COMPLEX SYSTEMS

Systemic trade risk of critical resources

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In the wake of the 2008 financial crisis, the role of strongly interconnected markets in causing systemic instability has been increasingly acknowledged. Trade networks of commodities are susceptible to cascades of supply shocks that increase systemic trade risks and pose a threat to geopolitical stability. We show that supply risk, scarcity, and price volatility of nonfuel mineral resources are intricately connected with the structure of the worldwide trade networks spanned by these resources. At the global level, we demonstrate that the scarcity of a resource is closely related to the susceptibility of the trade network with respect to cascading shocks. At the regional level, we find that, to some extent, region-specific price volatility and supply risk can be understood by centrality measures that capture systemic trade risk. The resources associated with the highest systemic trade risk indicators are often those that are produced as by-products of major metals. We identify significant strategic shortcomings in the management of systemic trade risk, in particular in the European Union.

INTRODUCTION

Commodity price volatility has long been identified by political economists as a hindrance to sustainable economic development [for example, the Dutch Disease (1)] as well as a catalyst of geopolitical crises. Although traditionally associated with fossil fuel resources, the criticality of nonfuel mineral resources has become increasingly relevant because of their increasing importance in cutting-edge technological and medical applications (2). With the explosive growth of financial derivatives on commodities and a subsequent investment boom (and bust) in the mid-2000s, there is growing evidence that resource criticality, loosely defined as the importance of a resource to production processes, has become increasingly susceptible to financial perturbations from both within and outside the commodities sector (3, 4). A better understanding of the interconnected nature of commodity markets would allow policy-makers to hedge against threats to industrial sectors and reduce the risk of geopolitical instabilities induced by the price volatility of critical resources.

Systemic risk is often defined as the risk that a large fraction of a system will collapse as a consequence of seemingly minor and local shocks that initially only affect a small part of the system. Because of the interconnectedness of the system, these shocks may cause secondary effects that eventually propagate through the entire network. Awareness of systemic risk has greatly increased in the finance literature in the wake of the 2008 financial crisis (5, 6). For financial systems, it has been shown that systemic risk is, to a large extent, a network effect in which external shocks to a single financial institution result in a sudden reduction of financial flows to other institutions, causing distress for them as well (7). This chain of reduced financial flows can spread through the system, potentially leading to positive feedback dynamics and resulting in a strong reduction of the total net worth of financial institutions (8). It has been shown that the vulnerability of a system to such cascading shocks can be assessed by network centrality measures and related concepts (9–13).

It is becoming increasingly clear that the security of supply can only be understood in a framework that acknowledges the global interconnections among systems of resource production and trading (14, 15). Here, we show that the likelihood of price disruptions in mineral prices is strongly related to the structure of the trade network of a particular resource. We introduce a novel method to assess the systemic risk level of trade networks and demonstrate its validity on 71 actual trade networks of resources. At the global level, we show that the scarcity of a resource is strongly related to the structural properties of its underlying trade network. The scarcer a resource is, the more susceptible it is to cascading shocks in the trade network. At the regional level, we show that the volatility of mineral prices within several world regions, in particular the United States and the European Union (EU), is closely related to specific network centrality measures that we propose to quantify systemic trade risk. We find that price disruptions in mineral resources also reflect cascades of supply shocks in the underlying trade network. The impact of these cascades, to some extent, can be mitigated by lowering trade barriers. We find the highest systemic trade risks in resources that are produced as by-products of other resources. It has been argued that these resources are especially prone to price disruptions because it is hard to predict whether their global supply will react to changes in global demand (16).

RESULTS

"TradeRisk": An indicator for systemic trade risk

We work with 71 nonfuel mineral resources as provided by the U.S. Geological Survey (USGS) in *Mineral Commodity Summaries* (17). For readers not familiar with the concepts and centrality measures of network science, we refer to the Supplementary Materials and Methods, where we give a brief and self-contained introduction to the network concepts used in this work. For each of these resources, *r*, we construct the network of international cross-border trade flows $M_{ij}^r(t)$. The result is a so-called multiplex network where nodes (*i,j*) represent countries that are connected by different types of links, *r*, that represent trade in different commodities. The entries in $M_{ij}^r(t)$ represent the amount of resource *r* in U.S. dollars that flows from country *i* to country *j* within year *t*. Details on how $M_{ij}^r(t)$ is extracted from the data are discussed in Materials and Methods.

