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A Country-Level Study of Exposure to Battery Price Fluctuations through Trade Networks

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Abstract

This study examines the impact of critical raw materials (CRMs) and their processed derivatives on countries' exposure to lithium-ion battery price fluctuations. Specifically, we investigate how a country's position within the global trade network of CRMs and batteries influences the volatility of its terms-of-trade (TOT) for batteries. To this end, we construct a new country-level TOT price index for batteries and a series of network indicators at the country and supply chain levels. Using a panel regression framework covering up to 150 countries over 21 years, we analyze how these indicators affect exposure to price volatility. Our results show that the volatility-network relationship is conditional on both the stage of the supply chain and the direction of trade. Export diversification and network centrality play a limited role, whereas import dependence, especially on processed materials and batteries, emerges as the key driver of vulnerability.

JEL Classification: E3, F14, Q37, Q02, Q4.

Keywords: Critical Raw Materials, Battery Price, Exposure, Trade Networks.

1 Introduction

Achieving Net Zero Emissions (NZE) targets depends on the rapid deployment of green technologies for renewable energy generation, storage, and mobility. As the cornerstone of these technologies, batteries play a crucial role in determining the overall costs of clean energy solutions, including hybrid and electric vehicles (EVs), wind turbines, and solar panels (Kittner et al., 2017). Battery prices are, in turn, heavily influenced by the costs of their material components, specifically Critical Raw Materials (CRMs) and their processed derivatives (IEA, 2024).

At first glance, the relationship between raw materials and downstream technologies may appear straightforward: rising mineral prices should lead to higher battery costs.

However, as shown by Figure 1, this does not appear to be the case. Battery prices have continued to decline steadily, despite increases in mineral prices. This apparent disconnect warrants further investigation, particularly in light of the structure and complexity of the supply chain.

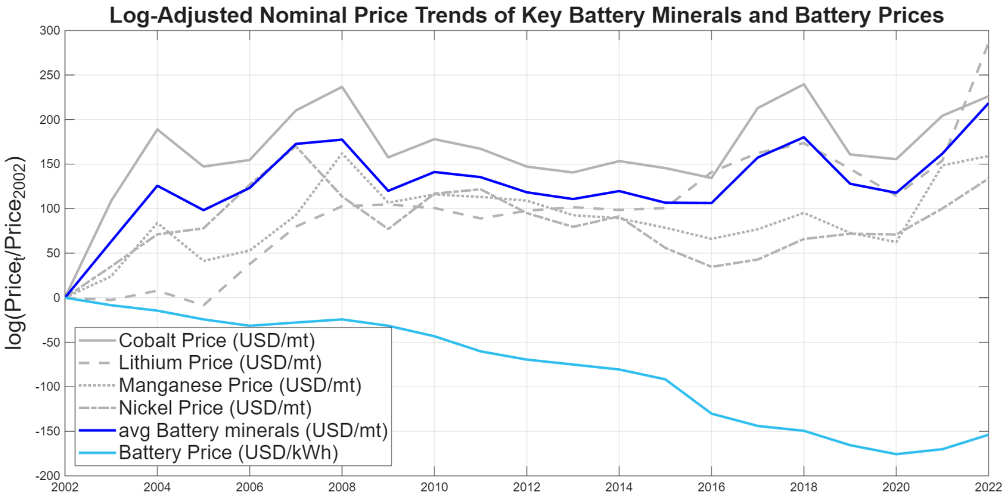


Figure 1: Percentage change, with respect to 2002, for battery (interpolated from Kittner et al. (2017) and Orangi et al. (2024)) and four mineral prices (IMF).

The interconnected nature of global supply chains modifies the impact of upstream (i.e. raw minerals) and midstream (i.e., processed minerals) dynamics on downstream costs, through pass-through effects. Several challenges undermine the stability of the lithium-ion (Li-ion) battery supply chain, potentially exerting pressure on prices. At the upstream level, critical raw materials are by definition subject to high supply risks and have limited substitutes (Schrijvers et al., 2020). In fact, due to the geographical concentration of deposits and other market entry barriers, such as high fixed capital costs, their production is concentrated in a handful of countries. For example, in 2024, 76% of global cobalt production came from the Democratic Republic of Congo (DRC), 59% of global nickel production from Indonesia, 37% of global lithium production from Australia, and 37% of global manganese production from South Africa (USGS, 2025). The midstream layer, i.e., processed materials, is even more concentrated, with China accounting for nearly half of the market value from refining all critical minerals, reaching approximately 75% for cobalt and 65% for lithium, respectively (IEA, 2024). As a result, different countries are involved at different stages of the supply chain, exposing the market to disruptions from geopolitical tensions, protectionist trade policies, and cartelization risks.

Understanding the relationship between supply chain interconnections and price dynamics is key to the success of the energy transition, as price volatility may affect both the affordability and adoption rate of battery-based clean technologies, which must compete in a tight marketplace against low-cost, fossil-fuel-based incumbent technologies (Leader et al., 2019). Moreover, several battery mineral markets are still immature and illiquid, with high price volatility, which creates additional uncertainty for stakeholders across the supply chain. A further complication is the lack of reliable price data for both raw materials and batteries, particularly at the country level and across various stages of the supply chain (Ku et al., 2024).

These challenges pose serious risks for governments and policymakers, who are increasingly adopting protectionist measures such as export restrictions or trade tariffs, and for private-sector stakeholders, who face challenging investment environments due to long lead times of mining projects and price instability. Furthermore, persistent volatility in battery prices could slow or even derail the energy transition, while the growing role of batteries in global trade may have broader implications, potentially increasing macroeconomic volatility. In fact, due to the increasingly interconnected nature of global value chains, even highly localized supply chain disruptions can have a significant negative impact on global industrial production and trade, as well as a positive impact on inflation.

In this context, our study investigates how trade network characteristics across different layers of the battery chain influence the exposure to battery price fluctuations. Specifically, we focus on the volatility of a newly developed country-specific price terms-of-trade (TOT) index for Li-ion batteries and its relationship with the trade network structure. We begin by mapping the Li-ion battery supply chain, covering the upstream (raw materials), midstream (materials processing), and downstream (batteries) stages at the single-product (HS6) level. Next, we employ network analysis techniques to examine the characteristics and topology of international trade, constructing a set of trade network indicators for each supply chain layer (Fagiolo et al., 2010). These indicators serve as our country-specific independent variables. As our dependent variable, we develop a novel country-level TOT battery price volatility index. Finally, through a series of panel regressions, we analyze how changes in the trade network structure influence the index volatility.

Our empirical analysis draws on the literature of international trade, the concept of granularity, and trade network theory. By applying these theoretical frameworks to the context of critical minerals and battery markets, we recognize that the relationship between a country's position in the supply chain and exposure to battery price changes is theoretically ambiguous. On one hand, greater trade connectivity and centrality within the network may enhance stability through diversified partnerships and increased influence, potentially reducing price volatility and exposure. On the other hand, such a position may heighten exposure to global disruptions, thereby amplifying such vulnerability.

Our results, which are robust across several specifications, support the second hypothesis – particularly when considering the impact of a country's number of importers at the downstream (i.e., batteries) and midstream (i.e., processed minerals) levels on battery price exposure. This relationship does not hold when network interconnection is measured in terms of export destinations or centrality position.

The remainder of the paper is structured as follows: Section 2 analyzes the literature and states the hypothesis. Section 3 explains the methodology. Section 4 present the main empirical results. Section 5 concludes.

2 Existing Literature and Hypotheses

Our work spans several strands of theoretical literature, including international trade openness, the concept of granularity, and trade network theory, proposing a novel application in the context of critical minerals and battery markets. In what follows, we review the main theoretical literature of reference and use it to inform the hypotheses that will later be tested through empirical analysis.

The emergence of global value chains has spurred extensive research on the impacts of international trade on prices and volatility. While trade openness is widely recognized as a driver of economic growth (Frankel and Romer, 2017), its effects on volatility are more nuanced. On one hand, trade can protect economies from domestic demand shortages and productivity shocks through natural hedging mechanisms (Cavallo and Frankel, 2008; Caselli et al., 2020; Allen and Atkin, 2022). On the other hand, it exposes countries to idiosyncratic supply shocks, which can propagate through spillover effects across commodities, sectors, and nations, amplifying macroeconomic volatility (Di Giovanni and Levchenko, 2009, 2012; Kramarz et al., 2020).

In this context, it is important to consider the links between the macroeconomy and the individual "grain" - to use the terminology of the granularity literature - whether this refers to a specific commodity, sector, or country. The granularity concept emphasizes that large shocks to influential firms (Gabaix, 2011; Eaton et al., 2012; Freund and Pierola, 2015) or sectors (Acemoglu et al., 2012; Contreras and Fagiolo, 2014; Barrot and Sauvagnat, 2016; Acemoglu et al., 2016) can generate aggregate economic fluctuations rather than averaging out. Studies investigating these dynamics highlight the need to focus on commodity-specific prices or technology-specific prices to fully grasp the role of potentially influential grains. For example, Bogmans et al. (2024) argue that most commodity markets exhibit high granularity, with sizeable consumer or producer countries that, when hit by an idiosyncratic demand or supply shock, can shift the global demand or supply curve and thus move global commodity prices. Moreover, several trade economics papers have analyzed export and import prices at the country level, considering both separate indicators (export and import unit values) and combined measures such as terms of trade (Spatafora and Tytell, 2009; Gruss and Kebhaj, 2019). These studies emphasize the importance of accounting for country-specific factors rather than relying solely on global price indices.

While, as shown above, the link between terms of trade volatility and macroeconomic aggregates has been extensively explored in the literature, much less attention has been paid to the relationship between terms of trade and the characteristics and dynamics of global value chains. In a context of rising trade protectionism, autarky, and concerns about import dependency, understanding the impact of supply chain structures is highly relevant for stakeholders and policymakers. Trade networks provide a powerful framework for examining these relationships, as they capture both the structural and dynamic dimensions of international trade (Frohm and Gunnella, 2021; Dew-Becker, 2023; Barigozzi et al., 2021). Previous research has demonstrated the utility of network analyses in studying international trade and the propagation of shocks, providing a robust foundation for our study's approach (Kali and Reyes, 2007, 2010; Fagiolo et al., 2009; Chakrabarti, 2018).

A growing body of literature investigates mineral commodities through network analyses, primarily adopting a descriptive approach to examine patterns within trade networks. Most of these studies focus on a single commodity (Hou et al., 2018; Chen et al., 2020; Yu et al., 2022; Zhao et al., 2020; Dong et al., 2018) or a single technology (Guan et al., 2016), often neglecting the broader supply chain perspective. While some papers analyze multiple materials, they typically remain limited to the upstream segment of the supply chain (Tian et al., 2021). A few studies do consider the full supply chain, but mostly by comparing network characteristics across its different stages (Shi et al., 2022; Zhang et al., 2022). Others examine transmission mechanisms through risk propagation models (Hao et al., 2022; Zhou et al., 2023; Kang et al., 2023). Our work advances this empirical literature by embedding the role of supply chains (raw materials, processed minerals, and batteries) and international trade relationships into an empirical framework, to assess their impact on price volatility.

2.1 Hypotheses

Turning our focus to the Li-ion battery market, we begin by arguing that battery price dynamics within a country are influenced by its position in the trade network of critical minerals and batteries. A country's position in the network can be characterized by both the quantity and the centrality of its connections with trading partners. The former is captured by the *degree* network indicator, which measures how many countries a given country is connected to via import flows (*indegree*) or export flows (*outdegree*) for a specific product market. In other words, a country with a high indegree acts as an importer with several trading partners, while a country with a high outdegree acts as an exporter with several trading partners. In both cases, the country is highly connected (Fagiolo et al., 2009). The second dimension refers to a country's importance within the trade system and is typically assessed using *centrality* metrics, which indicate the extent to which a country can reach others through direct links. For our analysis, we use *betweenness centrality*, which approximates a country's strategic significance based on the frequency of shortest paths passing through it. In other words, the indicator measures how much removing a country would disrupt the connections between other countries (the so-called network broker).

In light of the literature reviewed, we then formulate two contrasting hypotheses regarding the impact of a country's position in the trade network (as represented by network indicators) on exposure to battery price fluctuations. Indeed, the direction of this impact remains unclear, and our empirical analysis aims to shed light on it.

H1 A country with more trading partners and a more central position in the trade network may benefit from greater stability due to diversified partnerships and its influential position, and thus experience lower exposure to price changes.

H2 A country with more trading partners and a more central position in the trade network may be more exposed to external shocks, and thus experience higher exposure to battery price changes.

