	Average annual price of indium	Annually	1970–2020		[77] & [82]
Li	Average annual price of lithium	Annually	1970–2020		[77] & [83]
Nd	Average annual price of neodymium	Annually	1970–2020		[84]
Ni	Average annual price of nickel	Annually	1970–2020		[77] & [85]
Pt	Average annual price of platinum	Annually	1970–2020		[77] & [86]

Variable names of the input factors, paired with data frequency and time span of the data as well as previous studies considering this attribute and the respective data source.

(commodity-specific) price determinants $\mathbf{x}_{i,t}^{all} = (x_{1,i,t}^{all}, \ldots, x_{K_i^{all},i,t}^{all})'$.[11] Therefore, univariate linear regression models are estimated, via ordinary least squares, of each factor $x_{k_i,t}^{all}$, for $k_i = 1, \ldots, K_i^{all}$ on the price ($price_{i,t}$) of commodity $i = 1, \ldots, N$ individually, see [15]:

$$price_{i,t} = \beta_0 + \beta_{k_i} x_{k_i,t}^{all} + \varepsilon_{i,t}, \quad (15)$$

where β_0 denotes the intercept, β_{k_i} the coefficient corresponding to the factor $x_{k_i,t}^{all}$ and $\varepsilon_{i,t}$ the error term. A standard t-test, see [15], is applied on the coefficient β_{k_i}, corresponding to the factor $x_{k_i,t}$ to test whether the factor significantly affects the commodity price. Hereby, the null hypothesis assumes the coefficient β_{k_i} equals zero ($\beta_{k_i} = 0$), implying the factor has no impact on the commodity's price. If the null hypothesis can be rejected for a specific factor at the 5% significance level, we assume the factor does affect the commodity price and this factor will be further considered. This pre-selection based on the univariate linear regression model identifies, for each commodity separately, a set of K_i^{pre} factors $\mathbf{x}_{i,t}^{pre} = (x_{1,i,t}^{pre}, \ldots, x_{K_i^{pre},i,t}^{pre})'$ which affect the price of a specific commodity i.

In the second step, the final set of K_i covariates $\mathbf{x}_{i,t} = (x_{1,i,t}, \ldots, x_{K_i,i,t})'$ for the commodity-specific logistic regression models is determined. Hereby, a bi-directional stepwise model selection, according to [15], using the Bayesian Information Criterion (BIC) is applied on the pre-selected set of factors. To ensure none of the final models suffers from multicollinearity, highly correlated variables are excluded from the analysis, such that the variance inflation factor, an indicator for multicollinearity, is equal to or smaller than 5, see [15].

Appendix B. Data description

See Tables 9–11. see Fig. 1

Appendix C. Expected scarcity per scenario

In Tables 12 and 13, the expected loss due to scarcity per commodity is displayed for the shock and extreme scenario, respectively. In line with the results of the mean scenario in Table 7, cobalt is outstanding in

[11] The index i attached to the vector of potential price determinants $\mathbf{x}_{i,t}^{all}$ allows for different sets of price determinants among the commodities. Hereby, some determinants may be pre-selected only for some commodities or the price determinants are commodity-specific, for example the supply and demand of a commodity, represented by the world production and the world apparent consumption, respectively.

Table 11
Descriptive statistics of covariates.