The vulnerability to supply shocks in mineral imports of countries has a strong geopolitical component. Imports from countries that are politically unstable are more prone to supply restrictions than are imports from countries that are politically stable (18). The World Bank indicator "Political Stability and Absence of Violence," $p_i(t)$, measures the likelihood of

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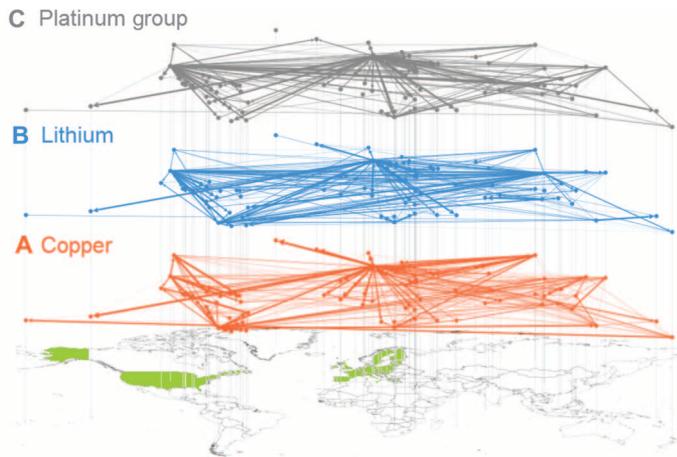
Fig. 1. The worldwide trade risk network for nonfuel minerals. (A to C) The worldwide trade risk network for nonfuel minerals, represented as a multiplex trade network $V_{ij}^r(t)$, where each layer corresponds to one mineral resource: (A) copper, (B) lithium, and (C) platinum group metals. We study the network topology of each of these layers and compute both regional (node-based, country-specific) and global (network-based) measures. We study the relationships between supply risk, price volatility, network central-ity, and trade barriers for the United States and the EU (world regions high-lighted in green on the world map).

political, social, or economic distress in country i in year t [19]. $p_i(t)$ ranges from 0 to 100. High values indicate high political stability. As an alternative to the Political Stability indicator, we also use the Resource Governance Index g_i instead of $p_i(t)$. g_i measures the quality of governance in the oil, gas, and mining sectors on a scale from 0 to 100 [20].

The network-based vulnerability of country j to shocks in the trade network of mineral r, due to supply restrictions from another country i, is given by the trade risk multiplex network $V_{ij}^r(t)$, defined as

$$V_{ij}^r(t) = \left(1 - \frac{p_i(t)}{100}\right) \frac{M_{ij}^r(t)}{\sum_i M_{ij}^r(t)} \quad (1)$$

$V_{ij}^r(t)$ is the fraction of country j's imports of commodity r from i in year t, weighted by how likely country i is to experience political or social disturbances. The trade risk vulnerability network $V_{ij}^r(t)$ is shown for copper, lithium, and platinum group metals in Fig. 1.

Imagine a country that receives its imports from a large number of politically stable countries that in turn all rely on imports from a single, politically unstable country. Clearly, any measure for supply risk that is only based on trade flows with direct neighbors in the trade network will not take such situations into account. However, these influences can be quantified by recursive centrality measures, for example, the PageRank [21]. The PageRank $P_i^r(t)$ of country i in the trade risk network for re-source r at time t is given by solutions to the recursive equation

$$P_i^r(t) = \alpha \sum_j \frac{1}{k_{\mathrm{out},j}^r(t)} V_{ji}^r(t) P_j^r(t) + (1 - \alpha) \quad (2)$$

of the PageRank, where $k_{\mathrm{out},j}^r(t)$ is the out-degree (number of countries into which r is exported) of j (note that, here, we use the convention that origins of trade flows are denoted by the first index and that recipients are denoted by the second index). These countries pass the shock on to countries that

import from them, and so on. The parameter $(1 - \alpha)$ can be understood as the contribution to supply shocks due to effects that are not related to the trade risk network. Equation 2 only converges for $\alpha < 1/\lambda^r(t)$, where $\lambda^r(t)$ is the largest eigenvalue of V^r. If not explicitly stated otherwise, we adopt the standard convention by setting $\alpha = 0.85/\lambda^r(t)$ [see, for example, the work of Newman [21]]. We next compute the time average of the normalized PageRank contributions, $P_i^r = \langle P_i^r(t)/|P^r(t)| \rangle_t$, where $\langle \cdot \rangle_t$ denotes the average over the years 2000 to 2012 and $|\cdot|$ denotes the 2-norm. P_i^r is a measure for how likely country i is to be affected by supply shocks in any other country, even when there is no direct trade relation between these countries. A potential shock in country j will be distributed in units of $(1/k_{\mathrm{out},j}^r(t))$ to all countries that import from j. This corresponds to the situa-tion where a certain reduction of outflows of resource r from country j is equally likely to be transmitted to each of the countries that receive r from j, but there is no multiplier effect such that all countries will inherit the total contributions to risk from j. Instead, this risk will be split among all the recipients.

