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RESEARCH ARTICLE

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Quantifying the drivers of long-term prices in materials supply chains

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Abstract

Raw materials costs form an increasingly significant proportion of the total costs of renewable energy technologies that must be adopted at unprecedented rates to combat climate change. As the affordable deployment of these technologies grows vulnerable to materials price changes, effective strategies must be identified to mitigate the risk of higher input costs faced by manufacturers. To better understand potential threats to deployment, a market modeling approach was developed to quantify economic risk factors including material demand, substitutability, recycling, mining productivity, resource quality, and discovery. Results demonstrate that price changes are determined by interactions between demand growth, mining productivity, and resource quality. In the worst cases with high demand and low productivity, development of material substitutes and large recycling rates help reduce the prevalence of price risk from over 90% to under 10%. Investing in these strategies yields significant benefits for manufacturers and governments concerned about costs of materials critical to decarbonization and other advanced technologies.

KEYWORDS
circular economy, critical materials, industrial ecology, materials policy, price risk, systems modeling

1 | INTRODUCTION

As we continue to leverage materials-intensive innovations to further clean energy (Lee et al., 2020), we become increasingly reliant on complex materials supply chains. Clean energy applications such as electric vehicles require notable quantities of materials like cobalt, lithium, nickel, and graphite, compared to conventional energy technologies like combustion-engine vehicles (Hund et al., 2020). The total demand for cobalt and lithium, for example, are projected to grow by more than 450% each by 2050, compared to current production (Hund et al., 2020). This raises concerns about materials availability and its impact on our ability to scale-up technologies that improve quality of life and address climate change. Research has shown that materials set practical lower bounds on technology cost and materials costs are becoming an increasingly larger portion of the costs of new technologies such as electric vehicle batteries (Hsieh et al., 2019). The growth in clean energy necessary to affordably, equitably, and efficiently achieve net-zero emissions may be limited by materials supply chains unable to meet increased demand at an economical price.

[Correction added on January 02, 2023, after first online publication: The typesetter mistakenly published the uncorrected version of the article to EarlyView. It has now replaced by this final version.]

Concerns about material price and availability are not restricted to producers of clean energy technology. Perceived or realized long-term resource depletion and short-term supply shortages can cause materials prices to rise, leading to high costs borne by manufacturers across the economy. Long-term price excursions in difficult to substitute, technology-dependent materials constitute a risk for firms in many different industries such as construction, electricity, and consumer goods (Alonso et al., 2007; Duclos et al., 2010; Lapko et al., 2016). The impacts stemming from materials availability are uncertain and dynamic; we need more robust approaches for evaluating risks concurrently with technology development.

Assessing the economic importance of materials and potential supply issues inform material criticality evaluations. Criticality evaluations are important to industry and policymakers alike and facilitate strategic planning for technology design, trade agreements, and investment decisions. These evaluations are conducted at different levels—global (Graedel et al., 2015), regional (Blengini et al., 2017; Hatayama & Tahara, 2015; Nassar et al., 2020), company specific (Duclos et al., 2010; Kolotzek et al., 2018) and product specific, and for different time horizons. Criticality assessments often assign a "criticality score" to materials based on evaluating various sources of risk—an important component of which is economic risk faced by manufacturers. For example, researchers (Nassar et al., 2020) assess economic vulnerability of US manufacturing based on the expenditure of an industry on a material and others (Graedel et al., 2015) quantify economic risk based on resource depletion time and substitutability. However, most assessments of economic risks in the criticality literature suffer from two major drawbacks: (i) estimates of future resources and consumption do not systematically account for price feedback and technological growth, and (ii) aggregation of risk indicators is inconsistent across studies and does not typically account for cause-and-effect mechanisms (Schrijvers et al., 2020).

While many criticality assessments use price increases as an indicator for economic risk and scarcity (Alonso et al., 2007; Gleich et al., 2013; Lapko et al., 2016), these assessments do not describe how different risk factors interact to impact materials prices. Moreover, many approaches (17 papers found in a review by Helbig et al.) use price volatility as an indicator which does not account for the impact of long-run prices on materials availability (Helbig et al., 2021). A key driver of criticality is resource depletion but studies of depletion often use a Hubbert peak model which consider mineral resources as "fixed stock" (Calvo et al., 2017; Hubbert, 1956). However, critics claim that this approach ignores technological innovation and material substitution, arguing that mining opportunity costs and material prices are a better indicator of availability (Tilton, 2018; Tilton et al., 2018). Crucially, as Gleich et al. (2013) demonstrate, correlations between different criticality indicators and material prices are not accounted for, and the importance of various indicators is a function of market structure. Since criticality assessments do not explicitly consider the economic feedback between prices, consumption, and availability, they are unable to provide a comprehensive estimate of long-term economic risks in a materials supply chain. We note that there have been recent attempts to address these two drawbacks in the criticality literature. For example, Yuan et al. (2020) assess the criticality of platinum group metals (PGMs) by calculating the interconnections between criticality indicators and market variables such as price. However, such criticality assessments that incorporate indicator correlations and market dynamics are rare and often restricted to examining certain materials (e.g., PGMs in Yuan et al.)

Beyond the criticality literature, materials availability are also analyzed via different economic models of material markets. Models either analyze (a) only demand, (b) only supply, or (c) supply–demand interaction leading to price formation (Olivetti et al., 2015). Given we have already argued for the importance of price feedbacks, we will focus on approaches that incorporate market clearing of both supply and demand (for common supply and demand modeling approaches, see the review by Watari et al., 2021). Broadly speaking, metals markets are studied using (i) econometric models (Fisher et al., 1972; Fu et al., 2017; Watkins & McAleer, 2004), (ii) agent-based models (Bollinger et al., 2012; Cao et al., 2021; Riddle et al., 2015), and (iii) system dynamics models (Elshkaki, 2013; Sprecher et al., 2015a; Sverdrup et al., 2017) or a combination of the three (Ryter et al., 2022). Econometric models often assume a partial equilibrium between demand and supply which are both estimated via statistical relationships with variables such as economic growth and population (Zink et al., 2016, 2018). However, these models do not directly incorporate information about market structure and future mining costs. Agent-based approaches model material price formation as an interaction between multiple "agents" that are acting based on a decision-making criteria (e.g., maximizing their individual profits). These models are very detailed and can incorporate behavior in markets but need a lot of data to construct which makes them hard to do for a wide range of materials. Finally, system dynamics models simplify the material system as a set of equations that govern the stocks and flows of materials (see Bollinger et al. for a comparison of system dynamics and agent-based models). They have been used for studying depletion in various materials systems (PGMs, aluminum, etc.) and incorporate price feedbacks within a market structure (Sverdrup et al., 2015; Sverdrup & Ragnarsdottir, 2016). Overall, market models incorporate great detail and therefore need a lot of input data to analyze a particular material. Moreover, most of these market models explain how price is formed for the specific metal they study, but do not explain the factors that impact materials prices across systems. The generalized understanding of the drivers of materials price, and consequently economic risk, is vital for criticality analyses which compare risk across a broad range of materials.