Several factors might influence whether hypothesis 1 or hypothesis 2 prevails.

One such factor is the direction of the trade relationships being analyzed, i.e., whether they involve exports or imports. For example, a non-influential exporter (i.e., a country with low outdegree) might seek to gain market shares by lowering its export prices as a way to remain competitive - a behavior known as pricing-to-market (Krugman, 1986). At the same time, an influential importer (i.e., a country with high indegree) might be targeted by the same pricing-to-market strategy, and therefore benefit from lower import prices (Dees et al., 2013). This potential price reduction might, in turn, translate into increased volatility for countries characterized by low outdegree or high indegree.

Another important factor is the level of the supply chain at which trade relationships occur, i.e., upstream, midstream, or downstream, as each may have different implications in terms of both magnitude and direction of impact. To the best of our knowledge, no study has yet examined the relationship between supply chain layers and downstream price volatility. However, some research has investigated how shocks propagate along supply chain layers, showing that these layers exhibit distinct dynamics. Consider, for instance, the increasing need for EVs and clean energy technologies as a positive demand shock for Li-ion batteries. This shock propagates upstream from one sector to its direct and indirect suppliers (Acemoglu et al., 2016). As a result, the goods produced as outputs in the upstream and midstream layers, and used as inputs in the downstream layers, are all appreciated. At the same time, this positive shock raises a sector's productivity, shifting the input supply curve to the right and thereby devaluing the sector's capital. This supply effect (the so-called vertical creative destruction) is stronger for downstream layers. Since they rely on inputs produced by all the layers above them, whose goods become cheaper to produce, downstream sectors experience a cumulative downward supply effect, which might lead to greater price volatility. In contrast, upstream layers have no suppliers and are thus not subject to vertical creative destruction, potentially resulting in lower volatility. However, vertical creative destruction can also be interpreted as a form of hedging, which might lead to the opposite volatility effects. Due to the cumulative supply effect, downstream layers are less sensitive to positive demand effect and thus productivity shocks, while upstream layers see their values appreciate in a cyclical, riskier, and therefore more volatile manner (Gofman et al., 2020). An alternative and more straightforward way to think about it is considering that upstream sectors' product inputs for the entire economy are more systemically risky than downstream sectors exclusively producing final outputs (Dew-Becker, 2023). This is generally true for the oil market, with firms involved in the exploration and production (upstream) being generally riskier than downstream ones involved in refining and distribution (Ewing et al., 2024). In the context of critical minerals, the relationship is even more complex, as some minerals function as substitutes (e.g., the ongoing development of sodium versus lithium in Li- and Na-ion batteries

(Yao et al., 2025)), while others are complements (e.g., cobalt and lithium jointly demanded for Li-ion batteries). When minerals are substitutes, greater trade participation can mitigate risk through hedging, thereby dampening volatility. By contrast, when they are complements, deeper trade ties heighten the risk of joint disruptions, amplifying volatility exposure.

The complex interactions between a country's position in the trade network (i.e., indegree, outdegree, betweenness centrality) and along the supply chain (i.e., upstream, midstream, downstream) make it difficult to determine, a priori, the direction of their impact on exposure to battery price fluctuations. For this reason, our work aims to shed light on this relationship through an empirical analysis using up-to-date real-world data.

3 Data and Methods

By focusing on exposure to battery price changes and its connection to global supply chain characteristics, our study explores the critical role of trade networks in the energy transition. The core of our empirical design is a country-level panel regression framework covering up to 150 countries, including the main exporters (e.g. China, Australia, Canada) and 21 years (2002-2022).

The main independent variables are country-specific network indicators, i.e. indegree, outdegree, and betweenness centrality. The dependent variable is a volatility measure of a country-specific TOT battery price index. Multiple regressions are carried out by varying the network indicator and the supply chain level of the independent variables, e.g., whether they refer to the upstream, midstream, or downstream segment.

3.1 Dataset

In light of the lack of data on prices for minerals and batteries, both at the country- and supply chain stage- level, our first contribution is the development of two novel panel datasets. The first dataset includes country-level price indices of batteries, the second a series of trade network indicators for each level of the supply chain, i.e., raw materials (upstream), processed materials (midstream), and Li-ion batteries (downstream).

To construct country-level TOT price indices for batteries, we start from a global nominal battery price series, using two main sources. Kittner et al. (2017) provide a global dataset of average prices for Li-ion consumer cells from 1991 to 2015, based on expert elicitation methods. Orangi et al. (2024) compile ten different estimates of Li-ion battery costs from both academic and industrial sources, covering the period 2010 to 2023. First, we convert both series from real to nominal terms using the Consumer Price Index (CPI) from the FRED dataset. Then, we apply the year-on-year percentage changes from the Orangi series, moving backward from 2023 to 2010. To extend the series further back, we use the percentage changes from the Kittner series from 2009 to 2002. This yields a continuous interpolated real price series, shown in the first panel of Figure 2. Battery prices have been decreasing steadily since 2002, recently reaching USD 100 per kWh, a level widely regarded as a key threshold for EVs to compete on cost with conventional models (IEA). This decline has been primarily driven by a combination of lower production costs and improved battery efficiency, resulting from technological progress, innovations in battery chemistry and manufacturing, and economies of scale, largely spurred by the rapid growth in EV demand. For the same reasons, the volatility of the cyclical component of battery prices has also declined over the years, except during the periods following the 2009 financial crisis and the 2020 pandemic (second panel of Figure 2).

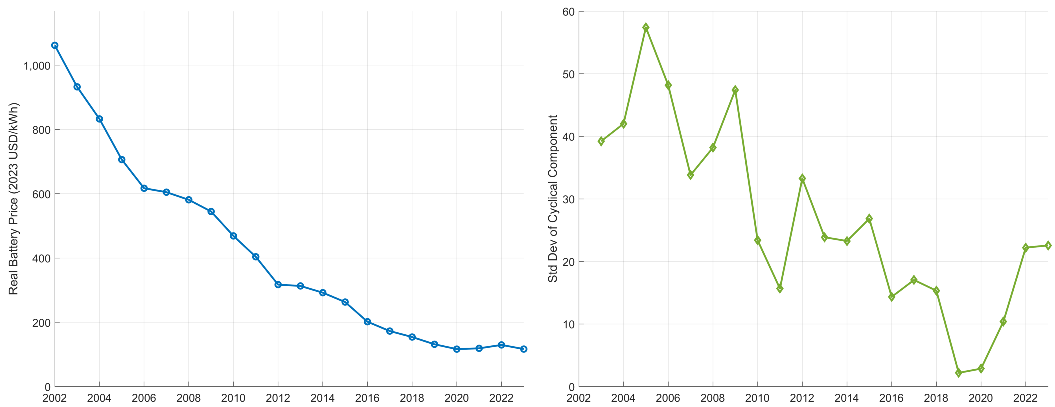


Figure 2: Li-ion Battery Price - Real and 4-Year Rolling Volatility.

To map the global supply chain for Li-ion batteries, we use yearly, commodity-level (HS-6 digit) trade data from the CEPII dataset BACI (Gaulier and Zignago, 2010). We opt for the CEPII variant instead of the raw data from UN Comtrade for several reasons. Firstly, BACI implements a harmonization procedure to provide a unique, reconciled trade flow, meaning that exports and re-exports from country i to country j for a given product and year are identical to imports and re-imports for the same product and year from country j to country i. Secondly, BACI provides comparable quantities of the trade flows: all the values are reported in USD thousands, and all the quantities are converted into tons.

Relevant commodities are identified through keyword searches (i.e., "cobalt", "lithium", "manganese", "nickel", and "battery"), and benchmarked against technical reports.[1] These commodities are then categorized into supply chain layers – upstream, midstream and downstream – and mineral type, informed by the United Nations Conference on Trade and Development (UNCTAD) and the Joint Research Centre (JRC) frameworks.[2] Table 1 provides more details about this categorization, which is employed for constructing both the dependent and independent variables in our panel regression analysis.

3.2 Supply chain mapping

To build our independent variables, we develop country-specific indicators capturing the structure (across layers, $\ell \in \{upstream, midstream, downstream\}$) and dynamics (through years, τ) of trade networks by applying different network theory measures.

We define the trade network as $G_\tau^{(\ell)} = (N_\tau^{(\ell)}, E_\tau^{(\ell)}, W_\tau^{(\ell)})$, where N is the number of nodes (countries), E the number of edges (imports and exports flows), W the edge weights (quantity), and τ years (ranging from 2002 to 2022).[3] If a country i exports to country j during a given year, the edge representing the trade relationship from i to j is drawn, so $a_{i,j,\tau}^{(\ell)} = 1$. Otherwise, no edge is drawn.

In addition, the distance between i and j is defined as g_{ij}, representing the number of edges in the shortest path connecting them, which may pass through an intermediary country k.

Based on these definitions, we construct the following network indicators:

- Indegree: $ID_{i,\tau}^{(\ell)} = \sum_{j=1}^{N} a_{j,i,\tau}^{(\ell)}$ counts the number of trading partners country i imports from;

[1] We employ the IMF Low Carbon Technology Harmonized System Codes (Source), and the OECD Inventory of Export Restrictions on Industrial Raw Materials by Kowalski and Legendre (2023).

[2] We use the UNCTAD Technical note on critical minerals - Supply chains, trade flows and value addition, link and the RMIS Dashboard by the JRC, link.

[3] The layer-specific trade networks are constructed by aggregating bilateral trade flow matrices across all commodities c that define each supply chain layer ℓ (see Table 1). For each ℓ, $G_\tau = \sum_c F_\tau(c)$, where $F_\tau(c)$ denotes the trade matrix for commodity c.

Supply chain layer	Mineral	HS code	HS description
Raw min.s (upstream)	Cobalt	260500	Cobalt ores and concentrates
	Lithium	283691	Lithium carbonate
	Manganese	260200	Manganese ores and concentrates
	Nickel	260400	Nickel ores and concentrates
		750110	Nickel mattes
		750120	Oxide sinters and other intermediate products of nickel metallurgy
Processed min.s (midstream)	Cobalt	282200	Cobalt oxides and hydroxides; commercial cobalt oxides
		810520	Cobalt; mattes and other intermediate products of cobalt metallurgy, unwrought cobalt, powders
	Lithium	282520	Lithium oxide and hydroxide
	Manganese	282010	Manganese dioxide
		282090	Manganese oxides
		284161	Manganese salts
		720211	Ferro-manganese, containing > 2% carbon
		720219	Ferroalloys; ferro-manganese, containing < 2% carbon
		720230	Ferro-alloys; ferro-silicomanganese
	Nickel	282540	Nickel oxides and hydroxides
		282735	Chlorides of nickel
		283324	Sulphates of nickel
Li-ion batteries (downstream)	Battery	850650	Cells and batteries; primary, lithium

Table 1: HS codes and description of the commodities, c, included in the three layers of the supply chain, ℓ.

- Outdegree: $OD^{(\ell)}_{i,\tau} = \sum_{j=1}^{N} a^{(\ell)}_{i,j,\tau}$ counts the number of trading partners country i exports to;
- Betweenness centrality: $BTW^{(\ell)}_{k,\tau} = \sum_{i,j} \frac{g^{(\ell),k}_{i,j,\tau}}{g^{(\ell)}_{i,j,\tau}}$ measures the extent to which country k lies on the shortest paths between other countries, indicating its critical position in the network.

For a detailed discussion of these indicators and their descriptive statistics, refer to Appendix A.

3.3 Battery Price Index

The dependent variable of our analysis is a measure of the volatility of a newly constructed country-specific TOT Li-ion battery price index (BPI).

To construct the country-specific battery price index, we follow the TOT index methodology of Gruss and Kebhaj (2019):

$$\Delta \log \mathrm{BPI}_{i,\tau} = W_{i,\tau} \cdot \Delta \log P_{\tau}, \tag{1}$$

where $\Delta \log$ indicates the log first differences, P_{τ} represents the international nominal price of batteries, defined in Subsection 3.1.[4] This price series is then weighted by a country-specific and time-varying factor, $W_{i,\tau}$, which captures the economic significance of net battery exports relative to country i's GDP (sourced from the IMF).

We smooth short-term fluctuations in trade flows by averaging net trade exposure over the three preceding years ($s = 3$). This approach reduces noise from temporary trade fluctuations and ensures that variations in the price index primarily reflect changes in international prices rather than short-term or endogenous shifts in trade volumes.[5]

$$W_{i,\tau} = \frac{1}{3} \sum_{s=1}^{3} w_{i,\tau-s}, \tag{2}$$

[4] Since this series is expressed in nominal terms, we deflate it using the Consumer Price Index for All Urban Consumers to obtain a real price index.