Countries will only be vulnerable to changes in their imports of mineral r if they have a nonzero import reliance I_i^r. I_i^r quantifies how strongly the economy of country i depends on imports of resource r (see Materials and Methods). Finally, we arrive at the network-based impact of supply shocks for resource r for country i, which we call TradeRisk T_i^r. It is given by

$$T_i^r = P_i^r I_i^r \quad (3)$$

For each network layer in $V_{ij}^r(t)$, all the following network measures are averaged over the years 2000 to 2012. The average degree $\bar{k}^r$ is the average number of nonzero links per node for a given resource r. C^r is the number of nodes that are part of the largest strongly connected component (SCC) divided by the number of nodes in the network. The SCC is the largest subset of nodes where each node can be reached on the network from every other node. The largest eigenvalue, λ^r, of V^r is a measure for how susceptible the trade risk network V^r is to epidemic spreading processes. The larger λ^r is, the easier it is for a small shock to propagate through the entire network [22]. In this sense, $1/\lambda^r$ can be seen as a measure for the resilience of the network. The scarcity s^r of a commodity r is defined as the logarithmic quotient of the total trade volume and the estimated exploitable reserves R^r, $s^r = \log(v^r/R^r)$. Results for several indicator values for individual resources are given in table S1.

We define the adjacency multiplex as $B_{ij}^r(t) = 1$, if $V_{ij}^r(t) > 0$ from Eq. 1, and $B_{ij}^r(t) = 0$ otherwise. The in-degree of country j, $k_{\mathrm{in},j}^r$, is given by $k_{\mathrm{in},j}^r = \langle \sum_i B_{ij}^r(t) \rangle_t$. $k_{\mathrm{in},j}^r$ is the number of countries that contribute to at least 1% i's of total imports of mineral r, averaged over all available years. The in-strength $w_{\mathrm{in},j}^r$ for country j is given by $w_{\mathrm{in},j}^r = \langle \sum_i V_{ij}^r(t) \rangle_t$. Note that $w_{\mathrm{in},j}^r$ can be seen as a weighted average of the political stability of the countries that export r to i. The weights are the fractions of i's total imports in r that the particular countries j provide. We consider an alter-native formulation of the TradeRisk indicator by replacing the PageRank P_i^r in Eq. 3 with the in-strength $w_{\mathrm{in},i}^r$. We call this indicator the In-Strength TradeRisk $T_i^{\mathrm{str},r} = w_{\mathrm{in},i}^r I_i^r$.

To test our results for significance of network effects, we generate several randomized versions of the data (see also Materials and Methods). In the first randomization, $M_{\mathrm{fix\ degree}}^r(t)$, we keep the average degree $\bar{k}^r$ fixed, and each trade flow gets assigned a randomly selected importing and exporting country. The second randomization, $M_{\mathrm{fix\ in\text{-}deg}}^r(t)$, randomizes the exporting country for each trade flow but keeps the importing country fixed. In the third randomization, $M_{\mathrm{fix\ in\text{-}/out\text{-}deg}}^r(t)$, the importing and exporting countries are fixed, but the values of the nonzero trade flows are randomly permuted.

Global results: Resilience and trade networks

We find that the composite supply risk S^r has a weak negative correlation with the largest eigenvalue λ^r of V^r (Pearson correlation coefficient $\rho = -0.32$, $P = 0.026$; see Table 1). S^r is also negatively correlated with the size of the SCC, C^r ($\rho = -0.41$, $P = 0.0039$). A high production concentration may indicate a small SCC and consequently an increased supply risk. Both the largest eigenvalue λ^r and the C^r show a significant correlation with the scarcity s^r. The scarcer a resource is, the less resilient the trade risk network is to supply shocks and the higher is the largest eigenvalue λ^r ($\rho = 0.47$, $P = 0.0011$). These correlations are not confounded by the influence of the trading volume, v^r, itself, as seen by the nonsignificant correlations of λ^r and C^r with v^r. The logarithmic average degree $\log \overline{k^r}$ has only a significant correlation with resource scarcity ($\rho = 0.31$, $P = 0.041$). This suggests that the scarcer the resource, the more vulnerable to cascading effects (of initially localized shocks) the underlying trade network. This network-based vulnerability cannot be explained by lower trade volumes of scarce resources. Note that the trade flows for each country are normalized by the country's total exports of that resource in Eq. 1.

Results for the supply risk S^r, scarcity s^r, and trade volume v^r for the randomized trade networks $M^r_{\text{fix degree}}(t)$ are shown in table S2. By con-

Table 1. Global properties of the trade networks for each resource r. The elements are Pearson correlation coefficients. The composite supply risk S^r is negatively correlated with the largest eigenvalue, λ^r, and the size of the SCC, C^r. C^r is positively correlated with both the total trading volume and the scarcity of the resource. The higher the scarcity of the mineral is, the lower is the resilience to shocks of the trade risk network. These correlations cannot be explained by a potentially confounding influence of the trade volume itself, as seen by the nonsignificant correlations of λ^r and C^r with v^r.