Quantifying long-term price changes faced by manufacturers requires the development of tools that indicate what may influence materials price, within the context of consumption and resource depletion. This paper aims to address these gaps by proposing a structural model that incorporates material demand, reserves, substitution, and discovery to better help understand how the commonly used indicators of criticality affect material prices over long time frames (we study annual price change over 30 years). These long-term price changes impact material availability and constitute a risk for manufacturers that should be accounted for in criticality assessments. We address the aforementioned gaps in criticality analyses by: (1) incorporating the economics of the system to shed light on the "cause-and-effect mechanisms" that are missing from criticality analyses (Schrijvers et al., 2020), and (2) by modeling the effect of technological innovation and price elasticity of demand to quantify how material prices, consumption, and resource depletion will evolve in the future under different scenarios. Our model takes a "simplified systems dynamics" approach where demand and supply are governed by equations that determine long-term materials stocks and flows. While systems dynamics models typically focus on evaluating a particular materials market in detail, we use a generalized market structure with fewer parameters so that we can comment broadly on the factors that drive materials price risk. Moreover, some of the underlying concepts in our model such as "incentive pricing" and "cumulative availability curves" are borrowed from other modeling approaches that are not commonly seen in systems dynamics models for metals.

The model simulation results lead to important implications for policymakers interested in mitigating materials price increases and promoting a fast-paced scale-up of new technologies. While researchers have often stated that productivity increases and recycling are important to mitigate economic risk, we go further by quantifying the effect of increased recycling rates and productivity growth on prices (Ferro & Bonollo, 2020; Gaustad et al., 2018; Silvestri et al., 2021; Steward et al., 2019). We find that the most important determinants of materials price (in order) are demand growth, productivity growth, price elasticity of demand, and secondary supply. We show that the interactions between these factors are complex and simple aggregation methods that evaluate risk are insufficient. Demand growth is a necessary condition for high risk, but not sufficient to cause high price conditions. When there is a large availability of mineral resources at low cost, high demand does not lead to significant price rises. Furthermore, prices can be lowered through increasing mining productivity, recycling, and material substitution. Manufacturers and countries that are susceptible to long-term materials price risk will benefit from investing in recycling and substitution.

2 | METHOD

We build a generalizable materials market model that examines the range of future materials price change over time based on future demand growth and changes in the costs of future supply. As ore grade depletion drives up mining costs, factors such as substitution, recycling, and technological innovation act to reduce depletion and lower prices. One could readily use this model as a tool to examine a specific material system, as long as they have the data to inform the model input values. However, our goal in this analysis is not to analyze a specific material but rather understand how different features of a material system interact and lead to long-term materials price risk. To demonstrate the methodology, we simulate price change across a literature-based range of input values (Table S1) and evaluate the sensitivity of the resulting price excursions to the interaction between demand growth, technological innovation, resource discovery, recycling, and materials substitution. The range of input values represents our best estimate of all reasonable potential values these inputs (e.g., volume growth) could have for a particular material system. The maximum and minimum of the range is determined by data we have collected from the literature.

2.1 | Model methodology

We characterize scarcity and risk through modeled long-term price increases. Materials price excursions constitute a risk to manufacturers and are considered an important factor of material criticality (Gleich et al., 2013). For each set of demand and supply side inputs to our model, we output a long-term price change that we use as an indicator for risk. As we do not incorporate short-term price cycles, the model output represents the expected long-term change in materials cost to manufacturers reliant on the material. In this section, we provide a general overview of the working of the model. For a full mathematical description of the model with all the inputs and parameters, see Supporting Information Section A.

For each year (see Figure 1), we calculate demand as a function of volume growth and the previous year's price, where rising price decreases demand via substitution (measured by price elasticity of demand). The required production from mining is determined by subtracting secondary supply from the demand calculation. Secondary supply evolves according to changes in recycling and commodity price, where rising price incentivizes scrap collection. We model operating mines using a linear supply curve, which is generated from user-supplied 25th and 90th percentile mine site costs (see SI A.a.i). Costs rise as ore grade declines and costs fall as technologies improve (Bartos, 2007; Topp, 2008); the annual percent change in these costs are model inputs. Mines with costs greater than the commodity price close, determining operating mine production. We use incentive price modeling (an alternative to marginal cost-based models) to determine the price in each period (Alexander et al., 2013). "Incentive mines" are mining projects that have not started production but will open if they are expected to be profitable. Incentive price modeling stipulates that supply must equal demand, and the price required to incentivize sufficient mine opening to close the gap between demand and the sum of operating mine production and secondary supply becomes the new commodity price.

As a result, we need two main pieces of information to calculate the market price of a material in a particular time period (Figure 2):

(i) Required mine opening O^t: the total capacity (in annual production) of mines that must open to close the supply–demand gap in that period. The required mine opening is represented by the large red arrow in Fig. 2.4 and Fig. 2.6.

(ii) The incentive cost curve $I^t(X)$: which quantifies the capital-adjusted operating cost of all "incentive" mines (i.e., mining projects that have not started production but will open if they are expected to be profitable). The incentive curve is demonstrated in Fig. 2.5 where the yellow region is the operating cost and the green region is the annualized capital cost.