[5] To avoid losing the observations of the first three years due to the lag, we use the average trade flows over those years, rather than lagged flows.

where $w_{i,\tau}$ is defined as:

$$w_{i,\tau} = \frac{\text{exp}_{i,\tau} - \text{imp}_{i,\tau}}{\text{GDP}_{i,\tau}}, \tag{3}$$

where $exp_{i,\tau}$ and $imp_{i,\tau}$ represent the trade flows of batteries, identified by HS code 850650 (see *cells and batteries* in Table 1). We use net exports – rather than exports or imports alone – to account for the trade balance. Moreover, including the GDP in the denominator allows the weights to reflect cross-country differences in the relative importance of battery trade. Both net exports and GDP are expressed in nominal thousand USD.

The resulting series in log differences ($\Delta \log$) is then exponentiated and rebased to levels ($2002 = 100$) for empirical analysis.

The TOT BPI essentially captures countries' battery-driven revenues, i.e., traded quantities of batteries multiplied by their prices (Makhlouf et al., 2023). Our interest lies in studying the volatility of the TOT BPI, in other words, in estimating changes in disposable income, relative to GDP, arising from movements in battery prices, thereby providing a convenient proxy for countries' exposure. To study the volatility, we extract the cyclical component of the TOT BPI using the Hodrick-Prescott (HP) filter with smoothing parameter $\lambda = 100$ and compute the logarithmic volatility over non-overlapping four-year rolling windows as follows:

$$\log \sigma_{i,t} = \log \left(\sqrt{\frac{1}{4} \sum_{j=1}^{4} \left(c_{i,4(t-1)+j} - \bar{c}_{i,t} \right)^2} \right), \tag{4}$$

where $c_{i,t}$ denotes the cyclical component of the log battery price index for country i, t indexes the non-overlapping four-year periods from 2002 to 2021 (e.g., $t = 1$ corresponds to 2002–2005, $t = 2$ to 2006–2009, and so forth), and $\bar{c}_{i,t}$ is its mean over the same window. In Appendix B, we conduct a sensitivity analysis on the time dimension of the rolling window of the volatility, reducing it to two years.

3.4 Empirical design

We employ panel regression models to analyze the relationship between different network measures, $X_{i,t}$ (i.e. indegree, outdegree, and betweenness centrality), and the logarithmic cyclical price volatility, $Y_{i,t} = \log \sigma_{i,t}$, which serves as a proxy for countries' exposure to fluctuations in battery prices.

To account for time-invariant country heterogeneity and common time shocks, we estimate generalized fixed effects regressions, which are implemented using the Frisch-Waugh-Lovell (FWL) theorem to partial out the fixed effects before estimating the coefficients of interest. Standard errors are clustered at the country level.

We use the following baseline regression set up:

$$Y_{i,t} = \alpha + \beta \log(1 + X_{i,t}^{(\ell)}) + \gamma_i + \delta_t + \lambda \log(1 + \mathbf{S}_{i,t}) + \theta D_{i,t}^{(\ell)} + \mu \big[\log(1 + X_{i,t}^{(\ell)}) \times D_{i,t}^{(\ell)} \big] + \epsilon_{i,t}, \quad (5)$$

where each network indicator $X_{i,t}^{(\ell)}$ enters the regression in log-transformed form, such that the coefficient β represents the change in volatility associated with 1% increase in the network indicator. t represents 4-year periods[6], ℓ indexes the supply chain layer (raw, processed minerals, batteries, aggregated or disaggregated), γ_i are country fixed effects, and δ_t are time fixed effects. This setup controls for characteristics that vary over time but remain constant across countries (e.g., inflation), as well as for country-specific characteristics that do not vary over time. We also include a set of control variables, $\mathbf{S}_{i,t}$, capturing a country's stage in the energy transition. Specifically, we include the share of renewable energy in total final energy consumption (Indicator $EE2$, 7.2.1, sourced from the UN Statistics, Energy Statistics) and installed renewable energy-generating capacity, expressed in watts per capita (Indicator $GN3$, 7.b.1, sourced from the United Nations Global SDG Database). As some countries reduce their reliance on fossil fuels, their demand for renewable technologies and batteries may increase, thereby stimulating trade in critical minerals.

The dummy variable $D_{i,t}^{(\ell)}$ equals 1 if country i is a net exporter within layer ℓ (e.g., of batteries, in our baseline case) at time t, or 0 otherwise. The interaction term μ captures heterogeneous effects by export status.

By varying the layer of the independent variable, we obtain results at different layers and aggregation levels, i.e. for the entire supply chain ($\ell = up + mid + down$), for minerals only

[6]Since volatility is computed over a four-year rolling window, the other variables entering the regression – whether independent or instrumental – are also averaged over the same four-year rolling window.

($\ell = mid + down$), or separately for the upstream, midstream, and downstream layers ($\ell = up, mid, down$).

These models assess how a country's network position within specific supply chain layers relates to the BPI volatility. A positive $\hat{\beta}$, indicates that greater proportional connectivity (e.g., more import trading partners or higher centrality) is associated with higher exposure to battery price fluctuations, while a negative $\hat{\beta}$ suggests that greater connectivity is linked to lower volatility. By contrast, a statistically insignificant $\hat{\beta}$ would imply that network position has no systematic effect on battery price volatility in that specific supply chain layer. As outlined in Section 2.1, we remain agnostic about the sign of $\hat{\beta}$ ex ante, as the net effect may depend on several factors. For instance, depending on the specific supply chain layer under consideration, a country with more import trading partners may enjoy a more stable trade position - leading to lower volatility - or might be more exposed to external shocks, resulting in higher volatility.

4 Results

4.1 Descriptive statistics

From the supply chain mapping, it is already possible to derive insightful descriptive statistics that highlight the role of key players along the Li-ion battery supply chain.

Figures 3a, 3b, and 3c provide a graphical representation of the trade network structure across the upstream, midstream, and downstream segments of the supply chain. The most striking feature is the variation in concentration along the supply chain: while the network for Li-ion batteries appears relatively evenly distributed, processed minerals – and even more so, raw minerals – exhibit a higher degree of concentration, with a few actors accounting for the majority of trade flows. At the processed materials level, the most connected countries are the Netherlands and Germany, followed by China, the US, and Canada. At the raw materials level, China and the Netherlands emerge as the most indegree-connected nodes, followed by South Korea, France, and Germany. Two main patterns can be distinguished. Some countries have a high number of importers because they play an active role in a specific segment of the supply chain - for instance, China, which imports raw materials from several countries to establish itself as the main processing hub. Others, however, are highly involved in the trade of these minerals without being central to the production process, as in the case of the Netherlands, whose high indegree largely reflects the presence of the Port of Rotterdam, the largest in Europe.

Looking at the value of trade flows helps refine this picture further. Table 2 reports the top three importing and exporting countries, averaged across the entire time span, for each of the three supply chain layers. In addition, Appendix A includes Table 8, which summarizes the average minimum, mean, and maximum values of each network indicator, as well as Figures 5 to 8, plotting the variation of the indicators across years and supply chain segments for a selection of countries.

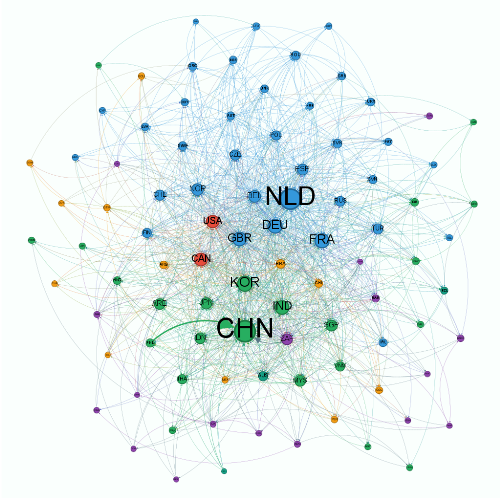
Some countries maintain a persistent presence across all three stages. For example, Indonesia ranks among the top three exporters of batteries, as well as processed and raw minerals. Others, such as the US, appear solely as major importers. Meanwhile, countries like China and Japan import significant amounts of raw and processed minerals before establishing themselves as major battery exporters. Notably, China has had the largest demand for EV batteries over the last decade, all of which has been met through domestic production. Conversely, the second- and third-largest EV markets, Europe and the US, still heavily rely on imports from other countries (see IEA Global EV Outlook 2024).

	Batteries (downstream)	Processed min.s (midstream)	Raw min.s (upstream)
First importer	HKG (8.17)	USA (684.37)	CHN (45,975)
Second importer	USA (5.05)	JPN (436.85)	JPN (5,190.6)
Third importer	CHN (4.86)	NLD (399.06)	KOR (2,623.9)
First exporter	CHN (16.08)	ZAF (781.18)	PHL (19,887)
Second exporter	JPN (5.10)	UKR (717.62)	IDN (13,637)
Third exporter	IDN (4.78)	IDN (648.71)	ZAF (10,114)

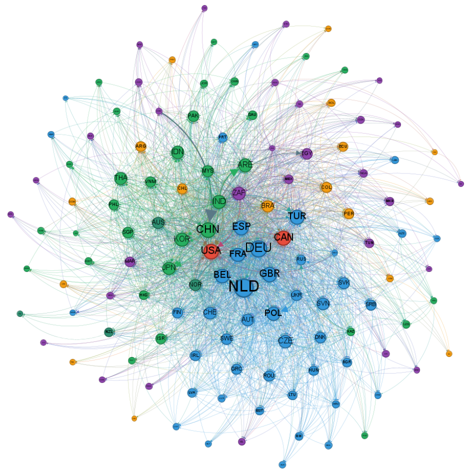
Table 2: Top three countries ranked according to average (2002–2022) imports and exports (million US dollars), by supply chain layer.

Considering the dependent variable of our analysis, i.e., the battery TOT index, across countries and years provides insights into the exposure of different countries to the battery market. To this end, Figure 4 plots the newly-built TOT BPI, both in levels and as a 4-year rolling volatility[7], and categorizes countries according to three distinct TOT BPI dynamics. The first

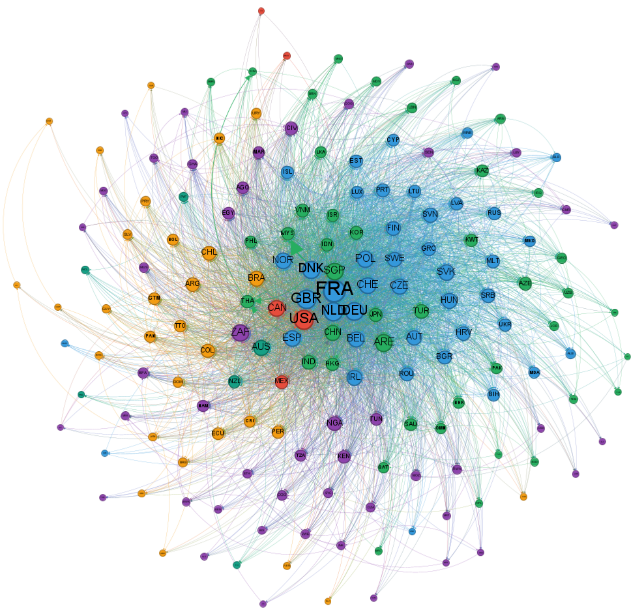
[7]We apply the HP filter to remove short-term fluctuations associated with the business cycle, highlighting long-term trends.



(a) Raw materials



(b) Processed materials



(c) Li-ion batteries

Figure 3: Trade networks of raw (a), processed materials (b), and batteries (c), in 2022. Each node represents a country, with node size proportional to its indegree and node color indicating geographical region. Directed edges represent import flows.

column shows countries experiencing a recent TOT boom followed by a bust, the second column includes countries experiencing recent busts and subsequent recoveries, and the third column focuses on countries with persistently higher TOT BPI levels since the early 2000s (note the change in y-axis scale).