Correlation coefficient	S^r	s^r	v^r
Largest eigenvalue, λ^r	−0.32*	0.47**	0.21
SCC size, C^r	−0.41**	0.45***	0.05

*Significant at $P < 0.05$. **Significant at $P < 0.01$. ***Significant at $P < 0.001$.

struction, the correlations of the average degree with both the supply risk and the scarcity of a resource are preserved under this randomization (see table S3). However, the largest eigenvalue λ^r has no significant correlation with the supply risk S^r or the scarcity s^r, respectively, in the randomized data. This shows that resilience to cascading shocks as observed in the real data is indeed a genuine network effect that cannot be explained by the number of trade flows alone, which is preserved under this randomization. To anticipate how the imports into a country of a particular resource will be affected by a shock in a different country, one therefore needs to take the structure of the entire trade network into account.

Region-specific results: Price volatility and network effects

Region-specific results are computed for the EU and the United States. Results for the EU are obtained by condensing the 25 EU members of 2012 into a single node and by computing the TradeRisk, T_{EU}^r, in the corresponding network. There is a highly significant correlation between price volatility of the resource r in the EU, σ_{EU}^r, and TradeRisk ($\rho = 0.71$, $P < 10^{-4}$) (see Fig. 2A). This correlation is a genuine network effect. To show this, we consider an alternative formulation of the TradeRisk indicator by replacing T_{EU}^r with the In-Strength TradeRisk $T_{\text{EU}}^{\text{str},r}$. Table 2 shows that the TradeRisk T_{EU}^r has a higher correlation with price volatility than with any of the other indicators: the import reliance I_{EU}^r, the PageRank P_{EU}^r, and the In-Strength TradeRisk $T_{\text{EU}}^{\text{str},r}$. To understand the impact of higher-order network effects on volatility of resource prices, we study the linear partial correlation, ρ_{partial}, between T_{EU}^r and σ_{EU}^r, controlling for the influence of $T_{\text{EU}}^{\text{str},r}$. The partial correlation ρ_{partial} can be interpreted as the amount of variance in σ_{EU}^r that can only be explained by knowledge of the entire trade risk network, after the influence of direct neighbors in the network has been removed. We find that $\rho_{\text{partial}} = 0.68$ ($P < 10^{-4}$), which means that about 96% of the original correlation between price volatility and TradeRisk (which was $\rho = 0.71$) can be attributed to genuine network effects. Basically, the same observations also hold for the United States (see Fig. 2B). The TradeRisk indicator explains price fluctuations, σ_{US}^r ($\rho = 0.58$, $P < 10^{-5}$), better than the In-Strength TradeRisk, the import reliance, or the PageRank alone. After controlling for the influence of the In-Strength TradeRisk $T_{\text{US}}^{\text{str},r}$, we find a partial correlation of $\rho_{\text{partial}} = 0.38$ ($P = 0.0032$)
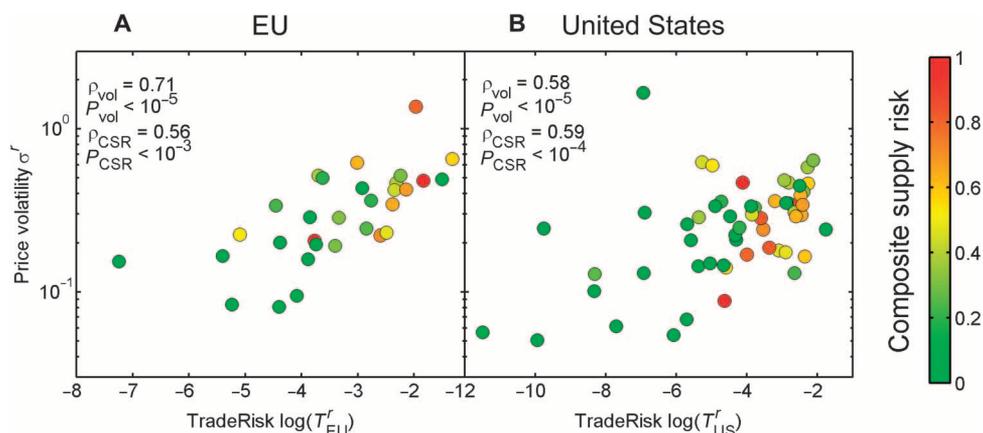
Fig. 2. TradeRisk versus price volatility for the EU and the United States. Each point represents a mineral resource. (**A** and **B**) The country-specific TradeRisk indicator for (A) the EU and (B) the United States is significantly correlated with both the average yearly price volatility of the specific mineral and the composite supply risk, indicated by color. Resources with high S^r tend to be on the right-hand side. We also show the correlation coefficients ρ_{vol} and ρ_{CSR} of the price volatility with TradeRisk and composite supply risk, respectively, together with the P values to reject the null hypothesis that the true correlation coefficient is 0.

between TradeRisk and price volatility. This substantiates that the "systemic trade risk" indicator TradeRisk is indeed "systemic" in the sense that the results are not driven by contributions to price volatilities from direct neighbors in the networks but by systemwide contributions from all over the network. In both regions, the EU and the United States, there is a significant correlation between TradeRisk and supply risk S^r (see Fig. 2). This result is not surprising because both indicators explicitly depend on the import reliance and political stability of the top-producing countries.