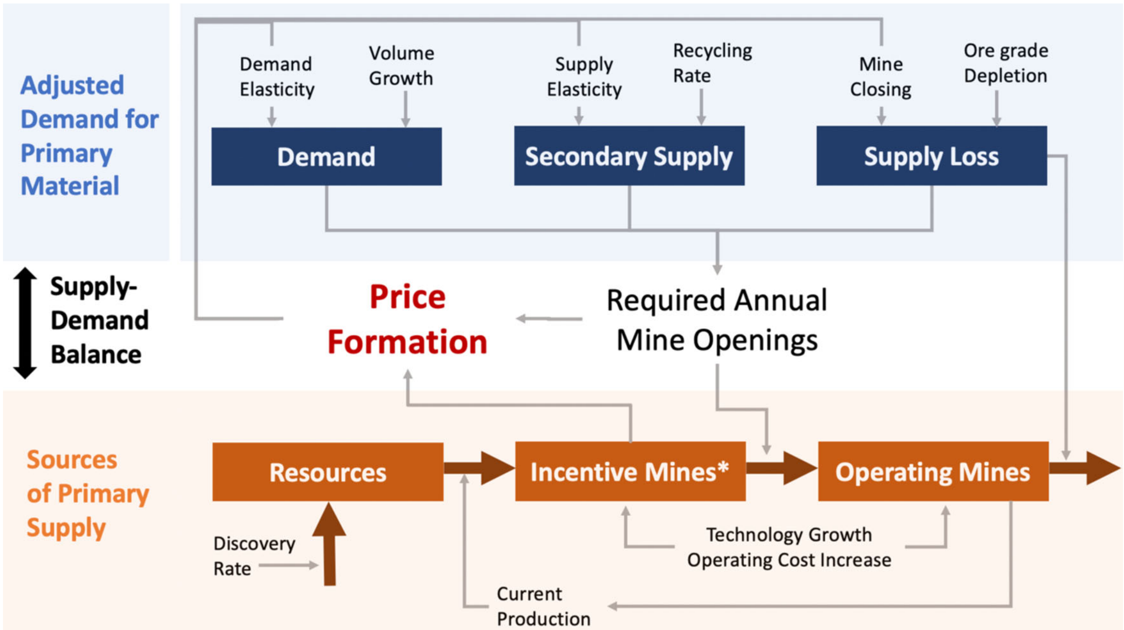

FIGURE 1 High-level model dynamics. New mines open in each period to ensure that demand for primary material equals supply. The price value calculated is such that none of the newly opened mines operate at a loss. Operating mines, incentive mines, and resources (depicted by the orange colored boxes) are sources of supply which are initialized with functions that determine quantity and cost. Dark brown arrows demonstrate the flow of material. Required openings are determined by the adjusted demand for primary material (a function of material demand, secondary supply, and mine supply loss shown by blue boxes). Price feeds back into the model to determine required mine openings in the next period. The goal of the model is to examine the impact of demand side model inputs (e.g., volume growth, recycling rate and ore grade loss) and supply side model inputs (e.g., technology growth, operating cost changes) on realized long-term material price.
*Incentive mines are mining projects that have not started production but will open if they are expected to be profitable.

We make two simplifying assumptions before we use this information to calculate price:

(a) We assume that the need for new material is met immediately by opening of incentive mines, that is, there are no delays in opening. While time lags in opening exist quite often in mining (Radetzki et al., 2008), they often lead to short-term price excursions and are not as relevant for our analysis of long-term price trends. Mining companies typically try and anticipate supply–demand imbalances and plan opening decisions accordingly.
(b) We further assume that opening of new mines is the only way to meet increased demand and operating mines cannot change capacity utilization. While mines often increase or decrease capacity in the short-run in response to price, long-run mining capacity is a function of ore grade and mine life (both of which we already account for in our model).

With these assumptions, once we know the required mine opening and the incentive cost function, we can directly calculate the material price in each period p^t as it is equal to the capital-adjusted cost of the most expensive incentive mine that is required to open (See Figure 2.7; Equation in SI A.b.v).

$$p^t = I^t\left(O^t\right)$$

In each period, therefore, the goal is to use the model input parameters to update the incentive cost function and calculate required mine openings.

2.1.1 | Calculating required openings

Mine openings are required to (a) meet increased demand, (b) compensate for loss in mine supply, and (c) overcome reductions in secondary supply (Fig. 2.2 - 2.4; Equation in SI A.b.iv). The growth in demand Q^t for material in any period is a function of (i) the growth in the volume of materials