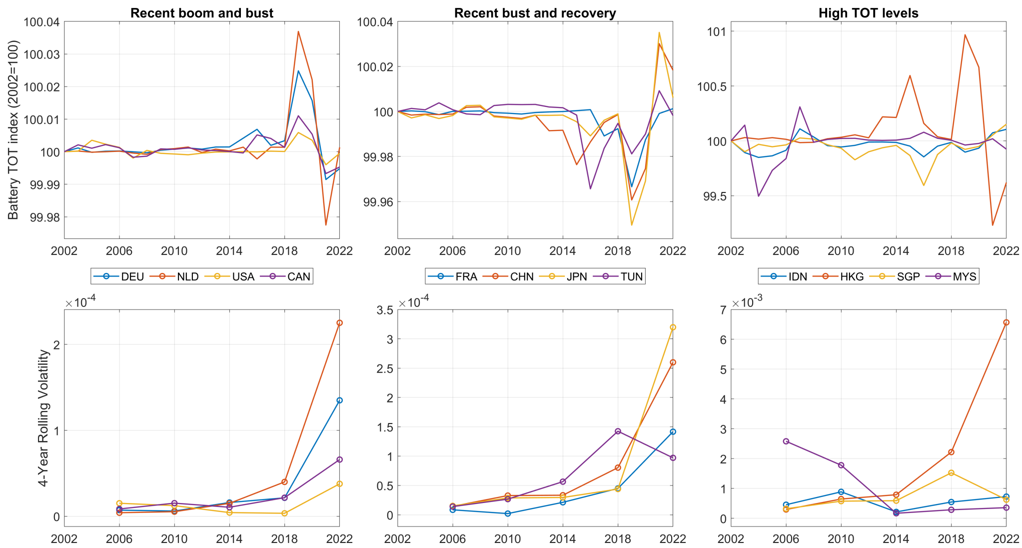


Figure 4: Li-ion Battery Price Index — Levels (top panel) and 4-Year Rolling Volatility (bottom panel). Columns include different country groups. First column: Germany (DEU), Netherlands (NLD), United States (USA), Canada (CAN). Second column: France (FRA), China (CHN), Japan (JPN), Tunisia (TUN). Third column: Indonesia (IDN), Hong Kong (HKG), Singapore (SGP), Malaysia (MYS).

Variations in the index provide an estimate of the windfall gains and losses of income associated with changes in international battery prices. That is, a one percentage point change in the TOT BPI can be interpreted as a change in aggregate disposable income equivalent to one percentage point of GDP (Gruss and Kebhaj, 2019).

By construction, the average yearly growth rate of the index across countries and over time is close to zero, as the price variations' effects on exporters and importers offset each other. However, the index exhibits substantial variability across countries and over time.

The persistently high TOT values of Malaysia, Indonesia, Hong Kong, and Singapore suggest that several East and Southeast Asian economies established themselves as active players in the battery trade since the early 2000s, while most of the rest of the world had not yet engaged in the market. After 2014, and especially after 2018, Western countries also entered the game, opening up new opportunities that some Asian countries were able to capitalize on. For example, Indonesia positioned itself among the world's top battery producers (in 2022 the country exported USD 391M of Li-ion batteries, while importing just USD 27.8M). Indonesia is also rich in mineral resources, especially nickel, and, in an effort to stimulate domestic battery production, banned nickel ore exports in 2020. A different strategy can be observed in Hong Kong, which, despite limited manufacturing capacities, established itself as a central financial hub and transit port, primarily for China and Japan. Accordingly, the index demonstrates a complementary pattern. For example, in 2019, the TOT BPI peaks for Hong Kong (third column, orange line), while it declines for Japan, China, France, and Tunisia (second column), reflecting the first country as net battery exporter and the second group of countries as net importers. By 2021, the situation reverses, illustrating the dynamic shifts in countries' exposure to battery price fluctuations.

4.2 Regression Results at the Aggregate Supply Chain Level

Table 3 presents the regression coefficients from Eq. (5), using indegree as network indicator. Different columns report alternative specifications, with one or two control variables, and with or without the dummy and the interaction term. As the results with the other two network indicators are almost never significant, we report them in Appendix B. In all cases, the dummy variable $D_{i,t}^{(\ell)}$ is constructed with reference to the battery layer.

This subsection focuses on the general results, where the network indicators are computed at the aggregate supply chain level, i.e., summing the upstream, midstream, and downstream layers.

The coefficient of the network indicator X (indegree) is always positive and significant. This suggests that when a country becomes more connected through its imports along the entire battery supply chain, it experiences higher battery price exposure. Since the independent variables enter the model as $\log(1+X)$, the coefficients can be interpreted as the approximate percentage change in battery exposure resulting from a 1% increase in the network indicator. In this case, in Regression n.7, which includes renewable capacity and the dummy as controls without an interaction term[8], a 1% increase in the number of import trading partners corresponds to about

[8] We focus on Regression n.7, as it consistently yields the highest adjusted R^2 across the empirical analyses (Tables 3-7).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
X	0.546***	0.636***	0.512**	0.588***	0.560***	0.648***	0.525***	0.603***	0.613***	0.701***	0.573***	0.653***
	(0.202)	(0.213)	(0.202)	(0.217)	(0.199)	(0.208)	(0.200)	(0.212)	(0.198)	(0.206)	(0.200)	(0.211)
Ren. consumption		0.284		0.225		0.281		0.231		0.280		0.235
		(0.236)		(0.254)		(0.230)		(0.247)		(0.231)		(0.248)
Ren. capacity			0.105*	0.0822			0.0991*	0.0753			0.0995*	0.0753
			(0.0596)	(0.0637)			(0.0592)	(0.0622)			(0.0596)	(0.0624)
Dummy					0.258	0.254	0.196	0.203	1.064**	1.058**	0.898*	0.919*
					(0.190)	(0.191)	(0.190)	(0.189)	(0.509)	(0.509)	(0.525)	(0.527)
$X \times D$									-0.244	-0.243	-0.210	-0.214
									(0.159)	(0.156)	(0.160)	(0.158)
Constant	-11.59***	-12.66***	-11.93***	-12.70***	-11.65***	-12.72***	-11.96***	-12.75***	-11.82***	-12.88***	-12.11***	-12.92***
	(0.639)	(1.092)	(0.663)	(1.108)	(0.629)	(1.051)	(0.656)	(1.074)	(0.626)	(1.045)	(0.661)	(1.074)
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	750	745	745	740	750	745	745	740	750	745	745	740
Adj. R^2	0.738	0.738	0.741	0.740	0.739	0.739	0.741	0.740	0.740	0.739	0.741	0.740

Table 3: Regression results — indegree, aggregate supply-chain level (1–12). Robust standard errors in parentheses. P-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

a 0.525% increase in battery price exposure at the aggregate supply chain level. This pattern is consistent with the hypothesis that higher import connectivity increases vulnerability to external shocks. No significant effects emerge for outdegree or betweenness centrality.

In the models with the dummy variable but without the interaction term (Columns 5–8), the coefficient on the dummy variable is positive but not statistically significant, suggesting that net exporters of batteries tend to have slightly higher average volatility of the BPI, but the effect is weak. When the interaction term is included (Columns 9–12), its coefficient is consistently negative (though not significant), indicating that the marginal effect of indegree in the supply chain network on BPI volatility is lower for net exporters of batteries. Importantly, the coefficient on the dummy becomes statistically significant once the interaction term is added because its interpretation changes: without the interaction, it measures the average difference in BPI volatility between net exporters (D=1) and non-exporters (D=0) across all levels of indegree; with the interaction, it measures this difference specifically when indegree is zero. In other words, while being a net exporter has no significant effect on average, among countries with no trade exposure (indegree = 0) the difference is significant and positive.

To better understand which part of the supply chain drives this relationship, the next subsection increases the level of disaggregation by considering network indicators at the mineral level, excluding the downstream layer.

4.3 Regression Results at the Mineral Level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
X	0.476***	0.510***	0.473***	0.498***	0.489***	0.523***	0.486***	0.512***	0.535***	0.566***	0.530***	0.554***
	(0.170)	(0.175)	(0.177)	(0.183)	(0.169)	(0.174)	(0.177)	(0.182)	(0.170)	(0.174)	(0.180)	(0.184)
Ren. consumption		0.229		0.164		0.224		0.169		0.217		0.166
		(0.228)		(0.246)		(0.224)		(0.240)		(0.224)		(0.240)
Ren. capacity			0.101*	0.0837			0.0948	0.0770			0.0949	0.0773
			(0.0606)	(0.0653)			(0.0604)	(0.0643)			(0.0608)	(0.0645)
Dummy					0.257	0.252	0.198	0.201	0.862**	0.836**	0.727*	0.722*
					(0.187)	(0.188)	(0.188)	(0.187)	(0.361)	(0.368)	(0.383)	(0.388)
$X \times D$									-0.216	-0.209	-0.186	-0.183
									(0.133)	(0.130)	(0.135)	(0.134)
Constant	-11.09***	-11.81***	-11.52***	-11.96***	-11.15***	-11.86***	-11.54***	-12.00***	-11.26***	-11.94***	-11.65***	-12.09***
	(0.430)	(0.876)	(0.506)	(0.883)	(0.430)	(0.849)	(0.503)	(0.862)	(0.430)	(0.847)	(0.511)	(0.863)
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	744	739	739	734	744	739	739	734	744	739	739	734
Adj. R^2	0.727	0.726	0.729	0.728	0.727	0.726	0.730	0.728	0.728	0.727	0.730	0.728

Table 4: Regression results — indegree, aggregate mineral level (1–12). Robust standard errors in parentheses. P-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4 reports results excluding the downstream layer and focusing on raw and processed minerals. As before, the table focuses on indegree as the network indicator of choice, while the results for outdegree and betweenness centrality are reported in Appendix B. The dummy variable $D_{i,t}^{(\ell)}$ continues to reference the battery layer.

The positive and significant effect of indegree persists, though with a smaller magnitude. For instance, in the Regression n.7, a 1% increase in mineral import indegree is now associated with an approximate 0.486% rise in battery price volatility.

In the next subsection, we further disaggregate the analysis by examining the supply chain layers separately.

4.4 Regression Results Disaggregated by Supply Chain Layer

Tables 5 through 7 show regression results disaggregated by supply chain layer – considering the downstream, midstream, and upstream segments, respectively. Again, the analysis focuses on indegree as the network indicator, with different columns corresponding to different regression specifications. The dummy variable $D_{i,t}^{(\ell)}$ is constructed with reference to the battery layer.

The indegree retains its positive and significant relationship with exposure in the downstream (Table 5) and midstream layers (Table 6), but not in the upstream (Table 7). In the downstream

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
X	0.563***	0.650***	0.545***	0.616***	0.567***	0.653***	0.549***	0.621***	0.590***	0.676***	0.567***	0.641***
	(0.178)	(0.183)	(0.177)	(0.185)	(0.176)	(0.181)	(0.175)	(0.182)	(0.176)	(0.181)	(0.175)	(0.182)
Ren. consumption		0.307		0.247		0.303		0.251		0.303		0.253
		(0.233)		(0.249)		(0.228)		(0.243)		(0.230)		(0.244)
Ren. capacity			0.112*	0.0878			0.107*	0.0819			0.107*	0.0826
			(0.0592)	(0.0625)			(0.0588)	(0.0612)			(0.0592)	(0.0615)
Dummy					0.244	0.237	0.180	0.184	0.727	0.718	0.572	0.584
					(0.189)	(0.191)	(0.188)	(0.188)	(0.540)	(0.538)	(0.551)	(0.553)
$X \times D$									-0.158	-0.157	-0.127	-0.129
									(0.179)	(0.174)	(0.179)	(0.177)
Constant	-11.51***	-12.63***	-11.94***	-12.74***	-11.55***	-12.65***	-11.94***	-12.75***	-11.61***	-12.72***	-12.00***	-12.82***
	(0.522)	(0.962)	(0.570)	(0.980)	(0.518)	(0.937)	(0.566)	(0.961)	(0.517)	(0.942)	(0.567)	(0.966)
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	750	745	745	740	750	745	745	740	750	745	745	740
Adj. R^2	0.740	0.740	0.742	0.742	0.740	0.740	0.742	0.742	0.740	0.740	0.742	0.742

Table 5: Regression results — indegree, battery level (1–12). Robust standard errors in parentheses. P-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

segment, a 1% increase in the number of battery importers corresponds to about a 0.549% increase in battery price exposure (Reg. 7, in Table 5). Moving along the supply chain, at the midstream level, a 1% increase in the number of processed minerals importers corresponds to about a 0.432% increase in battery price exposure (Reg. 7, in Table 6). Finally, at the raw minerals level, the effect vanishes, as the coefficient of 0.163 is not statistically significant (Reg. 7, in Table 7).

This pattern suggests that greater import connectivity in the downstream and midstream layers of the battery supply chain increases countries' exposure to battery TOT volatility, but this relationship weakens upstream, where raw materials are involved.