To further emphasize the importance of trade network effects, we study the influence of the PageRank parameter α (see Eq. 2) on the correlation coefficients between TradeRisk and price volatility for the EU and the United States. Note that for $\alpha = 0$, the network contributions in Eq. 2 are completely neglected and the contributions to TradeRisk originate only from the import reliance. By increasing α, one puts increasing weight on network contributions; that is, countries inherit systemic trade risk if they import from countries that are systemically risky themselves. As α approaches 1, PageRank is dominated by these recursive network effects. Indeed, as shown in fig. S1, we find an increasing trend of both correlations by increasing α. This confirms that the results shown in Fig. 2 are driven by the susceptibility of individual countries to cascading effects that are transmitted through the trade networks.

Table 2 shows significant differences between the United States and the EU with respect to the correlations of TradeRisk with the applied level of protection of domestic industries from the import of resource r, the trade barriers b_i^r. The United States tends to use lower trade barriers for the import of resources with high systemic trade risk, whereas there is no significant relation between TradeRisk and b_{EU}^r in the EU. Table 2 also shows that the high correlation between TradeRisk and b_{US}^r is driven by the PageRank contributions to systemic trade risk, which shows that the United States has lower barriers for resources where it has a high network-based vulnerability (and not necessarily a high import reliance). These results are noteworthy because they offer hints at how countries could use trade barriers to protect themselves against systemic trade risk (see Discussion).

Replacing the political stability $p_i(t)$ with the Resource Governance Indicator g_i in Eq. 1 does not change the region-specific results, as reported in table S3. This suggests that $p_i(t)$ and g_i basically convey the same information in terms of network-based vulnerability to systemic trade risk. Table S3 also shows region-specific results for the case where each country is assigned the same score for $p_i(t) = 0$. This eliminates all information on the political stability of the individual countries. In this

case, the TradeRisk indicator T_i^r still shows a higher correlation with price volatility than with import reliance I_i^r.

To study the robustness of the region-specific results, we compare the correlation coefficients of the price volatilities of Table 2 with results from three randomized data sets, as described in Materials and Methods. Results are shown in table S3. For the import reliance, the results do not change under any of the randomization schemes by construction. Results for the In-Strength TradeRisk are preserved under the randomizations $M^r_{\text{fix in-deg}}(t)$ and $M^r_{\text{fix in-/out-deg}}(t)$, which keep the in-degrees and both the in-degrees and the out-degrees fixed, respectively. This is not the case for the randomization $M^r_{\text{fix degree}}(t)$, which only preserves the average degrees of the networks. Here, we still find significant correlations between the In-Strength TradeRisk and price volatilities that are substantially lower than those for the real data. These correlations can be attributed to the influence of the importing countries' $p_i(t)$ values, which do not change under any of the randomization schemes. The correlations between price volatilities and both TradeRisk and PageRank are only significant for the randomization scheme $M^r_{\text{fix in-/out-deg}}(t)$. The numbers of the exporting and importing trading partners of a country (that is, the in- and out-degrees) only partially determine the TradeRisk of a given country. This confirms again that there are substantial contributions to systemic trade risk that can only be explained by taking the entire network of trade flows into account.

High-risk resources

The resource with the highest TradeRisk for the EU is beryllium. The primary application of beryllium is in manufacturing connectors and switches for lightweight precision instruments in the aerospace and defense industries (17). Eighty-five percent of the world supply of beryllium is mined in the United States; much of the remainder comes from China. Consequently, the TradeRisk for the United States is much lower than that for the EU. Indium has the second highest TradeRisk in the EU and the third highest TradeRisk in the United States. It is essential for manufacturing liquid crystal displays. Indium is produced almost exclusively as a by-product of zinc mining (23). If demand for indium goes up, its availability will not necessarily increase because this availability is largely determined by zinc economics. The highest TradeRisk for the United States is found for thallium, which is crucial for medical imaging. Global supply of thallium is relatively constrained for the United States, especially because China eliminated several tax benefits on the export of thallium in 2006 (17). We also find a high TradeRisk in the United States for gallium and vanadium. Gallium is almost exclusively produced as a by-product of aluminum mining, whereas vanadium is

Table 2. Regional results for the correlations of TradeRisk indicators, price volatilities, and trade barriers. Price volatility of mineral resources is best explained using the TradeRisk indicator for both the EU and the United States. There are also significant correlations between price volatility and import reliance, PageRank, and In-Strength TradeRisk. The level of applied protection (trade barriers) b_i^r is negatively correlated with TradeRisk in the United States but not in the EU.