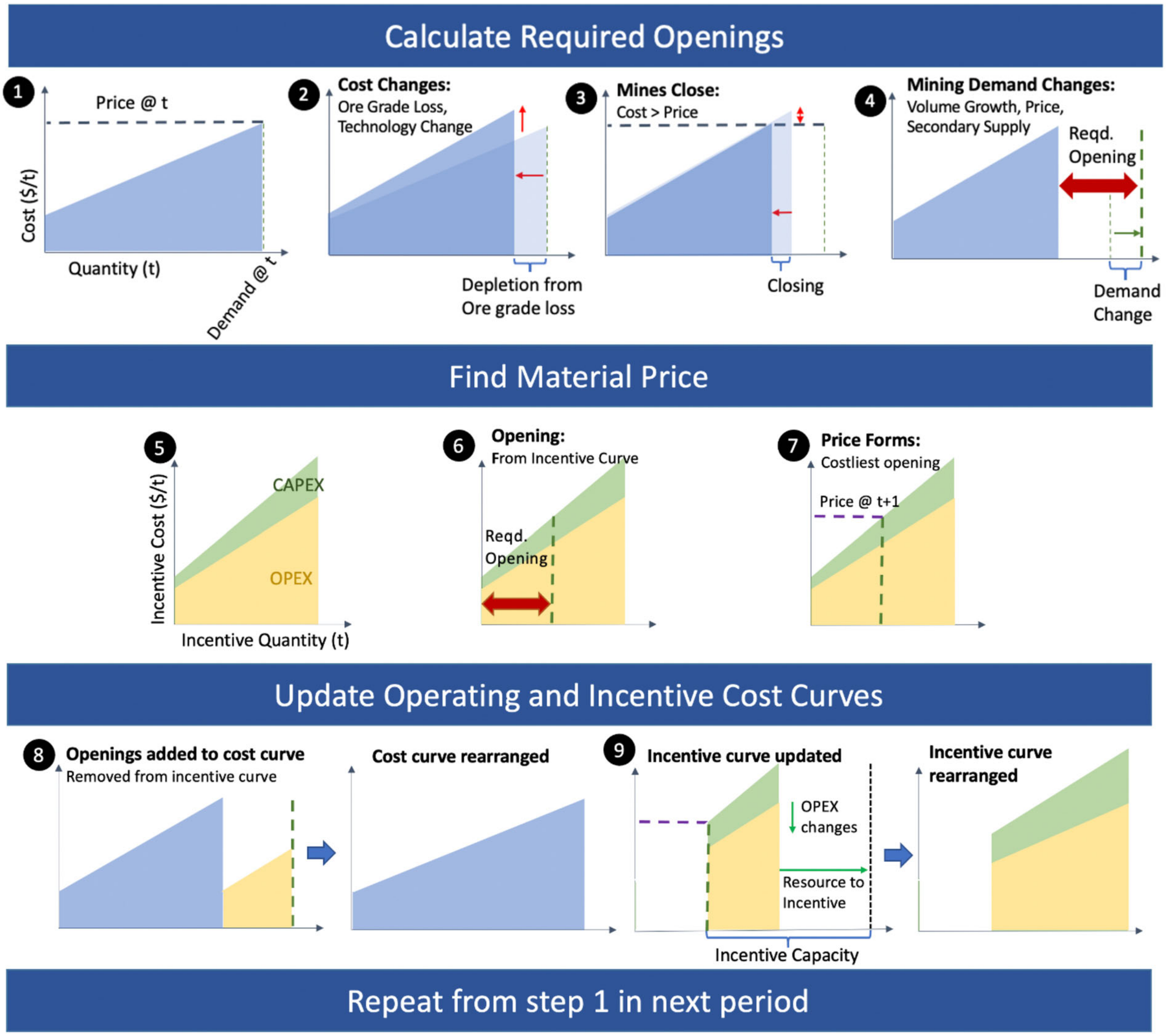

FIGURE 2 Key calculations in each model period. Light blue region represents the operating mine cost curve. Yellow and green region represents the incentive cost curve: the yellow region is the operating cost, while the green region is the annualized capital cost. Numbers are ordered model steps. The model first calculates how much mining capacity needs to open based on demand and supply evolution. We then use required openings and the incentive cost curve to calculate the material price. We then update the operating and incentive mine cost curves to account for openings, and operating cost changes due to technological advancement. Once the new operating and incentive mine curves are generated, we re-run the model from step 1 for the next period.

needed to provide products and services for a growing and richer global population, and (ii) elasticity to a change in materials price (e.g., higher prices incentivize manufacturers to reduce material consumption). The price elasticity of demand and the volume growth rate are both model input parameters that govern this demand change (Equation in SI A.b.i). The supply losses L^t in a period occur due to two reasons: (i) reduction in the ore grade of operating mines (fewer tons of metal extracted from each additional ton of ore mined), (ii) closing of operating mines that cannot remain profitable (Equation in SI A.b.iii). Finally, secondary supply R^t evolves due to changes in the recycling rate and due to price elasticity (Equation in SI A.b.ii).

2.1.2 | Updating the incentive cost curve

When incentive mines open in each year, their production is removed from the incentive curve (Fig 2.8). Without replenishment, depletion of the incentive curve would lead to unrelenting cost increases as the lowest-cost mines are removed. We simulate expansion of incentive mine capacity through the conversion of resources, under the Canadian Institute of Mining definition, into reserves (Champigny et al., 2005). We simulate a linear resource base supply curve as a function of the cumulative availability curve (CAC) described by Tilton et al. (2018) and Yaksic and Tilton (2009). The slope of the CAC is user defined and describes the current cumulative production as a function of operating cost with values calculated for various materials (equations for resource initialization in SI A.a.iii; CAC slope values in SI Table S2). The total available resources may also be replenished by discovery, with a discovery rate defined by the user (equations for resource depletion and discovery are in SI A.b.vii). As a result, the incentive cost function updates as incentive production moves to the operating pool, as resources are converted to incentive mines, and as operating costs change due to technological advancement and factor prices (the equations governing the initialization of the incentive cost curve can be found in SI A.a.ii, the equations for incentive curve updating are in SI A.b.viii).

2.2 | Simulation

We simulate price change across a literature-based range of input values (Table S1). The long-term price risk for material systems can be analyzed by our model if we input the appropriate parameter values for the material. Although there are only a handful of material systems in the world, there are many possible combinations of input values to our model. For all our input parameters (initialization and model run), we define a range of possible values based on a review of real material systems. The range of values forms a parameter space that includes all major material systems as well as parameter combinations we do not observe in the real world. Table S1 describes the input ranges for parameters used in initialization and Table S3 describes the distribution of parameters used in the model run. One could readily use this model to examine a specific material system, as long as they have the data to inform the input values (see an example of input values for the copper system in Table S4). However, our goal in this analysis is not to analyze a specific material system but rather understand how different features of a material system interact and lead to long-term materials price risk.

By running the model repeatedly over the parameter space, we can reveal useful insights about the factors that lead to long-term price risk. We run 50,000 simulations of our model over a 30-year time frame. We choose a time frame of 30 years because government institutions and academics often analyze materials risk till 2050 (Hund et al., 2020). In each simulation, we randomly sample parameter values from their distributions (uniform across their range of possible values). Every simulation, therefore, represents a possible scenario for a hypothetical commodity. Although not all these scenarios will be observed in the real world, they form a set of realistic potential scenarios that we can examine.

We assume that input parameters are uncorrelated, and we sample parameters independently. Some of the parameters are expected to be correlated in the real world. For example, it is likely that the amount of secondary supply is influenced by the volume growth rate as consumption determines the amount of material available for recycling. Even though our simulations sample parameters independently, in Section 3, we will discuss the interactions between the parameters and comment on which combinations of inputs can lead to realistic scenarios of price risk. We also compare the distribution of price predictions from our model against historic long-run price change values for 20 materials (see SI Section F).

We consider simulations that result in price increases greater than the 80th percentile price increase (of all simulations) as having "high risk" to manufacturers. We choose this threshold because historic price changes over 100 years for most major metals are lower than the 80th percentile price change in our simulated results. The 80th percentile price is 2.2% per year (see Results). The average yearly copper price increase over the last 100 years is 1.32% (Fig. S2.). The 80th percentile price represents a long-term price change that has not been observed before and is representative of significant price risk. While we had to choose a particular risk threshold to describe the results in this paper, other analysts could use our model and select a threshold they consider appropriate.