	Min.	5% Q.	Med.	Mean	95% Q.	Max.	St.Dev.
Ag D	−1.97	−1.59	0.01	0.02	1.77	2.48	1.01
Ag S	−2.28	−1.77	0.14	0.01	1.50	2.11	0.96
Ag HHI	−2.94	−1.56	−0.04	−0.06	0.96	3.90	0.95
Ag P	49834	58257	187611	292565	663269	1135242	225224
Ag Ret.	−0.67	−0.33	−0.00	0.05	0.62	0.72	0.30
Co D	−2.49	−1.94	−0.05	−0.03	1.58	3.46	1.05
Co S	−4.43	−1.68	0.17	0.01	1.25	1.57	0.97
Co HHI	−2.55	−1.46	−0.08	0.00	1.57	3.35	1.00
Co P	4850	5596	27772	31232	71625	86002	20369
Co Ret.	−0.78	−0.59	0.09	0.06	0.76	1.47	0.44
Cu D	−3.08	−2.60	0.10	0.00	1.36	1.98	1.09
Cu S	−2.52	−1.49	−0.11	−0.04	1.75	2.31	1.07
Cu HHI	−1.91	−1.78	−0.19	−0.10	1.83	2.89	1.06
Cu P	1073	1105	1863	2871	7302	8820	2152
Cu Ret.	−0.53	−0.30	−0.01	0.02	0.44	0.60	0.23
Dy D	−2.68	−1.63	0.01	−0.00	1.38	2.32	0.93
Dy S	−2.54	−1.48	0.07	0.02	1.65	2.29	1.00
Dy HHI	4303.69	4398.14	5384.65	5513.77	6676.06	6758.57	1032.90
Dy P	248654	249057	317505	396422	751062	860568	211877
Dy Ret.	−0.49	−0.43	0.14	0.02	0.37	0.40	0.36
In D	−4.27	−1.38	−0.12	−0.02	2.33	3.50	1.21
In S	−3.73	−1.33	−0.10	−0.12	1.74	2.87	1.05
In HHI	−2.87	−1.06	−0.09	0.00	1.64	3.21	1.00
In P	56907	80377	232289	288394	677136	960740	20699
In Ret.	−0.81	−0.59	−0.06	0.01	0.92	1.31	0.44
Li D	−2.97	−2.08	−0.04	−0.02	1.54	2.66	1.00
Li S	−4.01	−1.48	−0.04	−0.02	0.83	3.85	1.15
Li HHI	−1.70	−1.62	−0.21	−0.05	1.32	2.49	1.02
Li P	18034	18034	57486	57772	99220	131431	27917
Li Ret.	−0.24	−0.12	0.04	0.04	0.18	0.42	0.10
Nd D	−2.68	−1.63	0.01	−0.00	1.38	2.32	0.93
Nd S	−2.54	−1.48	0.07	0.02	1.65	2.29	1.00
Nd HHI	4303.69	4398.14	5384.65	5513.77	6676.06	6758.57	1032.90
Nd P	53555	56139	69904	69585	87961	95179	12335
Nd Ret.	−0.27	−0.23	−0.03	0.02	0.34	0.40	0.24
Ni D	−1.81	−1.64	−0.07	0.01	1.62	3.99	1.11
Ni S	−2.75	−1.96	0.13	−0.03	1.27	3.02	1.02
Ni HHI	−2.26	−1.45	−0.21	−0.09	1.55	3.12	0.94
Ni P	2932	3129	6004	8667	21737	37149	6405
Ni Ret.	−0.57	−0.37	0.05	0.03	0.39	1.05	0.25
Pt D	−4.32	−1.18	−0.04	0.00	1.16	2.26	1.01
Pt S	−2.74	−1.51	−0.21	0.00	2.03	2.79	1.01
Pt HHI	−2.70	−1.60	0.00	−0.03	1.38	2.10	0.98
Pt P	3890237	4030093	13677408	18266025	49507897	55273028	13757821
Pt Ret.	−0.41	−0.31	−0.01	0.04	0.50	0.53	0.23
FX	−2.14	−1.76	0.12	0.02	1.52	1.63	1.02
LIR	−2.67	−1.31	0.08	0.08	1.42	1.89	0.96
SIR	−3.61	−1.20	0.04	0.02	1.37	2.34	0.93
CPI	−3.44	−0.35	−0.08	−0.01	0.47	5.73	0.88
GDP	−2.21	−1.36	0.19	0.11	1.64	2.25	1.02
UIP	−3.40	−1.77	0.16	0.03	1.54	1.71	1.07
EMP	−3.52	−1.57	0.21	0.05	1.61	2.11	1.05
POP	−2.70	−1.71	0.20	0.02	1.52	2.06	1.04
MSC	−3.51	−1.71	0.28	0.00	1.15	1.51	0.98
SPX	−3.33	−1.95	0.26	−0.02	1.17	1.32	1.01
KOF	−3.56	−1.67	0.04	−0.03	1.35	4.19	1.01
ND	−2.22	−1.55	0.01	0.03	1.56	2.68	1.02
OIL	−2.58	−1.42	0.01	0.07	1.62	3.38	1.01
GDPc	−2.14	−1.43	0.21	0.11	1.67	2.23	1.02
MB	−1.87	−0.69	−0.15	−0.02	1.18	5.48	0.88

Descriptive statistics including the minimum (Min.), 5% quantile (5% Q.), median (Med.), mean (Mean), 95% quantile (95% Q.), maximum (Max.) and standard deviation (St.Dev.).

regard to its scarcity risk. Additionally, the risk of the precious metals is almost neglectable. In contrast to the mean scenario, lithium bears a relatively high risk of scarcity due to its high probability of scarcity in the shock and extreme scenario.

Table 12
Commodity-specific expected loss due to scarcity — Shock.

	Ag	Co	Cu	Dy	In	Li	Nd	Ni	Pt
REMod - REF	0.01	1.88	0.02	0.15	0.16	0.34	0.02	0.50	0.00
REMod - SUF	0.00	1.26	0.01	0.11	0.11	0.23	0.02	0.34	0.00
REMod - PER	0.01	1.35	0.02	0.14	0.16	0.25	0.02	0.40	0.00
REMod - UNA	0.01	1.92	0.02	0.07	0.24	0.35	0.01	0.50	0.00
ISI - REF	0.00	0.56	0.01	0.04	0.03	0.10	0.01	0.14	0.00
ISI - LIN	0.00	0.56	0.01	0.06	0.03	0.10	0.01	0.14	0.00
ISI - RED	0.00	0.56	0.01	0.05	0.03	0.10	0.01	0.14	0.00
ISI - LRE	0.00	0.56	0.01	0.05	0.02	0.10	0.01	0.14	0.00

Expected scarcities based on the shock scenario for all paths per commodity.