Correlation with	Comments	σ_{EU}^r	σ_{US}^r	b_{EU}^r	b_{US}^r
TradeRisk T_i^r	Full network effects and import reliance	0.71***	0.58***	−0.11	−0.39**
Import reliance I_i^r	No use of trade networks	0.48**	0.51***	−0.15	−0.10
PageRank P_i^r	Full network effects, no import reliance used	0.56***	0.45***	−0.23	−0.43***
In-Strength TradeRisk $T_i^{\text{str},r}$	No network effects (only contributions from the nearest neighbors and import reliance)	0.39*	0.50***	−0.12	−0.11

*Significant at $P < 0.05$.   **Significant at $P < 0.01$.   ***Significant at $P < 0.001$.

produced as a by-product of uranium mining (23). We find a comparably high TradeRisk for tellurium in the EU (data for the United States are withheld to avoid disclosing proprietary company data). Tellurium is mined as a by-product of copper and is critical for manufacturing solar panels (23). Overall, these findings suggest that resources that are mined as a by-product of others and for which supply is therefore not necessarily directly determined by demand exhibit higher systemic trade risks than major metals or other minerals. Note that being mined as a by-product does not strictly imply a decoupling of supply and demand because sometimes the intensity of by-product extraction can be adjusted to meet changes in demand. Also, our analysis does not include private trade in by-products that is not captured in public databases. Incompleteness in the data here corresponds to missing links in the trade networks. However, the network approach developed in this work is well equipped to overcome such limitations because many of the statistical properties of networks studied in this work, for example, the largest eigenvalues, SCC, or centrality measures, show relatively high levels of robustness under the random removal of individual links and therefore incomplete or missing data (21).

In general, we find higher TradeRisk values in the EU than in the United States (see table S3). The highest value of TradeRisk in the EU is 0.44 for beryllium, whereas its maximum is 0.19 for thallium in the United States.

The TradeRisk rank of individual resources for the EU and the United States is presented in Fig. 3. Each resource is ranked according to its TradeRisk values in the EU and the United States. The lowest rank corresponds to the highest TradeRisk, and the highest rank corresponds to the lowest. Colors in Fig. 3 indicate whether the resources are cate-
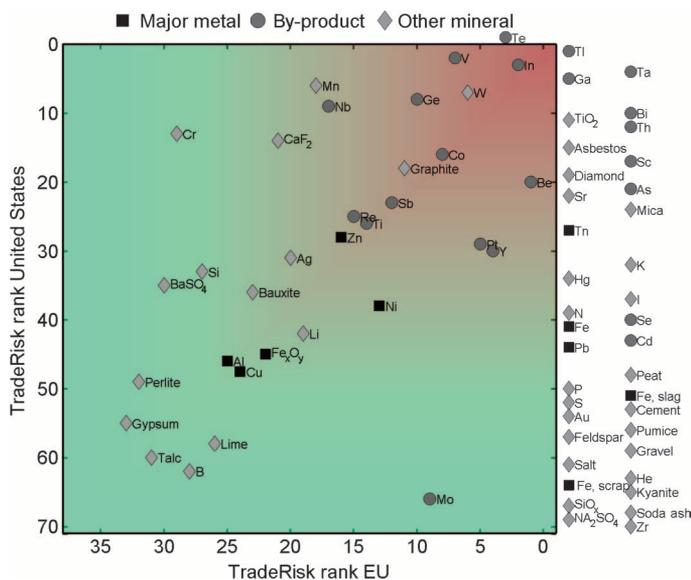
Fig. 3. Ranks of TradeRisk in the EU and the United States. Each point represents a single resource. Rank 1 is given to the resource with the highest TradeRisk in the given region, rank 2 is given for the second highest TradeRisk, and so on. Resources where information is only available for either the EU or the United States are shown outside the plot area. Major metals are shown as black boxes, minerals that are by-products are shown as gray circles, and other minerals are shown as light gray diamonds. It is clearly visible that minerals that have high TradeRisk values in both regions are mined as by-products, whereas the major metals exhibit intermediate TradeRisk values.

gorized as (i) major metals, (ii) by-products of major metals, or (iii) other resources (16). Minerals that have relatively high TradeRisk values in both countries tend to be mined as by-products, whereas major metals have intermediate TradeRisk values.