We also carry out a series of additional regression analyses. First, we vary the network indicator of choice, using outdegree and betweenness centrality (Tables 9 to 18 in Appendix B). Then, as a robustness check, we vary the layer to which the dummy refers. Since it yields almost identical results, we do not report the full regression outputs. As a further robustness check, we reduce the temporal dimension of the rolling window, carrying out the same analysis considering five two-year long windows (Tables 19 to 23 in Appendix B). Finally, to assess the role of all three layers simultaneously, we estimate an extended specification with the three layers as separate regressors (Equation 6 and Table 24 in Appendix B).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
X	0.424**	0.453**	0.422**	0.439**	0.434**	0.462**	0.432**	0.450**	0.468***	0.494***	0.465**	0.482**
	(0.174)	(0.178)	(0.183)	(0.186)	(0.174)	(0.177)	(0.184)	(0.186)	(0.174)	(0.177)	(0.184)	(0.187)
Ren. consumption		0.217		0.148		0.213		0.152		0.206		0.149
		(0.226)		(0.242)		(0.222)		(0.237)		(0.223)		(0.238)
Ren. capacity			0.106*	0.0910			0.100*	0.0847			0.101	0.0851
			(0.0609)	(0.0652)			(0.0606)	(0.0642)			(0.0609)	(0.0644)
Dummy					0.250	0.245	0.190	0.192	0.794**	0.768**	0.656*	0.649
					(0.187)	(0.189)	(0.188)	(0.188)	(0.369)	(0.378)	(0.387)	(0.394)
$X \times D$									-0.202	-0.194	-0.170	-0.167
									(0.140)	(0.138)	(0.141)	(0.141)
Constant	-10.92***	-11.59***	-11.37***	-11.75***	-10.97***	-11.63***	-11.39***	-11.78***	-11.04***	-11.68***	-11.46***	-11.85***
	(0.423)	(0.847)	(0.513)	(0.857)	(0.426)	(0.823)	(0.512)	(0.839)	(0.424)	(0.822)	(0.515)	(0.840)
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	744	739	739	734	744	739	739	734	744	739	739	734
Adj. R^2	0.726	0.725	0.728	0.727	0.726	0.725	0.729	0.727	0.727	0.726	0.729	0.727

Table 6: Regression results — indegree, processed mineral level (1–12). Robust standard errors in parentheses. P-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5 Conclusion

This paper has investigated how countries' positions in the global trade network of critical raw materials, processed materials, and batteries shape their exposure to Li-ion battery price volatility. We constructed a novel country-level TOT price index for batteries and combined it with network indicators across different stages of the supply chain. Using a panel regression framework, we showed how trade structures propagate or mitigate volatility, linking supply chain characteristics to downstream price dynamics.

Our analysis shows that the connection between trade along the Li-ion battery supply chain and exposure to battery price volatility appears to be conditional rather than universal. Our findings suggest that the relationship depends on the nature of the traded product (raw materials versus processed materials versus batteries) and the position of a country along the supply chain. Upstream trade (of raw materials) links seem less critical for determining downstream battery price volatility, whereas midstream and downstream connections play a more important role. This underlines the need to distinguish between different supply chain stages when assessing trade-related vulnerabilities.

We further find that export diversification (outdegree) and centrality (betweenness) in the trade network matter less than import diversification (indegree). In other words, the number of exporters and the network position do not systematically influence battery price fluctuations. By

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
X	0.195	0.188	0.161	0.158	0.195	0.188	0.163	0.160	0.211	0.203	0.178	0.175
	(0.153)	(0.151)	(0.150)	(0.150)	(0.152)	(0.151)	(0.150)	(0.150)	(0.152)	(0.151)	(0.150)	(0.150)
Ren. consumption		0.162		0.100		0.160		0.102		0.158		0.0986
		(0.228)		(0.241)		(0.225)		(0.237)		(0.225)		(0.237)
Ren. capacity			0.132**	0.121*			0.128**	0.117*			0.128**	0.117*
			(0.0632)	(0.0685)			(0.0630)	(0.0675)			(0.0632)	(0.0676)
Dummy					0.168	0.165	0.139	0.139	0.424	0.410	0.401	0.394
					(0.185)	(0.187)	(0.182)	(0.182)	(0.358)	(0.371)	(0.358)	(0.366)
$X \times D$									-0.123	-0.118	-0.126	-0.122
									(0.158)	(0.158)	(0.155)	(0.156)
Constant	-10.22***	-10.66***	-10.74***	-10.96***	-10.24***	-10.67***	-10.73***	-10.96***	-10.26***	-10.68***	-10.76***	-10.97***
	(0.263)	(0.740)	(0.371)	(0.731)	(0.263)	(0.724)	(0.369)	(0.721)	(0.263)	(0.721)	(0.370)	(0.719)
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	715	710	713	708	715	710	713	708	715	710	713	708
Adj. R^2	0.718	0.716	0.721	0.719	0.718	0.717	0.721	0.719	0.718	0.716	0.721	0.719

Table 7: Regression results — indegree, raw mineral level (1–12). Robust standard errors in parentheses. P-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

contrast, import-dependent countries are more directly exposed to volatility transmitted through their suppliers, confirming the intuition in Hypothesis 2.

Import-dependent economies, particularly those relying heavily on processed materials and batteries, are the most vulnerable. A high number of import origins amplifies exposure to external shocks, since each additional supplier increases the risk of transmitting volatility. This vulnerability does not hold for imports of raw materials, which show little connection to downstream price fluctuations. Instead, exposure intensifies when countries import at later stages of the supply chain, where vertical creative destruction and cumulative supply effects magnify volatility. Thus, dependence on midstream and downstream imports is the key driver of vulnerability.

Another reason behind the increased price exposure following import diversification lies in the complement versus substitute reasoning. When the imported good is a substitute for a domestically available input, trade integration may mitigate volatility through hedging. By contrast, when imports are complements to other inputs, deeper integration heightens the risk of joint disruptions and thereby amplifies volatility exposure. Our findings suggest that the latter case is particularly relevant for the Li-ion battery sector, where multiple minerals are jointly demanded and cannot be easily substituted.

In terms of policy implications, we can assert that reducing vulnerability requires strategic import concentration rather than simple diversification. Mineral-dependent countries may reduce their exposure to battery price volatility by lowering the number of origin countries from which they import processed materials and batteries. This runs counter to the conventional diversification logic that more trading partners reduce risk, highlighting instead the asymmetry between exporting and importing positions in the trade network. For mineral-importing economies, resilience lies in building more stable, possibly long-term contractual relationships with fewer suppliers, or in developing domestic midstream and downstream capacities. In addition, fostering research, innovation, and industrial policies that encourage the substitution of scarce or complementary critical minerals with more abundant alternatives could further mitigate vulnerability by reducing the risk of joint supply disruptions.

Finally, we acknowledge the potential for endogeneity of the relationship between trade position and price exposure: countries may adjust their trade structures not only in response to structural or technological changes but also in reaction to price dynamics. For instance, a surge in battery prices might prompt mineral-exporting economies to broaden or shift their trading partnerships to secure better terms or mitigate risks. Conversely, a decline in battery prices may incentivize countries with strong processing or manufacturing capabilities to reposition themselves more centrally within the supply network to capture value and improve competitiveness. Future research will address this concern using approaches such as Shift-Share Instrumental Variables (SSIV) (Goldsmith-Pinkham et al., 2020; Borusyak et al., 2022), to isolate the causal impact of trade network structure on price exposure.

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A Network indicators

Table 8 reports descriptive statistics for the three network indicators, averaged across all countries and years, for each of the three supply-chain layers.

	Upstream			**Midstream**			**Downstream**		
	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
Indegree	33.84	0.00	62.25	42.85	0.00	70.50	46.51	0.00	70.00
Outdegree	52.19	0.00	74.00	85.49	0.00	125.50	133.80	0.00	181.75
Betweenness	1733.38	0.00	4425.14	1548.45	0.00	4083.64	1865.73	0.00	4264.86

Table 8: Average descriptive statistics of network indicators across supply-chain layers.

The interpretation of indegree and outdegree indicators is relatively straightforward, as they represent actual counts. The average number of source (destination) countries a country imports from (exports to) ranges is about 34 (52) to 46 (134) across layers.

In contrast, betweenness centrality is a centrality score that depends on network size and structure, rather than being directly scaled to a simple count like indegree or outdegree. In our data, average betweenness values range between about 1548 and 1866.

The maximum possible value for betweenness occurs for the central node of a star network, where one country is connected to all others, and those others are only connected to the central country. In this case, the central country lies on every shortest path between any two peripheral countries. The number of such paths is $\frac{(n-1)(n-2)}{2}$, where n is the total number of countries. At the other extreme, the minimum value for betweenness occurs for a leaf node (a country connected to only one other country), which does not lie on any shortest path between pairs of other countries. In this case, the betweenness is zero.

A key part of our analysis examines the variation in network indicators across countries and over time, shown in Figures 5 to 8 for a selection of countries (China, USA, Germany, and Indonesia).

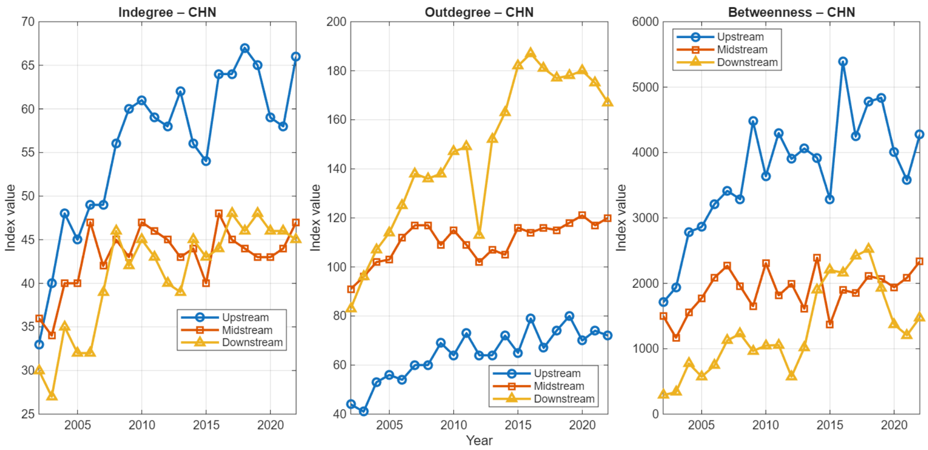

Figure 5: Variation of the network indicators across years and supply chain segments, for China.

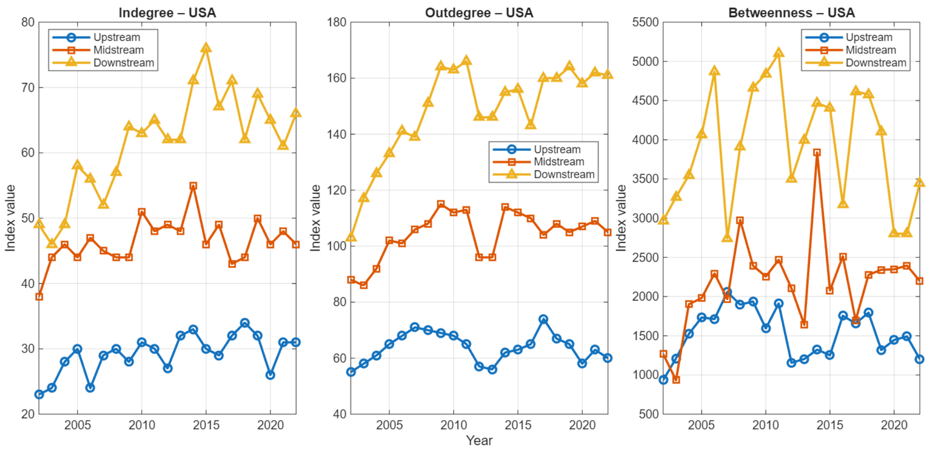

Figure 6: Variation of the network indicators across years and supply chain segments, for the USA.

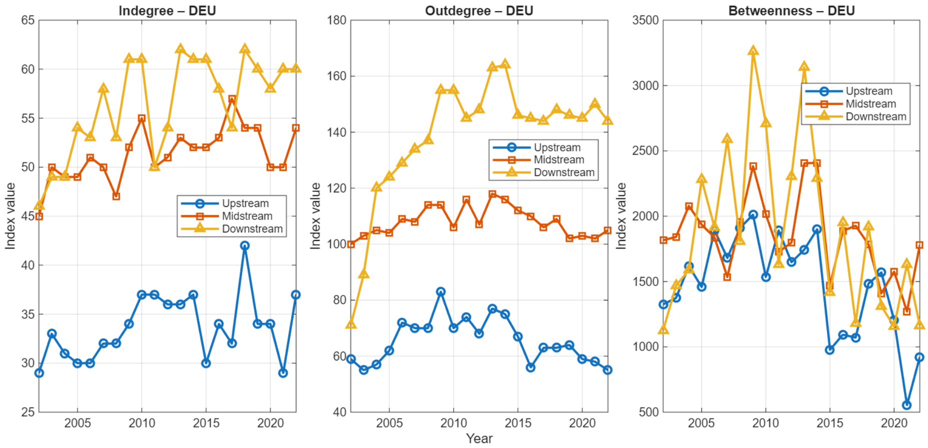

Figure 7: Variation of the network indicators across years and supply chain segments, for Germany.