Table 13
Commodity-specific expected loss due to scarcity — Extreme.

	Ag	Co	Cu	Dy	In	Li	Nd	Ni	Pt
REMod - REF	0.01	3.24	0.03	0.52	0.20	0.34	0.08	0.83	0.00
REMod - SUF	0.01	2.18	0.02	0.37	0.15	0.23	0.06	0.56	0.00
REMod - PER	0.01	2.34	0.03	0.50	0.21	0.25	0.07	0.66	0.00
REMod - UNA	0.01	3.32	0.03	0.25	0.31	0.35	0.03	0.83	0.00
ISI - REF	0.00	0.97	0.01	0.16	0.03	0.10	0.03	0.23	0.00
ISI - LIN	0.00	0.97	0.01	0.20	0.04	0.10	0.04	0.23	0.00
ISI - RED	0.00	0.97	0.01	0.17	0.03	0.10	0.03	0.23	0.00
ISI - LRE	0.00	0.97	0.01	0.17	0.02	0.10	0.04	0.23	0.00

Expected scarcities based on the extreme scenario for all paths per commodity.

Appendix D. Robustness analysis

D.1. Robustness to the loss given scarcity

This robustness analysis investigates the sensitivity of the model to the LGS, which reflects the substitutability of the commodities. As substitute materials may be equally or even more scarce than the current material and the study of Graedel et al. (2015) [54] reveals several metals have no substitute or the product performance will suffer from substitution, we analyze the resource scarcity under the assumption neither commodity is substitutable, i.e. the LGS equals one for each commodity.

The resulting expected loss due to scarcity per scenario and path is displayed in Table 14. Similar to the results in the main part of this study, the expected loss due to scarcity values for the four ISI paths are comparable, independent of the scenario considered, due to the comparable required amounts of the commodities. Moreover, the aggregated expected loss due to scarcity measure is significantly lower for the ISI pathways, compared to the $REMod$ ones. Within the four $REMod$ pathways, the sufficiency path $REMod - SUF$ bears the lowest scarcity risk, whereas the $REMod - UNA$ path shows the highest expected loss due to scarcity values of all pathways, in the mean and shock scenario, where its expected loss due to scarcity is closely followed by those of the $REMod - REF$ path. Comparing the expected loss due to scarcity of this robustness analysis under the assumption of no substitutability with the results of the study under substitutability, the expected loss due to scarcity values are higher if no substitutes are available. However, as the findings, in particular, the ordering of the pathways equals, the framework is robust with regard to the substitutability.

Table 14
Project-specific expected loss due to scarcity.

	Mean	Shock	Extreme
REMod - REF	0.97	4.90	8.19
REMod - SUF	0.67	3.32	5.56
REMod - PER	0.78	3.72	6.27
REMod - UNA	1.07	5.02	8.14
ISI - REF	0.26	1.42	2.40
ISI - LIN	0.28	1.45	2.48
ISI - RED	0.26	1.43	2.41
ISI - LRE	0.25	1.42	2.41

Expected scarcities on path level for all transformation paths and scenarios under the assumption neither commodity is substitutable.

D.2. Robustness to the threshold

The price threshold is calculated based on the average price of the last decade. In order to consider the sensitivity to the sample period, the expected loss due to scarcity values are calculated based on data from 2005 to 2019. The resulting expected loss due to scarcity values per scenario and path are displayed in Table 15. Similar to the results of this study, the expected loss due to scarcity values for the four ISI paths are comparable, independent of the scenario considered, due to the comparable required amounts of the commodities. Moreover, the aggregated expected loss due to scarcity measure is significantly lower for the ISI pathways, compared to the $REMod$ ones. Within the four $REMod$ pathways, the sufficiency path $REMod - SUF$ bears the lowest scarcity risk. In contrast, the $REMod - UNA$ path shows the highest expected loss due to scarcity values of all pathways, in the mean scenario, whereby the $REMod - REF$ scenario has the highest risk in the shock and extreme scenario. However, the findings are comparable to those based on the sample period from 2010 to 2019.

Table 15
Project-specific expected loss due to scarcity.

	Mean	Shock	Extreme
REMod - REF	0.29	1.20	2.60
REMod - SUF	0.20	0.82	1.78
REMod - PER	0.24	0.93	2.06
REMod - UNA	0.30	1.16	2.37
ISI - REF	0.08	0.35	0.77
ISI - LIN	0.09	0.37	0.83
ISI - RED	0.08	0.35	0.78
ISI - LRE	0.08	0.35	0.79

Expected scarcities on path level for all transformation paths and scenarios, where the price threshold is derived using data in the period from 2005 to 2019.

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