DISCUSSION

The core of this study is that we demonstrate that the structure of the international trading network of critical resources contains information that explains a large fraction of the price volatility of these resources. This information is quantified by a systemic risk measure, TradeRisk. We find that TradeRisk shows strongly significant correlations with the price volatilities of resources in the EU (Pearson correlation coefficient $\rho = 0.71$, which is the square root of the explained variance) and in the United States ($\rho = 0.58$). The correlation between TradeRisk and price volatility is therefore substantially higher in the EU than in the United States. These results are driven by the network contributions to TradeRisk. To show this, we consider the partial correlation, $\rho_{partial}$, between TradeRisk and price volatilities after removing the influence of all nonnetwork contributions to TradeRisk. These contributions are given by the In-Strength TradeRisk measure that depends only on the import reliance of a country and its trade with direct neighbors in the network. The partial correlation between TradeRisk and price volatilities given the In-Strength TradeRisk can be interpreted as the variation in the price volatilities of resources that can only be explained by network effects. We find that the remaining correlation between TradeRisk and price volatilities, after the removal of all nonnetwork contributions, remains strongly significant in the EU, $\rho_{partial} = 0.68$, whereas it is substantially lower in the United States, $\rho_{partial} = 0.38$. In addition, we find that the United States systematically uses lower trade barriers for resources of high systemic trade risk and high network-based vulnerability, whereas there are no such measures used by the EU. Therefore, there is reason to assume that lower trade barriers for systemically risky resources might indeed reduce the impact of cascading supply shocks on the prices of resources.

These findings indicate that there are currently significant shortcomings in the risk management of nonfuel mineral resources, in particular in the EU. This arises because systemic failure due to cumulative effects of cascading shocks on an intricately interconnected system is not taken into account. This is particularly salient in light of the observation that many of the resources that are most susceptible to systemic risk are only produced as by-products and play a crucial role in industries vital to national interests.

A number of policy implications emerge from this analysis of systemic trade risk. Although trade in commodities or critical resources will always involve some degree of imperfect information, better monitoring and data transparency are needed to adopt a more robust approach to understanding risks that can be foreseen by taking network effects into account. Policy instruments capable of mitigating systemic risk would allow decision-makers to implement measures, such as strategic physical reserves and trade regulations, that mitigate market volatility while ensuring physical supply. In financial networks, it has been shown that systemic financial risk can be almost completely eliminated by means of a so-called systemic risk tax (24). This is a macroprudential regulation approach where a levy is placed on systemically risky financial transactions to offset the systemic risk increase associated with that transaction. Motivated by this approach, it is conceivable that similar

policy measures, such as commodity risk tax, could be developed to create more resilient markets of commodities that are essential to our society.

MATERIALS AND METHODS

Minerals trade data

The minerals included in this study were taken from *Mineral Commodity Summaries*, which is published by the USGS annually (*17*). These summaries contain information on industry structure, salient statistics, and world production and resources for 71 mineral commodities. The summaries also list tariff codes for each mineral in the Harmonized System classification. We collected trade data for tariff codes for each commodity as provided by the UN Comtrade data, spanning the years 2000 to 2012 (*25*). Tariff codes that were not specific to a particular resource, such as the code 2530.90 ("other mineral substances"), were excluded. Note that the tariff codes for the resources provided by the USGS do not include products that contain the particular resource and that might be used for its extraction. Therefore, we did not consider transformation along the value chain of resources. We included all countries for which trade data for any of the minerals exist in any of these years. This amounts to 107 countries. Trade flows between country i and country j in resource r in year t were recorded in the matrix $M_{ij}^r(t)$. $M_{ij}^r(t)$ is the value of resource r measured in U.S. dollars that flows from country i to country j.

For each trade flow, there should exist two records in the data: one for the importing country j and one for the exporting country i. Because of the incompleteness of the data in some cases, these two entries do not match. $M_{ij}^r(t)$ is defined as the larger value of these two entries. $M_{ij}^r(t)$ is a time-dependent multiplex network in which the nodes correspond to countries and where each network layer is the international trade network of a given mineral r. In a similar manner, we constructed the multiplex $K_{ij}^r(t)$, where each entry corresponds to the trade flow of resource r from country i to country j in year t, as measured in kilograms. We only included trade flows that make up more than 1% of a country's imports, meaning that $M_{ij}^r(t)/\sum_i M_{ij}^r(t) > 0.01$ holds.

Price and volatility

The price for resource r as measured in U.S. dollars per kilogram in country i, $x_i(r,t)$, was obtained from the trade data as $x_i(r,t) = \sum_j M_{ij}^r(t)/\sum_j K_{ij}^r(t)$. $x_i(r,t)$ corresponds to the average free-on-board value of resource r in country i, that is, the transaction value of the goods and the value of services performed to deliver the goods to the border of the exporting country. The logarithmic annual return on resource r in country i is $y_i(r,t) = \log(x_i(r,t)/x_i(r,t-1))$. The volatility of resource r in country i, σ_i^r, is the SD of $y_i(r,t)$, computed over the time span $t \in [2000,2012]$.