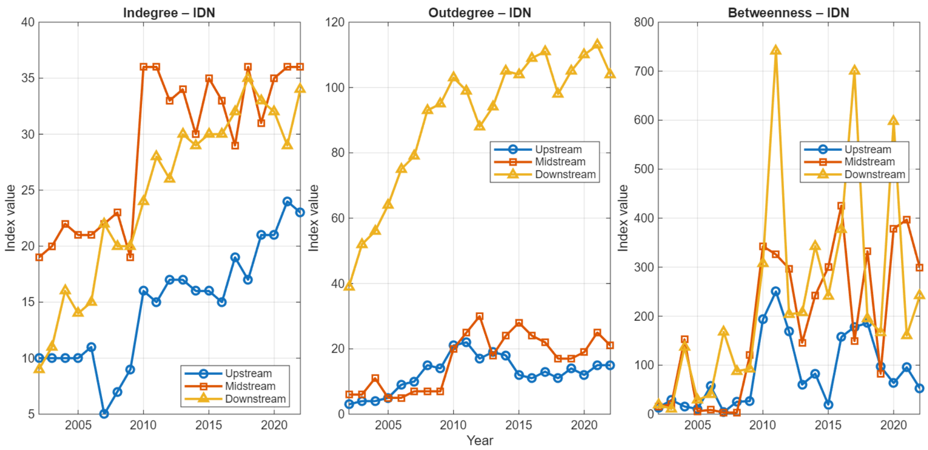

Figure 8: Variation of the network indicators across years and supply chain segments, for Indonesia.

B Regression results and robustness checks

B.1 Regression results using outdegree as network indicator

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
X	0.245*	0.252*	0.194	0.198	0.234*	0.241*	0.188	0.193	0.234*	0.241*	0.189	0.193
	(0.133)	(0.133)	(0.135)	(0.134)	(0.133)	(0.133)	(0.135)	(0.135)	(0.133)	(0.133)	(0.135)	(0.135)
Ren. consumption		0.178		0.109		0.173		0.110		0.169		0.106
		(0.213)		(0.228)		(0.210)		(0.224)		(0.211)		(0.225)
Ren. capacity			0.108*	0.0975			0.104*	0.0931			0.105*	0.0946
			(0.0600)	(0.0635)			(0.0597)	(0.0627)			(0.0600)	(0.0628)
Dummy					0.207	0.200	0.152	0.153	0.444	0.420	0.387	0.375
					(0.183)	(0.185)	(0.185)	(0.185)	(0.355)	(0.359)	(0.355)	(0.358)
$X \times D$									-0.0736	-0.0680	-0.0726	-0.0687
									(0.115)	(0.114)	(0.113)	(0.113)
Constant	-10.46***	-10.98***	-10.80***	-11.06***	-10.46***	-10.95***	-10.78***	-11.05***	-10.45***	-10.94***	-10.78***	-11.04***
	(0.328)	(0.694)	(0.439)	(0.717)	(0.327)	(0.691)	(0.438)	(0.715)	(0.328)	(0.692)	(0.439)	(0.719)
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	750	745	745	740	750	745	745	740	750	745	745	740
Adj. R^2	0.736	0.735	0.738	0.736	0.736	0.735	0.738	0.736	0.736	0.735	0.738	0.736

Table 9: Regression results — outdegree, aggregate supply-chain level (1–12). Robust standard errors in parentheses. P-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
X	0.102	0.103	0.102	0.103	0.0968	0.0983	0.0983	0.0989	0.103	0.104	0.101	0.102
	(0.131)	(0.132)	(0.130)	(0.131)	(0.132)	(0.133)	(0.131)	(0.132)	(0.132)	(0.133)	(0.131)	(0.132)
Ren. consumption		0.170		0.105		0.165		0.107		0.155		0.102
		(0.220)		(0.236)		(0.216)		(0.232)		(0.218)		(0.233)
Ren. capacity			0.107*	0.0963			0.102*	0.0913			0.103*	0.0923
			(0.0608)	(0.0650)			(0.0605)	(0.0639)			(0.0608)	(0.0643)
Dummy					0.228	0.223	0.162	0.163	0.621**	0.602**	0.480	0.474
					(0.188)	(0.190)	(0.187)	(0.187)	(0.295)	(0.301)	(0.314)	(0.318)
$X \times D$									-0.155	-0.149	-0.121	-0.119
									(0.107)	(0.105)	(0.110)	(0.110)
Constant	-10.08***	-10.56***	-10.54***	-10.78***	-10.09***	-10.56***	-10.53***	-10.77***	-10.10***	-10.53***	-10.53***	-10.76***
	(0.250)	(0.692)	(0.371)	(0.709)	(0.250)	(0.681)	(0.371)	(0.703)	(0.250)	(0.686)	(0.373)	(0.706)
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	744	739	739	734	744	739	739	734	744	739	739	734
Adj. R^2	0.723	0.721	0.726	0.724	0.723	0.722	0.726	0.724	0.724	0.722	0.726	0.724

Table 10: Regression results — outdegree, mineral level (1–12). Robust standard errors in parentheses. P-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
X	0.123	0.123	0.0601	0.0574	0.105	0.105	0.0494	0.0466	0.104	0.104	0.0481	0.0452
	(0.119)	(0.119)	(0.116)	(0.115)	(0.119)	(0.119)	(0.117)	(0.117)	(0.119)	(0.120)	(0.117)	(0.117)
Ren. consumption		0.161		0.0899		0.155		0.0910		0.152		0.0871
		(0.213)		(0.228)		(0.211)		(0.225)		(0.211)		(0.225)
Ren. capacity			0.113*	0.104			0.108*	0.0998			0.109*	0.101
			(0.0600)	(0.0633)			(0.0597)	(0.0624)			(0.0599)	(0.0625)
Dummy					0.215	0.210	0.160	0.161	0.370	0.352	0.326	0.318
					(0.185)	(0.187)	(0.185)	(0.186)	(0.309)	(0.312)	(0.308)	(0.310)
$X \times D$									-0.0518	-0.0473	-0.0554	-0.0524
									(0.109)	(0.108)	(0.107)	(0.106)
Constant	-10.11***	-10.56***	-10.46***	-10.67***	-10.10***	-10.53***	-10.44***	-10.64***	-10.09***	-10.52***	-10.44***	-10.63***
	(0.244)	(0.646)	(0.369)	(0.664)	(0.243)	(0.644)	(0.369)	(0.665)	(0.245)	(0.644)	(0.371)	(0.667)
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	750	745	745	740	750	745	745	740	750	745	745	740
Adj. R^2	0.734	0.733	0.737	0.735	0.735	0.733	0.737	0.735	0.734	0.733	0.736	0.734

Table 11: Regression results — outdegree, battery level (1–12). Robust standard errors in parentheses. P-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
X	0.0342	0.0345	0.0313	0.0312	0.0272	0.0276	0.0260	0.0260	0.0311	0.0311	0.0276	0.0274
	(0.121)	(0.122)	(0.121)	(0.122)	(0.123)	(0.124)	(0.123)	(0.124)	(0.123)	(0.124)	(0.123)	(0.124)
Ren. consumption		0.167		0.101		0.162		0.103		0.151		0.0977
		(0.219)		(0.236)		(0.216)		(0.232)		(0.217)		(0.233)
Ren. capacity			0.109*	0.0982			0.104*	0.0931			0.103*	0.0933
			(0.0607)	(0.0650)			(0.0604)	(0.0640)			(0.0608)	(0.0644)
Dummy					0.231	0.226	0.165	0.166	0.573**	0.554**	0.437	0.432
					(0.188)	(0.190)	(0.187)	(0.187)	(0.271)	(0.276)	(0.285)	(0.289)
$X \times D$									-0.143	-0.137	-0.110	-0.107
									(0.104)	(0.102)	(0.106)	(0.105)
Constant	-9.946***	-10.41***	-10.40***	-10.64***	-9.955***	-10.41***	-10.39***	-10.63***	-9.957***	-10.38***	-10.39***	-10.61***
	(0.208)	(0.672)	(0.342)	(0.686)	(0.209)	(0.661)	(0.342)	(0.680)	(0.209)	(0.666)	(0.345)	(0.684)
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	744	739	739	734	744	739	739	734	744	739	739	734
Adj. R^2	0.722	0.721	0.725	0.723	0.723	0.721	0.725	0.723	0.723	0.722	0.725	0.723

Table 12: Regression results — outdegree, processed mineral level (1–12). Robust standard errors in parentheses. P-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
X	0.160	0.149	0.151	0.143	0.152	0.141	0.145	0.136	0.155	0.144	0.148	0.140
	(0.153)	(0.152)	(0.152)	(0.151)	(0.154)	(0.153)	(0.153)	(0.153)	(0.155)	(0.154)	(0.154)	(0.153)
Ren. consumption		0.157		0.0902		0.156		0.0922		0.151		0.0846
		(0.228)		(0.240)		(0.225)		(0.236)		(0.224)		(0.236)
Ren. capacity			0.138**	0.128*			0.134**	0.124*			0.136**	0.127*
			(0.0642)	(0.0693)			(0.0640)	(0.0683)			(0.0638)	(0.0683)
Dummy					0.153	0.151	0.123	0.125	0.426	0.416	0.415	0.410
					(0.189)	(0.190)	(0.185)	(0.185)	(0.347)	(0.358)	(0.345)	(0.352)
$X \times D$									-0.142	-0.138	-0.152	-0.149
									(0.151)	(0.151)	(0.148)	(0.149)
Constant	-10.10***	-10.52***	-10.68***	-10.87***	-10.10***	-10.52***	-10.67***	-10.87***	-10.10***	-10.51***	-10.68***	-10.86***
	(0.203)	(0.703)	(0.357)	(0.695)	(0.204)	(0.694)	(0.358)	(0.693)	(0.205)	(0.695)	(0.357)	(0.692)
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	715	710	713	708	715	710	713	708	715	710	713	708
Adj. R^2	0.718	0.716	0.722	0.719	0.718	0.716	0.721	0.719	0.718	0.716	0.722	0.719

Table 13: Regression results — outdegree, raw mineral level (1–12). Robust standard errors in parentheses. P-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

B.2 Regression results using betweenness centrality as network indicator

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
X	0.0328	0.0320	0.0252	0.0246	0.0279	0.0271	0.0220	0.0214	0.0348	0.0338	0.0278	0.0270
	(0.0514)	(0.0524)	(0.0511)	(0.0523)	(0.0522)	(0.0533)	(0.0518)	(0.0531)	(0.0513)	(0.0523)	(0.0510)	(0.0521)
Ren. consumption		0.154		0.0876		0.149		0.0893		0.136		0.0811
		(0.218)		(0.234)		(0.215)		(0.229)		(0.215)		(0.228)
Ren. capacity			0.113*	0.105			0.108*	0.100			0.112*	0.104
			(0.0602)	(0.0644)			(0.0598)	(0.0633)			(0.0604)	(0.0639)
Dummy					0.227	0.223	0.162	0.163	0.764**	0.746**	0.656**	0.650*
					(0.189)	(0.192)	(0.189)	(0.189)	(0.305)	(0.320)	(0.329)	(0.339)
$X \times D$									-0.124*	-0.121*	-0.111*	-0.110
									(0.0646)	(0.0650)	(0.0664)	(0.0671)
Constant	-9.966***	-10.39***	-10.42***	-10.62***	-9.971***	-10.38***	-10.41***	-10.61***	-9.986***	-10.36***	-10.43***	-10.62***
	(0.162)	(0.691)	(0.309)	(0.695)	(0.161)	(0.675)	(0.309)	(0.687)	(0.158)	(0.673)	(0.311)	(0.683)
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	750	745	745	740	750	745	745	740	750	745	745	740
Adj. R^2	0.734	0.732	0.737	0.735	0.734	0.733	0.737	0.735	0.736	0.734	0.738	0.736