2.3 | Classification

We run a decision tree on the simulations which inputs our model parameters and tries to predict whether the resulting materials system has "high price risk" (top 20 percentile price rise). The decision tree is a method of predictive modeling where a set of features are used to predict class labels, represented as "leaves." The branches of the tree are "decisions" and represent conjunctions of features that lead to the class labels. The decision tree (Figure 6) works by splitting each node into child nodes using three steps. First, we determine each feature's best split using the Gini impurity, which gives the probability of misclassifying an observation. Second, we select the best split (maximizing the probability of correct classification) from the previously generated set of feature splits. Finally, we split the node and repeat this process until the stopping criteria is met (our stopping criteria is a maximum tree-depth of 7 and a minimum 10 samples in a leaf). The decision tree has a prediction accuracy of 89% when tested against 25% randomly selected observations that were excluded from training.

3 | RESULTS AND DISCUSSION

Simulating price change across a literature-based range of input values (Table S1) reveals that while over 25% of cases have decreasing price, in certain realizable cases the input parameters interact in ways that lead to large price increases (Figure 3). We consider price increases greater than

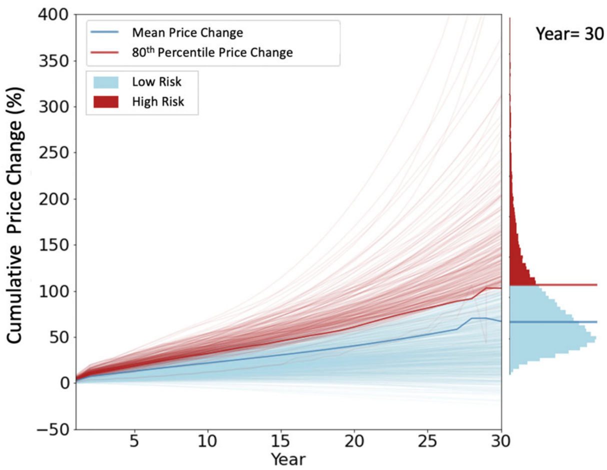

FIGURE 3 Price change trajectories over all simulated cases. Input values from Table S.1. Each line is one model simulation over randomly sampled set of inputs. Bold red line is the 80th percentile price increase, which we use as our cutoff for determining price risk. Mean price increase is given by the bold blue line. Red lines are simulations which had a price increase at 30 years greater than the 80th percentile price increase. Histograms for cumulative price change over 30 years to the right of the figure. Data underlying this figure can be found in t figshare data repository at https://doi.org/10.6084/m9.figshare.19242858.v1.

the 80th percentile as "high risk" to manufacturers (thin red lines in Figure 3). The 80th percentile price increase over 30 years is 96% (2.2% annual growth; dark red line). The median cumulative price increase is 51% (1.3% per year; dark blue line). Notably, the price change distribution has a long tail, that is, a small number of very large price excursions. As demand for material continues to grow in the long run and reserves get depleted, material prices increase nonlinearly. The goal of our analysis is to explore what combinations of inputs lead to the cases of high price risk.

Most criticality assessments use various (linear) averaging techniques such as weighted averages and geometric means of criticality indicators (BGS, 2015; Frenzel et al., 2017; Glöser et al., 2013; Graedel et al., 2012; Kolotzek et al., 2018; Nassar et al., 2020; Schneider et al., 2014). However, as argued by Gleich et al. (2013) and as we will demonstrate in the results, these indicators (or parameters) interact in a complex way based on market structure. We explore certain specific parameters interactions (demand, mining productivity, and resource quality) through scenario analyses in Sections 3.1–3.3. To further examine the interactive effects of all indicators on risk, we use a decision tree approach. The decision tree (Figure 7) is a useful diagnostic tool because it is a nonlinear model with which stakeholders can identify price risk. The decision hierarchies of the tree provide a set of conditions to indicate whether a combination of inputs is likely to cause price risk.

Table S4 lists all the features used to create the decision tree and how they are derived from user inputs. "Demand Growth" is the combination of demand due to volume growth and ore grade loss of operating mines. "Recycling" is the quantity of supply that comes from secondary sources in the final time period. "Net Productivity" is the change in annual operating cost (increases due to more expensive inputs and taxes, decreases due to technological growth). Price elasticity is percentage change in demand resulting from a 1% change in price, while resource quality is measured by the slope of the CAC (Tilton et al., 2018; Yaksic & Tilton, 2009). Each of the predictive features is divided into three equal length intervals (high, medium, low). For example, net productivity is considered "high" between 1% and 3% and "low" between −3% and −1%

3.1 | Demand growth is a necessary condition for price risk

We analyze (in Figure 4) how the simulated price change trajectories differ based on the values of annual demand growth (combination of demand due to volume growth and ore grade loss of operating mines). We observe that a high demand growth is a necessary condition for price risk as almost none of the cases with low demand growth have price risk. Forty-eight percent of the cases with high demand growth are considered to have price risk, while only 1% of the cases with low demand growth have price risk. We further see that the effect of demand growth on price is nonlinear, that is, 48% cases with high demand growth are risky but only 14% cases with medium demand growth have risk. Demand growth has the largest impact on price risk because demand for new material drives the extraction of more expensive resources with declining ore grades. If there was no increase in demand, most materials systems would have enough resources available to cover the (stagnant) need for material without price rises.

Without high demand growth, we observe price risk only in certain specific instances. We see 83% of cases with medium demand growth can have high risk if there is also low productivity, low resource quality and low price elasticity of demand (Branch 11 in Figure 6). This scenario can realistically occur when the material has low substitutability, low productivity growth in mining, and a high increase in operating costs due to expensive inputs or increasing environmental costs. These conditions may be indicative of current conditions, because while mining productivity has risen in the past (Bartos, 2007; Topp, 2008), Atta and Tholana (2021) argue that it is falling and show it to be negative. Net productivity in mining has been reported to be decreasing by −3.5% per year (Lala et al., 2016). Moreover, increasing costs due to environmental and social consequences

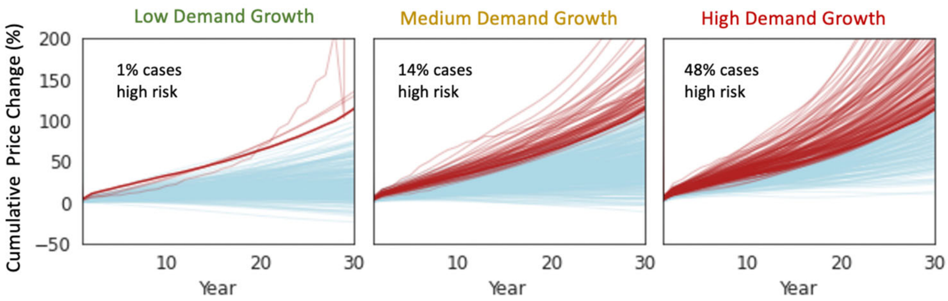

FIGURE 4 Price change trajectories differentiated by values for demand growth. Red line represents the 80th percentile price increase over all simulations of the model. Each box is a subset based on values of demand. Demand growth is the sum of volume growth rate and ore grade loss. High demand growth occurs when the sum is >6.33%. Low demand growth occurs when the sum is <3.66%. Data underlying this figure can be found in the figshare data repository at https://doi.org/10.6084/m9.figshare.19242858.v1.