Total trade volume and reserves

The total trade volume of a resource r in year t, $v(r,t)$, is the sum over all trade flows measured in kilograms, that is, $v(r,t) = \sum_{i,j} K_{ij}^r(t)$. Estimates for the available reserves of a mineral r, R^r, were taken from the latest estimates from the USGS (*17*). These estimates reflect the future supply of identified and currently undiscovered resources that are economically extractable, taking into account recycled resources as well.

Import reliance

The vulnerability of a country i to supply shocks in resource r is strongly related to the net import reliance of i on r. If i is a net exporter of r, then i will be less affected by supply shocks than a country where the economy relies on imports of resource r. The level of import reliance is quantified by the import reliance indicator $I_i^r(t)$ for country i on resource r in year t. For the United States, the data on $I_i^r(t)$ are provided by the USGS on an annual basis and are defined as the imports minus exports, plus adjustments for government and industry stock exchanges (*17*). $I_i^r(t)$ is measured as a percentage of this apparent consumption, averaged over the time span $t \in [2000,2012]$. Values for the import reliance of the EU are available from the European Commission (EC) (*26*) for the year 2006.

Composite supply risk

There exist various ways to quantify the supply risk for resources. The (U.S.) National Research Council (NRC) provides estimates of supply risks for 11 minerals based on import reliance, concentration of the production of the resource, and substitutability (*27*). The British Geological Survey (BGS) publishes supply risk indicators for 41 minerals, taking into account their scarcity, production concentration, reserve distribution, recycling rate, substitutability, and governance aspects of the top-producing and reserve-hosting nations (*28*). The EC releases supply risk indicators for 41 materials based on production concentration, political stability of the producing countries, and substitutability and recycling of the materials (*26*). We rescaled each of these lists of values such that the mineral with the highest supply risk was assigned a value of 1 and the lowest supply risk was assigned a value of 0. The composite supply risk for mineral r, S^r, is defined as the average over the rescaled supply risks provided by the NRC, the BGS, and the EC. Note that although the individual supply risk indicators are often region-specific, we regard the composite supply risk S^r as a global indicator.

Trade barriers

The trade barriers b_i^r are defined as the average value of all ad valorem equivalent tariffs per unit applied to all trade flows into region i that involve resource r, as obtained from the MAcMap database (*29*).

Randomized data sets

To investigate the robustness of our results, we considered three different randomization schemes of the trade flow matrix $M^r(t)$. The randomization $M^r_{\text{fix degree}}(t)$ was obtained as a random permutation of all elements of $M^r(t)$. That is, each trade flow in $M^r(t)$ was assigned a new importing and exporting country that was chosen at random from all countries. $M^r_{\text{fix degree}}(t)$ had the same average degree and total trade volume as $M^r(t)$ but was otherwise completely randomized. The second randomization, $M^r_{\text{fix in-deg}}(t)$, was obtained from $M^r(t)$ by replacing the exporting country for each trade flow by a randomly chosen country. This randomization procedure preserves not only the average degree and the trade volume but also the in-strength and in-degree of each country. Network properties that involve the nearest neighbors of a node, such as eigenvalues, may change under this randomization. In the third randomization, we constructed the trade flow matrix $M^r_{\text{fix in-/out-deg}}(t)$ in the following way. Let $L^r(t)$ be the set of links (that is, nonzero trade flows) in $M^r(t)$, and let $W^r(t)$ be the corresponding set of link weights. $M^r_{\text{fix in-/out-deg}}(t)$ was obtained by keeping $L^r(t)$ fixed and by replacing $W^r(t)$ by a random permutation of its elements. $M^r(t)$ and $M^r_{\text{fix in-/out-deg}}(t)$ only differ by the volumes of the nonzero trade flows. All results involving randomized data were averaged over 100 independent realizations of the randomization procedure.

SUPPLEMENTARY MATERIALS

Supplementary material for this article is available at http://advances.sciencemag.org/cgi/content/full/1/10/e1500522/DC1

Materials and Methods

Fig. S1. Dependence of the correlations between price volatilities and TradeRisk on α.

Table S1. Network-based properties, supply risk, and indicators obtained from trade data for 71 nonfuel mineral resources.

Table S2. Global properties of the randomized trade networks $M^r_{\text{fix degree}}(t)$.

Table S3. Pearson correlation coefficients between various price volatilities with TradeRisk, import reliance, PageRank, and in-strength for the EU and the United States and for several variants of the calculations.

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