Table 14: Regression results — betweenness, aggregate supply-chain level (1–12). Robust standard errors in parentheses. P-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
X	0.0629	0.0633	0.0575	0.0578	0.0584	0.0589	0.0545	0.0549	0.0695	0.0699	0.0643	0.0647
	(0.0515)	(0.0519)	(0.0520)	(0.0527)	(0.0522)	(0.0527)	(0.0526)	(0.0533)	(0.0516)	(0.0519)	(0.0521)	(0.0526)
Ren. consumption		0.172		0.109		0.167		0.110		0.163		0.112
		(0.220)		(0.238)		(0.217)		(0.233)		(0.212)		(0.228)
Ren. capacity			0.105*	0.0940			0.101*	0.0894			0.103*	0.0916
			(0.0608)	(0.0655)			(0.0604)	(0.0644)			(0.0611)	(0.0651)
Dummy					0.220	0.215	0.156	0.157	0.754***	0.746**	0.665**	0.665**
					(0.189)	(0.192)	(0.188)	(0.189)	(0.284)	(0.296)	(0.304)	(0.310)
$X \times D$									-0.143**	-0.142**	-0.132**	-0.132**
									(0.0648)	(0.0645)	(0.0661)	(0.0661)
Constant	-10.06***	-10.54***	-10.49***	-10.74***	-10.06***	-10.53***	-10.48***	-10.73***	-10.09***	-10.54***	-10.51***	-10.77***
	(0.139)	(0.664)	(0.295)	(0.671)	(0.139)	(0.652)	(0.294)	(0.664)	(0.137)	(0.637)	(0.296)	(0.650)
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	744	739	739	734	744	739	739	734	744	739	739	734
Adj. R^2	0.723	0.721	0.726	0.724	0.723	0.722	0.726	0.724	0.726	0.724	0.728	0.726

Table 15: Regression results — betweenness, mineral level (1–12). Robust standard errors in parentheses. P-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
X	0.0121	0.0126	0.00920	0.00859	0.0112	0.0117	0.00868	0.00813	0.0181	0.0181	0.0146	0.0138
	(0.0441)	(0.0453)	(0.0437)	(0.0450)	(0.0443)	(0.0455)	(0.0439)	(0.0451)	(0.0445)	(0.0455)	(0.0442)	(0.0453)
Ren. consumption		0.155		0.0869		0.150		0.0889		0.139		0.0809
		(0.219)		(0.233)		(0.215)		(0.229)		(0.216)		(0.229)
Ren. capacity			0.115*	0.107*			0.110*	0.102			0.112*	0.105
			(0.0606)	(0.0643)			(0.0602)	(0.0632)			(0.0609)	(0.0639)
Dummy					0.234	0.229	0.167	0.168	0.609**	0.591**	0.501*	0.494*
					(0.187)	(0.189)	(0.186)	(0.186)	(0.271)	(0.281)	(0.284)	(0.290)
$X \times D$									-0.0939	-0.0906	-0.0813	-0.0794
									(0.0632)	(0.0626)	(0.0633)	(0.0633)
Constant	-9.898***	-10.33***	-10.38***	-10.58***	-9.917***	-10.33***	-10.37***	-10.58***	-9.931***	-10.32***	-10.39***	-10.58***
	(0.127)	(0.667)	(0.298)	(0.678)	(0.128)	(0.650)	(0.296)	(0.668)	(0.127)	(0.655)	(0.299)	(0.671)
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	750	745	745	740	750	745	745	740	750	745	745	740
Adj. R^2	0.734	0.732	0.737	0.735	0.734	0.733	0.737	0.735	0.735	0.733	0.737	0.735

Table 16: Regression results — betweenness, battery level (1–12). Robust standard errors in parentheses. P-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
X	-0.0250	-0.0220	-0.0235	-0.0224	-0.0249	-0.0220	-0.0235	-0.0223	-0.0141	-0.0114	-0.0138	-0.0126
	(0.0463)	(0.0473)	(0.0467)	(0.0477)	(0.0461)	(0.0471)	(0.0465)	(0.0476)	(0.0457)	(0.0464)	(0.0462)	(0.0470)
Ren. consumption		0.160		0.0930		0.155		0.0952		0.151		0.0965
		(0.221)		(0.238)		(0.217)		(0.233)		(0.215)		(0.230)
Ren. capacity			0.109*	0.0996			0.104*	0.0943			0.105*	0.0947
			(0.0611)	(0.0654)			(0.0607)	(0.0643)			(0.0616)	(0.0652)
Dummy					0.233	0.228	0.167	0.168	0.651**	0.642**	0.554**	0.554**
					(0.185)	(0.187)	(0.184)	(0.184)	(0.262)	(0.271)	(0.276)	(0.280)
$X \times D$									-0.120*	-0.119*	-0.107*	-0.107*
									(0.0629)	(0.0623)	(0.0634)	(0.0631)
Constant	-9.823***	-10.28***	-10.29***	-10.51***	-9.845***	-10.28***	-10.28***	-10.51***	-9.866***	-10.29***	-10.31***	-10.53***
	(0.119)	(0.670)	(0.293)	(0.678)	(0.120)	(0.652)	(0.290)	(0.667)	(0.118)	(0.643)	(0.294)	(0.658)
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	744	739	739	734	744	739	739	734	744	739	739	734
Adj. R^2	0.722	0.721	0.725	0.723	0.723	0.721	0.725	0.723	0.725	0.723	0.727	0.725

Table 17: Regression results — betweenness, processed mineral level (1–12). Robust standard errors in parentheses. P-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
X	0.0228	0.0188	0.00606	0.00405	0.0176	0.0137	0.00216	0.000136	0.0249	0.0209	0.00972	0.00755
	(0.0532)	(0.0525)	(0.0531)	(0.0532)	(0.0544)	(0.0538)	(0.0543)	(0.0545)	(0.0531)	(0.0526)	(0.0531)	(0.0532)
Ren. consumption		0.164		0.0977		0.163		0.0994		0.160		0.0922
		(0.227)		(0.240)		(0.224)		(0.236)		(0.222)		(0.234)
Ren. capacity			0.139**	0.128*			0.135**	0.124*			0.141**	0.131*
			(0.0638)	(0.0695)			(0.0635)	(0.0684)			(0.0634)	(0.0689)
Dummy					0.163	0.161	0.136	0.137	0.415	0.408	0.423	0.418
					(0.190)	(0.192)	(0.186)	(0.186)	(0.340)	(0.352)	(0.340)	(0.349)
$X \times D$									-0.0767	-0.0754	-0.0876	-0.0858
									(0.0810)	(0.0811)	(0.0797)	(0.0808)
Constant	-9.933***	-10.38***	-10.50***	-10.72***	-9.937***	-10.38***	-10.49***	-10.71***	-9.948***	-10.38***	-10.53***	-10.73***
	(0.113)	(0.677)	(0.303)	(0.667)	(0.114)	(0.667)	(0.302)	(0.662)	(0.112)	(0.658)	(0.299)	(0.651)
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	715	710	713	708	715	710	713	708	715	710	713	708
Adj. R^2	0.717	0.716	0.721	0.718	0.717	0.716	0.721	0.718	0.718	0.716	0.721	0.719

Table 18: Regression results — betweenness, raw mineral level (1–12). Robust standard errors in parentheses. P-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

B.3 Regression results using indegree as network indicator, with 2 years rolling window

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
X	0.496***	0.552***	0.478***	0.528***	0.500***	0.562***	0.485***	0.542***	0.559***	0.622***	0.545***	0.604***
	(0.159)	(0.164)	(0.158)	(0.165)	(0.157)	(0.162)	(0.156)	(0.163)	(0.158)	(0.162)	(0.158)	(0.163)
Ren. consumption		0.238		0.198		0.261		0.226		0.263		0.232
		(0.220)		(0.235)		(0.210)		(0.225)		(0.212)		(0.227)
Ren. capacity			0.108*	0.0887			0.106*	0.0839			0.107*	0.0837
			(0.0566)	(0.0597)			(0.0557)	(0.0585)			(0.0563)	(0.0589)
Dummy					0.330**	0.346**	0.301**	0.317**	1.516***	1.536***	1.451***	1.480***
					(0.137)	(0.136)	(0.138)	(0.137)	(0.286)	(0.277)	(0.295)	(0.288)
$X \times D$									-0.365***	-0.367***	-0.351***	-0.355***
									(0.0935)	(0.0908)	(0.0941)	(0.0920)
Constant	-11.63***	-12.47***	-12.04***	-12.66***	-11.68***	-12.61***	-12.08***	-12.80***	-11.86***	-12.79***	-12.27***	-13.01***
	(0.502)	(0.911)	(0.552)	(0.933)	(0.497)	(0.877)	(0.548)	(0.900)	(0.498)	(0.881)	(0.558)	(0.906)
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	1,500	1,490	1,490	1,480	1,500	1,490	1,490	1,480	1,500	1,490	1,490	1,480
Adj. R^2	0.705	0.704	0.707	0.705	0.706	0.706	0.708	0.707	0.708	0.708	0.710	0.709

Table 19: Regression results — indegree, aggregate supply-chain level (1–12) with 2 years rolling window. Robust standard errors in parentheses. P-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Y	0.380***	0.402***	0.373***	0.389***	0.384***	0.408***	0.379***	0.398***	0.414***	0.438***	0.413***	0.431***
	(0.117)	(0.122)	(0.121)	(0.125)	(0.116)	(0.121)	(0.120)	(0.124)	(0.118)	(0.122)	(0.123)	(0.127)
Ren. consumption		0.206		0.155		0.225		0.178		0.227		0.181
		(0.218)		(0.234)		(0.208)		(0.225)		(0.209)		(0.225)
Ren. capacity			0.109*	0.0928			0.107*	0.0889			0.111*	0.0924
			(0.0575)	(0.0619)			(0.0565)	(0.0608)			(0.0567)	(0.0610)
Dummy					0.322**	0.333**	0.293**	0.304**	0.988***	1.001***	0.950***	0.964***
					(0.137)	(0.135)	(0.137)	(0.136)	(0.252)	(0.244)	(0.264)	(0.262)
$Y \times D$									-0.246***	-0.247***	-0.239**	-0.239***
									(0.0893)	(0.0870)	(0.0919)	(0.0911)
Constant	-11.06***	-11.69***	-11.50***	-11.90***	-11.10***	-11.79***	-11.55***	-12.01***	-11.17***	-11.86***	-11.64***	-12.11***
	(0.297)	(0.759)	(0.402)	(0.768)	(0.295)	(0.728)	(0.398)	(0.739)	(0.299)	(0.734)	(0.408)	(0.744)
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	1,482	1,472	1,472	1,462	1,482	1,472	1,472	1,462	1,482	1,472	1,472	1,462
Adj. R^2	0.693	0.692	0.695	0.694	0.695	0.694	0.697	0.695	0.696	0.695	0.698	0.696

Table 20: Regression results — indegree, mineral level (1–12) with 2 years rolling window. Robust standard errors in parentheses. P-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Z	0.478***	0.532***	0.474***	0.520***	0.475***	0.533***	0.473***	0.524***	0.519***	0.577***	0.517***	0.569***
	(0.145)	(0.146)	(0.144)	(0.146)	(0.143)	(0.144)	(0.142)	(0.144)	(0.145)	(0.146)	(0.144)	(0.146)
Ren. consumption		0.249		0.208		0.269		0.232		0.269		0.235
		(0.217)		(0.231)		(0.208)		(0.222)		(0.211)		(0.224)
Ren. capacity			0.115**	0.0952			0.113**	0.0909			0.114**	0.0915
			(0.0565)	(0.0592)			(0.0557)	(0.0582)			(0.0565)	(0.0588)
Dummy					0.320**	0.334**	0.290**	0.305**	1.328***	1.341***	1.260***	1.281***
					(0.136)	(0.135)	(0.137)	(0.136)	(0.288)	(0.280)	(0.282)	(0.279)
$Z \times D$									-0.335***	-0.334***	-0.319***	-0.320***
									(0.0997)	(0.0969)	(0.0967)	(0.0952)
Constant	-11.47***	-12.33***	-11.95***	-12.58***	-11.49***	-12.42***	-11.97***	-12.67***	-11.62***	-12.54***	-12.09***	-12.81***
	(0.425)	(0.819)	(0.494)	(0.844)	(0.422)	(0.792)	(0.491)	(0.818)	(0.427)	(0.804)	(0.501)	(0.831)
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	1,500	1,490	1,490	1,480	1,500	1,490	1,490	1,480	1,500	1,490	1,490	1,480
Adj. R^2	0.705	0.704	0.708	0.706	0.707	0.706	0.709	0.708	0.709	0.708	0.710	0.709