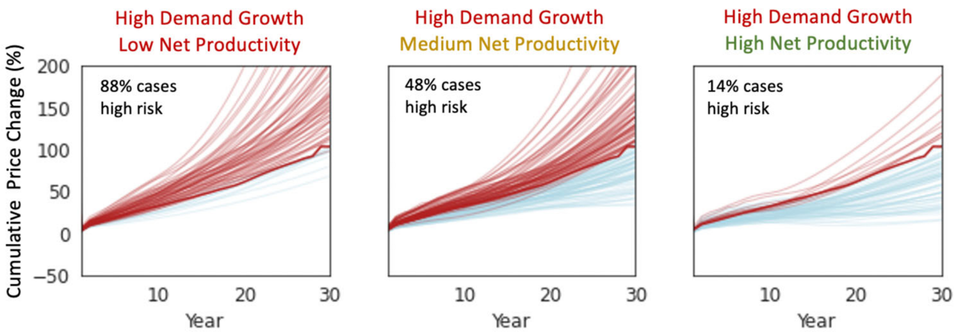

FIGURE 5 Price change trajectories in high demand scenarios differentiated by values for net productivity. Net productivity is the sum of reductions due to technological advancements and increases due to more expensive inputs in mining. High productivity occurs when the sum is >1%. Low productivity occurs when the sum is <−1%. Data underlying this figure can be found in the figshare data repository at https://doi.org/10.6084/m9.figshare.19242858.v1.

are already occurring in mining (Castillo & Eggert, 2020; Prior et al., 2012). These increasing costs combined with the fact that most materials have low price elasticity (Stuermer, 2017) means that many cases of medium demand growth may also lead to high price risk and stakeholders need to consider ways to mitigate risk in those instances.

3.2 | Cases with significant price risk have high demand and low productivity

The most frequent conditions for high price increases occur when demand is high and yearly net productivity change is low (88% simulations have price risk; Figure 5) In these cases, technological innovation is not large enough to mitigate cost increases due to environmental factors, taxation, and/or increases in input costs for energy and water. Conversely, when there are large productivity increases, long-run prices are low despite high demand (only 14% cases have risk; Figure 5). As we will discuss in section 3.4.2, increasing productivity can be a strategy used for mitigating price risk as only 25% of high demand cases have price risk when productivity is high.

3.3 | Resource quality is an important determinant of long-term price change

We focus on cases with high demand and medium net productivity (−1% to 1%) to examine the mechanism through which demand growth drives long-term price changes. We find that resource quality (slope of the CAC) determines whether a scenario is likely to have high prices. Only 10% cases with high-quality resources have price risk while 80% of the cases with low-quality resources have price risk. This result demonstrates that demand growth drives the extraction of new resources and, in the absence of mining productivity improvements, the quality of these resources is a key determinant of long-term prices. Therefore, materials with a small resource pool and rapidly declining ore grades (both of these factors increase

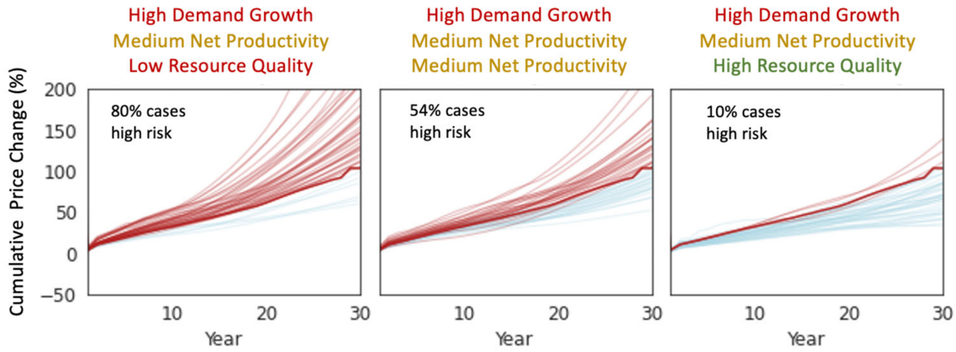

FIGURE 6 Price change trajectories in high demand and medium net productivity scenarios differentiated by values for resource quality. Resource quality is measured by the slope of the cumulative availability curve (CAC). Resource quality is high when the CAC slope is below 1.17% and the quality is low when the CAC slope is higher than 1.83%. Medium net productivity refers to cases where productivity is nearly constant, that is, net annual changes in mining costs are between −1% to 1%. High demand growth refers to the scenarios where the sum of volume growth and yearly ore grade loss in mining is greater than 6.33%. Data underlying this figure can be found in the figshare data repository at https://doi.org/10.6084/m9.figshare.19242858.v1.