Table 21: Regression results — indegree, battery level (1–12) with 2 years rolling window. Robust standard errors in parentheses. P-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
W	0.306**	0.325**	0.298**	0.311**	0.308**	0.329***	0.303**	0.318**	0.338***	0.359***	0.337**	0.351***
	(0.124)	(0.127)	(0.129)	(0.131)	(0.123)	(0.126)	(0.129)	(0.131)	(0.125)	(0.127)	(0.131)	(0.133)
Ren. consumption		0.197		0.143		0.216		0.166		0.216		0.167
		(0.216)		(0.232)		(0.207)		(0.223)		(0.208)		(0.223)
Ren. capacity			0.112*	0.0974			0.110*	0.0937			0.114**	0.0968
			(0.0580)	(0.0623)			(0.0570)	(0.0612)			(0.0571)	(0.0613)
Dummy					0.316**	0.327**	0.286**	0.296**	1.009***	1.019***	0.966***	0.977***
					(0.137)	(0.136)	(0.138)	(0.137)	(0.259)	(0.256)	(0.273)	(0.274)
$W \times D$									-0.265***	-0.265***	-0.256**	-0.256**
									(0.0954)	(0.0943)	(0.0990)	(0.0990)
Constant	-10.84***	-11.44***	-11.30***	-11.66***	-10.88***	-11.53***	-11.34***	-11.76***	-10.94***	-11.60***	-11.43***	-11.85***
	(0.303)	(0.739)	(0.413)	(0.752)	(0.302)	(0.711)	(0.410)	(0.725)	(0.305)	(0.717)	(0.419)	(0.731)
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	1,479	1,469	1,469	1,459	1,479	1,469	1,469	1,459	1,479	1,469	1,469	1,459
Adj. R^2	0.692	0.691	0.695	0.693	0.694	0.693	0.696	0.694	0.695	0.694	0.697	0.695

Table 22: Regression results — indegree, processed mineral level (1–12) with 2 years rolling window. Robust standard errors in parentheses. P-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
V	0.214**	0.207**	0.196*	0.192*	0.221**	0.213**	0.202**	0.199*	0.229**	0.222**	0.211**	0.208**
	(0.105)	(0.104)	(0.102)	(0.102)	(0.105)	(0.104)	(0.102)	(0.102)	(0.104)	(0.104)	(0.102)	(0.102)
Ren. consumption		0.204		0.143		0.224		0.162		0.229		0.165
		(0.224)		(0.238)		(0.215)		(0.229)		(0.215)		(0.229)
Ren. capacity			0.111*	0.0941			0.110*	0.0911			0.113*	0.0938
			(0.0618)	(0.0677)			(0.0609)	(0.0665)			(0.0609)	(0.0667)
Dummy					0.269*	0.283**	0.259*	0.268*	0.437	0.470*	0.448	0.462*
					(0.139)	(0.138)	(0.138)	(0.137)	(0.284)	(0.278)	(0.278)	(0.276)
$V \times D$									-0.0860	-0.0957	-0.0965	-0.0987
									(0.116)	(0.113)	(0.114)	(0.113)
Constant	-10.47***	-11.03***	-10.93***	-11.24***	-10.52***	-11.13***	-10.97***	-11.33***	-10.53***	-11.15***	-10.99***	-11.36***
	(0.186)	(0.692)	(0.343)	(0.682)	(0.185)	(0.665)	(0.339)	(0.657)	(0.185)	(0.664)	(0.340)	(0.655)
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	1,377	1,367	1,375	1,365	1,377	1,367	1,375	1,365	1,377	1,367	1,375	1,365
Adj. R^2	0.680	0.679	0.682	0.680	0.682	0.680	0.683	0.681	0.681	0.680	0.683	0.681

Table 23: Regression results — indegree, raw mineral level (1–12) with 2 years rolling window. Robust standard errors in parentheses. P-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

B.4 Regression results with contemporaneous regressors

As a robustness check, to assess the role of all three layers simultaneously, we estimate the following extended specification, which includes the three layers as separate regressors:

$$
\begin{aligned}
Y_{i,t} = {} & \alpha + \beta_1 \log(1 + X_{i,t}^{down}) + \beta_2 \log(1 + X_{i,t}^{mid}) + \beta_3 \log(1 + X_{i,t}^{up}) + \gamma_i + \delta_t + \lambda \log(1 + \mathbf{S}_{i,t}) + \theta D_{i,t}^{up} \\
& + \mu_1 \big[\log(1 + X_{i,t}^{down}) \times D_{i,t}^{up} \big] + \mu_2 \big[\log(1 + X_{i,t}^{mid}) \times D_{i,t}^{up} \big] + \mu_3 \big[\log(1 + X_{i,t}^{up}) \times D_{i,t}^{up} \big] + \epsilon_{i,t}
\end{aligned}
\tag{6}
$$

Table 24 displays the results from regression 6. The results are coherent with all the others: only the indegree at the battery level yields a significant and positive coefficient, across the four regression specifications tested.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
X^{down}	0.402*	0.499**	0.413**	0.488**	0.402*	0.498**	0.412**	0.489**	0.373*	0.471**	0.387*	0.463**
	(0.213)	(0.215)	(0.207)	(0.211)	(0.212)	(0.214)	(0.207)	(0.211)	(0.205)	(0.208)	(0.201)	(0.205)
X^{mid}	0.147	0.153	0.121	0.123	0.158	0.163	0.130	0.132	0.181	0.184	0.149	0.151
	(0.219)	(0.220)	(0.222)	(0.223)	(0.221)	(0.223)	(0.224)	(0.225)	(0.225)	(0.225)	(0.227)	(0.227)
X^{up}	0.0583	0.0256	0.0297	0.0107	0.0550	0.0224	0.0283	0.00902	0.0614	0.0306	0.0381	0.0195
	(0.158)	(0.150)	(0.158)	(0.152)	(0.158)	(0.151)	(0.158)	(0.152)	(0.157)	(0.152)	(0.158)	(0.154)
D									0.129	0.156	0.122	0.139
									(0.675)	(0.667)	(0.666)	(0.663)
$X^{down} \times$ D									0.488	0.435	0.430	0.400
									(0.542)	(0.526)	(0.530)	(0.521)
$X^{mid} \times$ D									-0.453	-0.399	-0.370	-0.341
									(0.582)	(0.573)	(0.565)	(0.563)
$X^{up} \times D$									-0.103	-0.110	-0.138	-0.139
									(0.478)	(0.480)	(0.468)	(0.473)
Ren. consumption		0.306		0.243		0.304		0.246		0.295		0.238
		(0.245)		(0.260)		(0.241)		(0.254)		(0.239)		(0.253)
Ren. capacity			0.137**	0.110			0.132**	0.105			0.129**	0.104
			(0.0629)	(0.0682)			(0.0627)	(0.0669)			(0.0623)	(0.0669)
Constant	-11.56***	-12.66***	-12.07***	-12.83***	-11.59***	-12.69***	-12.08***	-12.85***	-11.57***	-12.64***	-12.05***	-12.81***
	(0.634)	(1.097)	(0.682)	(1.093)	(0.633)	(1.070)	(0.680)	(1.073)	(0.625)	(1.072)	(0.679)	(1.076)
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	715	710	713	708	715	710	713	708	715	710	713	708
Adj. R^2	0.722	0.721	0.725	0.723	0.722	0.722	0.725	0.723	0.721	0.721	0.724	0.723

Table 24: Regression results — indegree, all layers (1–12). Robust standard errors in parentheses. P-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
X^{down}	0.121	0.127	0.0680	0.0690	0.112	0.118	0.0601	0.0611	0.102	0.108	0.0517	0.0526
	(0.127)	(0.127)	(0.128)	(0.127)	(0.127)	(0.127)	(0.128)	(0.127)	(0.127)	(0.127)	(0.128)	(0.127)
X^{mid}	-0.0201	-0.0189	-0.0168	-0.0148	-0.0206	-0.0194	-0.0169	-0.0149	-0.0158	-0.0147	-0.0145	-0.0123
	(0.132)	(0.133)	(0.134)	(0.134)	(0.133)	(0.134)	(0.134)	(0.134)	(0.132)	(0.133)	(0.134)	(0.134)
X^{up}	0.151	0.139	0.148	0.139	0.145	0.133	0.143	0.134	0.162	0.150	0.160	0.151
	(0.151)	(0.150)	(0.151)	(0.150)	(0.153)	(0.151)	(0.153)	(0.151)	(0.153)	(0.151)	(0.152)	(0.151)
D									0.142	0.122	0.148	0.138
									(0.316)	(0.318)	(0.306)	(0.308)
$X^{down} \times D$									0.303	0.308	0.258	0.266
									(0.290)	(0.294)	(0.289)	(0.289)
$X^{mid} \times D$									-0.150	-0.147	-0.0635	-0.0711
									(0.245)	(0.242)	(0.260)	(0.260)
$X^{up} \times D$									-0.286	-0.290	-0.344	-0.340
									(0.403)	(0.410)	(0.403)	(0.411)
Ren. consumption		0.173		0.0995		0.170		0.100		0.171		0.100
		(0.224)		(0.238)		(0.223)		(0.235)		(0.210)		(0.223)
Ren. capacity			0.134**	0.123*			0.131**	0.120*			0.132**	0.121*
			(0.0636)	(0.0684)			(0.0634)	(0.0675)			(0.0631)	(0.0679)
Constant	-10.31***	-10.78***	-10.78***	-11.00***	-10.29***	-10.76***	-10.76***	-10.97***	-10.31***	-10.78***	-10.77***	-10.99***
	(0.344)	(0.744)	(0.456)	(0.746)	(0.347)	(0.748)	(0.460)	(0.754)	(0.348)	(0.713)	(0.461)	(0.721)
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	715	710	713	708	715	710	713	708	715	710	713	708
Adj. R^2	0.718	0.716	0.721	0.718	0.718	0.716	0.720	0.718	0.718	0.716	0.721	0.718

Table 25: Regression results — outdegree, all layers (1–12). Robust standard errors in parentheses. P-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
X^{down}	0.0183	0.0184	0.0136	0.0131	0.0174	0.0176	0.0130	0.0125	0.0124	0.0121	0.00804	0.00732
	(0.0461)	(0.0471)	(0.0456)	(0.0467)	(0.0463)	(0.0473)	(0.0458)	(0.0469)	(0.0485)	(0.0497)	(0.0481)	(0.0494)
X^{mid}	-0.0354	-0.0315	-0.0295	-0.0277	-0.0341	-0.0303	-0.0285	-0.0268	-0.0205	-0.0158	-0.0174	-0.0148
	(0.0500)	(0.0504)	(0.0503)	(0.0507)	(0.0500)	(0.0503)	(0.0503)	(0.0506)	(0.0521)	(0.0525)	(0.0524)	(0.0528)
X^{up}	0.0309	0.0259	0.0132	0.0107	0.0255	0.0207	0.00911	0.00664	0.0187	0.0132	0.00632	0.00320
	(0.0544)	(0.0534)	(0.0545)	(0.0543)	(0.0558)	(0.0548)	(0.0558)	(0.0556)	(0.0550)	(0.0543)	(0.0549)	(0.0546)
D									0.427	0.414	0.421	0.413
									(0.287)	(0.296)	(0.284)	(0.291)
$X^{down} \times D$									0.0711	0.0803	0.0672	0.0737
									(0.162)	(0.163)	(0.158)	(0.158)
$X^{mid} \times D$									-0.166	-0.176	-0.138	-0.147
									(0.156)	(0.155)	(0.164)	(0.161)
$X^{up} \times D$									0.0137	0.0162	-0.0184	-0.0139
									(0.178)	(0.179)	(0.187)	(0.189)
Ren. consumption		0.159		0.0934		0.157		0.0951		0.167		0.103
		(0.232)		(0.245)		(0.229)		(0.241)		(0.221)		(0.235)
Ren. capacity			0.136**	0.126*			0.133**	0.123*			0.133**	0.122*
			(0.0638)	(0.0697)			(0.0634)	(0.0685)			(0.0640)	(0.0701)
Constant	-9.910***	-10.35***	-10.47***	-10.68***	-9.915***	-10.35***	-10.46***	-10.67***	-9.918***	-10.38***	-10.46***	-10.69***
	(0.190)	(0.749)	(0.344)	(0.736)	(0.189)	(0.737)	(0.344)	(0.730)	(0.189)	(0.719)	(0.343)	(0.710)
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	715	710	713	708	715	710	713	708	715	710	713	708
Adj. R^2	0.717	0.715	0.720	0.718	0.717	0.715	0.720	0.718	0.717	0.715	0.720	0.718

Table 26: Regression results — betweenness, all layers (1–12). Robust standard errors in parentheses. P-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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