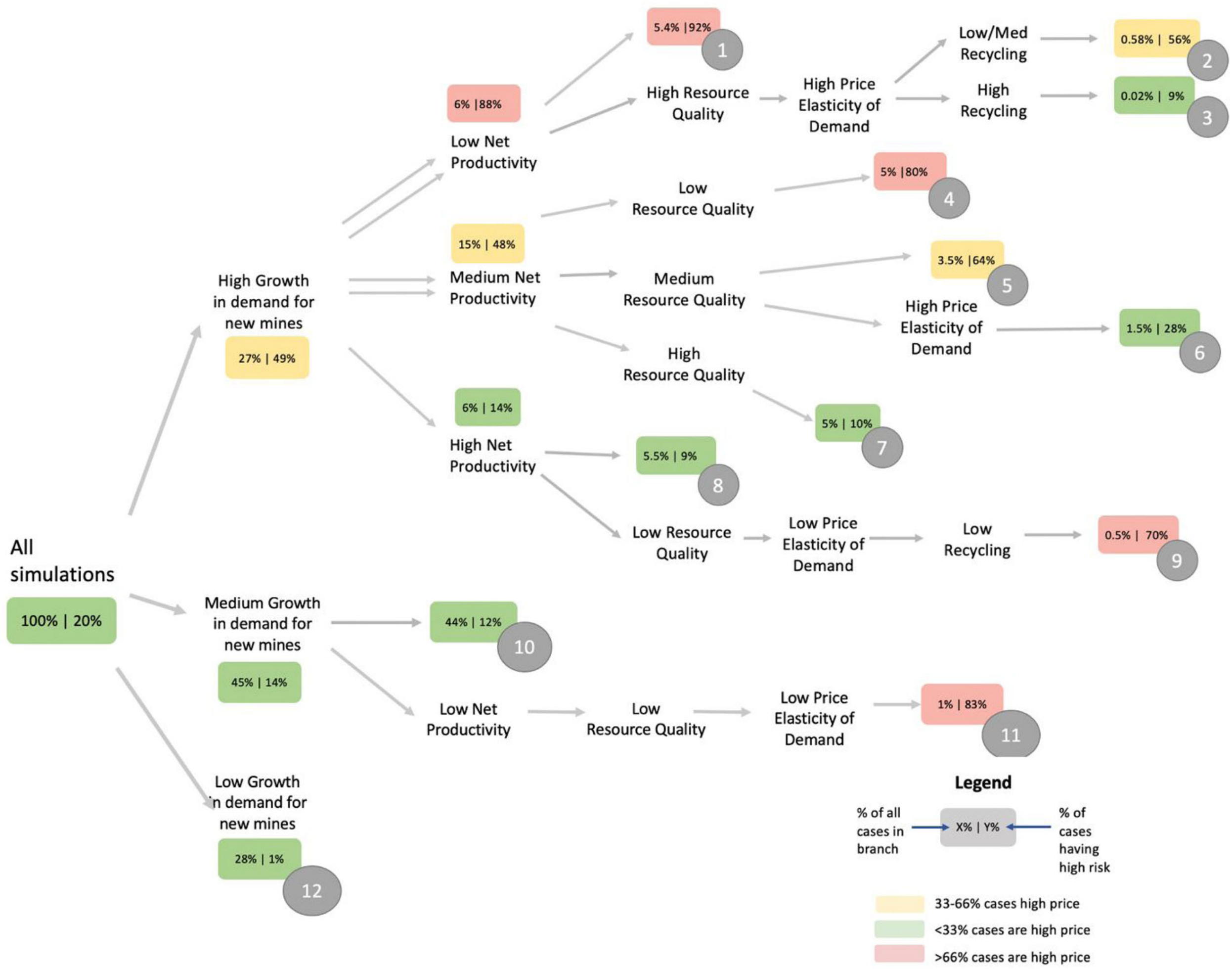

FIGURE 7 Decision tree. Decision tree takes all features as inputs and tries to if the simulation leads to high price risk. To understand how indicators combine to give low or high price excursions, follow the arrows to a red, yellow, or green group of simulations. If none of the branch conditions are true, the uppermost node represents the "other" cases. Each node is unique. Red leaves have >66% cases critical, while green leaves have <33% cases critical. A case is considered "high risk" if price rise is >80% (66% over 30 years). Each node consists of two numbers: the first (leftmost) value is the proportion of total cases that constitute that node, while the second (rightmost) value is the proportion of cases within that node that have high price risk. The numbers in circles indicate the branches and are used in the text to refer to the respective branch. Data underlying this figure can be found in the figshare data repository at https://doi.org/10.6084/m9.figshare.19242858.v1.

the CAC slope) will have large price increases. It is worth noting here that in the absence of high demand, we will not see an effect of bad resource quality because resources with high mining costs will not need to be extracted. The interaction between demand growth and CAC slope echoes the argument by other researchers who find that future price is a function of the future cost of extraction (measured via CAC slope) and demand defines the rate at which the stocks are depleted and costs rise (Castillo & Eggert, 2020; Tilton & Guzmán, 2016).

Mining higher quality (low ore grade resources) is considered more environmentally friendly than mining lower-quality resources, due to the lower energy required for extraction. However, environmental impact assessments should also account for the price feedback caused by mining higher-quality resources because it causes a fall in long-term material prices and a consequent increase in material consumption.

So far, we have analyzed the interactions between demand, productivity, and resource quality. To study further parameter interactions, we need to use the decision tree in Figure 7. The tree confirms the results visualized above: high demand is a necessary condition for most cases of price risk. When demand is high, low net productivity increases the likelihood of price risk while high productivity can reduce the number of price risk cases to 14% (Figures 5 and 7). Finally, in high demand and medium productivity cases, resource quality determines price risk (Figure 6 and Branches 4–7 in Figure 7). As we discuss in Section 3.4, the tree branches show how other parameters (recycling, substitution, etc.) act to mitigate these high-risk cases.

3.4 | Market and policy responses can help mitigate price risk

Some assessments of criticality use depletion time (ratio of reserves to current demand) as an indicator of economic risk (Graedel et al., 2012). Materials with high demand and poor geologic factors (low reserves) are therefore categorized as having high risk. While the analysis in Section 3.3 supports the finding that demand and resource quality are important, we find that geologic conditions alone are insufficient in measuring risk. Market responses to scarcity in the form of (a) price elasticity, (b) advances in mining technology, (c) increased recycling, and (d) resource discovery need to be considered in risk assessments. While risk assessment methodologies sometimes consider these four indicators independently, these indicators are far more likely to act together to impact demand, supply, and price in ways we discuss in the following paragraphs. The decision tree in Figure 7 examines the interaction between multiple parameters and identifies ways to mitigate price risk.

3.4.1 | Mitigation by increasing material substitution

If the price elasticity of demand for the material is high, even cases with high demand growth demonstrate price risk less than 28% of the time (Branch 6 in Figure 7). This emphasizes the importance of considering market response in criticality assessments rather than relying solely on geologic indicators. As prices rise due to poor geologic conditions, the market responds by reducing the demand for material and mitigating price risk in the future. Price elasticity of demand can be increased when substitutes exist for a material because as prices rise, manufacturers can use the substitute instead. By explicitly modeling price feedback, we are able to demonstrate how increasing substitutability can mitigate price risk for materials with high demand by influencing the price elasticity of materials.

3.4.2 | Mitigation by technological advancement in mining

When demand for materials rises, firms react by investing in technology that increase mining productivity. Within the high demand cases, 88% of cases with low net productivity were high risk while only 14% of cases with high net productivity had high risk (Figure 7). Increased productivity of mines makes it possible to mine deposits to a lower ore grade cutoff and can mitigate resource depletion and associated availability concerns (as argued by Tilton, 2018). Increased productivity also reduces operating costs and thereby suppresses price. However, increasing productivity can be challenging. As stresses on resources necessary in production, like water, increase and environmental regulation strengthens, the mining industry will need even stronger technological advances to mitigate price risk. While it may be difficult to predict the rate of technological advances, decision makers should identify stressors that drive cost and prioritize investment in appropriate technologies (e.g., lowering the cost of using green hydrogen to power mines).

3.4.3 | Mitigation by improving recycling rates

Other market responses that impact economic risk are recycling and resource discovery. “High Recycling” refers to the scenario where the secondary supply after 30 years is between 44% and 66% of *current* mining production. As demand growth increases by up to 500% (6% per year) in Branch 3, a secondary supply of 11% of the mineral consumption in Year 30 is considered as “High Recycling.” Achieving such recycling rates are reasonable and can reduce price risk. While 88% of cases with high demand and low productivity have price risk, a combination of resource quality, price elasticity, and recycling can decrease the number of high risk cases to 9% (Branch 3 in Figure 7). On comparing Branches 2 and 3 in Figure 7 we can see that recycling can, in certain instances, play a significant role in reducing price risk (even when productivity is low and demand is high). The reason for this effect is that recycling reduces the need for new mining projects and therefore counteracts the negative effects of high demand growth and bad resource quality that we saw in Sections 3.1–3.3. Building a circular economy through recycling has the dual benefit of reducing price risk as well as mitigating the environmental impact of materials production. Sustainability analyses should account for price feedback when considering the effect of recycling on overall material. As pointed out by recent research, increasing recycling can reduce materials prices and, in certain cases, incentivize an even larger consumption of material from primary sources (Ryter et al., 2020).

3.4.4 | Mitigation by investing in exploration and discovery

Finally, the proportion of high-risk cases reduces if there is sufficient amount of high-quality resources and therefore future supply has low costs (Branches 4–7 in Figure 7). As prices increase, investment in mining exploration and discovery may increase the availability of high-quality reserves and help mitigate risk. If decision makers want to mitigate risk in the long run, they should invest not only in mining technology but also strategies that work over longer time horizons such as recycling and discovery of high-quality resources. Reducing the price risk of materials essential for clean energy (such as nickel, cobalt, rare earth elements) will reduce the costs of renewable energy and further sustainability efforts.

4 | CONCLUSIONS AND FUTURE WORK

A steady supply of materials is essential to meet human needs but is difficult to realize in the face of economic, geologic, and geopolitical challenges. While assessing and mitigating the various risks in materials supply chains is vital, measuring these risks is complicated. As Nassar et al. noted, "supply risks are dynamic, increasing and decreasing with changing global market conditions that are specific to each commodity" (Nassar et al., 2020). Yet, there are few tools that incorporate dynamic market effects to evaluate these changing risks. We fill this gap by quantifying the long-term price risk in materials supply chain via explicitly modeled market interactions. Crucially, we demonstrate that materials price risk results from a complex interaction between various demand and supply variable and this risk cannot be adequately modeled as a linear combination of indicator scores.

Although we exercise the model to examine factors that impact materials price risk, the model can easily be used to examine specific material systems. Notably, researchers can use the model to specify future scenarios and use the resulting demand and supply projections to calculate the environmental implications of future material consumption (Van der Voet et al., 2019). The model is specifically useful in understanding the environmental impact of different secondary supply trajectories (informed by circular economy strategies) as we incorporate the price feedback from secondary supply on primary consumption.

The results we describe in this paper can vary if we assumed different ranges of input values for our parameters. Whether a particular scenario is "high risk" is a function of the input values and changing the ranges on the input can change the number of high-risk cases. In the Supporting Information Section G, we conduct various analyses to study how the model output (price risk) varies as a function of the input range for different parameters. While we have tried to create reasonable ranges for our input parameters (and justify them based on a literature review in Table S2 and S3), data on various parameters is scarce and the ranges are uncertain. Future research should put efforts in collecting or estimating key parameter values (e.g., slope of the CAC) for real materials systems (e.g., Co, Ni). Moreover, while our model analyzes long-term price risk, we are unable to comment on the impact of short-term shocks and disruptions. System dynamics models often incorporate price feedback to study the resilience of material supply chains to supply and demand disruptions (Sprecher et al., 2015b). The model we present is complimentary to the resilience models and the two approaches can be combined into a model that can analyze both long-term and short-term risk.

Future work should examine the changing price risk over different time horizons. In a recent article, Schrijvers et al (2020) argued for picking the analysis time frame of analysis carefully by discussing how changing the scope of criticality assessments can lead to different results. Mitigating price risk over different time frames will require varying strategies, and future research should study how we can reduce risk in both the short and the long run.

There are opportunities to improve this modeling tool. For example, we did not include some important components of materials supply chain in our risk assessment: such as the effect of co-production (Fu et al., 2019; Nassar et al., 2015), time delays in opening (Ali et al., 2017), systemic trade risk (Klimek et al., 2015), speculation in materials markets, geographic supply concentration, or the effect of monopolies. Policymakers and industry executives should promote the development of similar tools to inform strategies that mitigate supply risks, with future tools attempting to include more detail on these missing components. Supply risk mitigation can improve sustainability efforts by providing cheaper critical minerals and reducing the costs of clean energy technology. In particular, priority should be placed on measuring how innovation, substitution, and recycling may impact material markets over various time frames. An improved understanding of the effects of such interventions will help design the best solutions to the challenges posed by increasing reliance on fragile materials supply chains to meet human needs.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that supports the findings of this study are available in the supporting information of this article. Data used to make the figures, as well as results of all the model simulations are present in: https://doi.org/10.6084/m9.figshare.19242858.v1. Model code available at: https://colab.research.google.com/drive/12jsX5bArXbA4Av8q1T01G2uN2yLOqnDg?usp=sharing_%3B!!N11eV2iwtfs!vsstm8LPU3OSAKFShDencBhQO0xA-QsG06Z0L6w4QYEcUgqrwRaleaWZIA3YcaBSXFbI5rk9SIEDtwZBe4OQPHwK%24.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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