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Can strategic dependencies harm the acceleration towards net-zero transition? The case of the lithium-ion battery industry

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Abstract

This paper investigates whether accelerating the net-zero transition entails a trade-off with strategic dependency, focusing on the lithium-ion battery supply chain. It combines insights from the literatures on green-transition acceleration and technological sovereignty and develops a product-level strategic intelligence framework to identify critical products and stages characterized by import dependency and technological gaps. Using this framework, the paper examines how technological capabilities shape countries' competitive positions and whether environmental policy stringency is associated with greater dependency. The results show that stronger technological capabilities are generally linked to lower import dependency, although this relationship varies across stages of the supply chain. Environmental policy stringency, by contrast, has heterogeneous effects across countries. Overall, the findings suggest that the trade-off between decarbonization and strategic autonomy is not inevitable: when supported by targeted innovation and industrial policies, technological upgrading can reduce dependency while sustaining the acceleration of the net-zero transition in the long run.

Keywords: Strategic autonomy, Technological capabilities, Net-zero transition, Environmental policy, Lithium-ion batteries, Technological sovereignty.

JEL codes: Q550, O380, Q580, F140.

1 Introduction

The mounting pressure of climate change makes decarbonisation increasingly urgent (Geels et al., 2023; Sovacool et al., 2025; Goedeking and Rogge, 2026). However, the emergence of a new world (dis)order, marked by multiplying conflicts, trade and technology wars, and growing uncertainty, brings also other issues, such as technological sovereignty and strategic dependencies, to the forefront of the debate (Crespi et al., 2021; Edler et al., 2023; Rodrik and Walt, 2022; European Commission, 2024).

The contrast between these possibly conflicting objectives highlights two intertwined policy trade-offs (Matsuo and Schmidt, 2019). The first one concerns the need to accelerate the net-zero transition versus the risk of increasing strategic dependencies: where adequate productive/technological capabilities are missing, speeding-up the diffusion of green goods and technologies may turn into a persistent dependency on foreign suppliers (Archibugi and Iammarino, 1999; Caravella et al., 2021; Baldwin and Freeman, 2022). The second trade-off concerns balancing the efficiency gains arising from trade openness (i.e., economies of scale, technological specialisation, and knowledge spillovers) against the pursuit of strategic autonomy in key industries, including those instrumental to decarbonisation, through targeted industrial policies, protectionist measures, and reshoring strategies (Caravella et al., 2024).

This work investigates these issues by focusing on the lithium-ion battery supply chain (LBSC), one of the key sectors in shaping the net-zero transition (Malhotra et al., 2021). On the one hand, lithium-ion batteries are crucial for enabling both electric mobility as well as the deployment of renewable energies. On the other hand, global hierarchies in this sector have been profoundly reshaped, with growing dependencies and an increase in trade conflicts (IEA, 2024). For these reasons, the LBSC serves as a highly relevant case for identifying areas where import dependencies could significantly hinder the transition, as well as areas where gaining a competitive advantage may help mitigate dependencies while meeting environmental targets.

Despite issues such as dependency, technological sovereignty and industrial policy are gaining prominence in the policy debate, comprehensive, theoretically grounded analyses, discussing the relationships between technological capabilities, international competitiveness, and industrial policies in key sectors for the transition are still limited. Moreover, due to data limitations, most empirical contributions provide neither timely evidence nor sufficient granularity. As a result, they fail to identify critical products and technologies along the supply chain—namely, those for which economies are most dependent on dominant suppliers and are therefore in urgent need of targeted industrial and innovation policies to prevent bottlenecks that could hamper the green transition.

This paper advances in filling these gaps by providing four main contributions. First, we develop an original analytical framework that integrates two recent streams of literature – one focusing on the acceleration of the green transition and the other on structural dependencies and technological sovereignty – to examine potential trade-offs between these objectives. Second, we develop a strategic intelligence analysis (Edler et al., 2023) of the LBSC allowing to quantify import dependencies and technological capacity gaps, at a highly granular product/technology level. This allows to identify critical products and supply chain stages where policy action is needed to avoid the emergence of bottlenecks to the green transition. Third, we examine how technological capabilities influence import dependency, showing under what conditions technological upgrading strengthens competitive positions and mitigates dependency. Finally, we analyse how environmental policy stringency relates to import dependency, assessing whether and in which circumstances environmental goals may conflict with technological sovereignty and strategic autonomy ones.

Building on the empirical framework proposed by Caravella et al. (2024), we integrate data from BACI-UNComtrade and the OECD Regpat database, keeping the finest possible level of detail (HS 6-digits and CPC full digits). Our mapping of the different stages of the LBSC includes 26 product-technology combinations identified through literature review, textual analysis, and ultimately validated by field experts.

Results show that the LBSC has undergone significant structural changes in recent years (IEA, 2024): new incumbents have emerged (e.g., China), others have weakened their positions (e.g., EU and US), and concentration has increased in almost all market segments. Concerning technological capabilities, former followers have become leaders, exploiting both technology-push as well as demand-pull factors. The locus of innovation has shifted from the US and Japan to South Korea and China, with an important acceleration since 2020.

The econometric analysis confirms that stronger technological capabilities are generally associated with lower import dependency, particularly in downstream stages of the supply chain, with limited differences across countries. In contrast, the analysis of environmental policy stringency shows heterogeneous effects: it is negatively associated with import dependency in China, but positively associated in the case of the US.

Overall, our results reveal significant dependency among countries along the entire value chain, fueled by an asymmetric distribution of technological capabilities. This may exacerbate critical bottlenecks and geopolitical tensions, fostering more protectionist trade attitudes and inward-looking industrial policies, potentially increasing the costs of the net-zero transition and delaying decarbonisation efforts. In this respect, our findings suggest that a trade-off between strategic dependencies and green transition does not necessarily hold. Targeted policies for technological upgrading of specific segments of the supply chain can reduce dependencies without compromising environmental goals. Hence, a well-designed policy mix that integrates environmental targets with innovation and industrial policy can enhance both resilience and acceleration towards the net-zero transition. This highlights the importance to integrate in the design of policy mix specific considerations related to technological and productive asymmetries, as well as trade and geopolitical obstacles that may hamper the faster achievement of net-zero targets (Flanagan et al., 2011; Rogge and Reichardt, 2016; Costantini et al., 2017; Crespi et al., 2025).

The remainder of the paper is the following. Section 2 provides the background literature and context. It discusses the interaction between the acceleration in the net-zero transition and industrial and innovation policy in the new world order, with a focus on the LBSC. Section 3 presents the analytical framework and the research questions. The data and methodology are described in Section 4. Section 5 shows the long-term evolution of the LBSC supply chain and sets the ground for the empirical analysis, which is reported in Section 6. Finally, Section 7 concludes.

2 Background literature and context

2.1 Accelerating vs. hampering the net-zero transition: theory and concepts

A number of disciplinary fields have analysed the factors favoring as well as hampering the acceleration of the net-zero transition. Sovacool et al. (2025) carried out a thorough review of the extant literature, providing a useful assessment of the main drivers. Concerning economic elements, most of the emphasis is on costs. The diffusion of low-carbon technologies is likely to accelerate when their cost fall below 'dirty' ones (Strauch, 2020). Technological improvements, endogenously shaped by R&D and learning-by-doing, contribute to increase production efficiency and unleash economies of scale thereby further reducing costs (Acemoglu et al., 2012). In addition, network effects (i.e., the utility stemming from the consumption/adoption of a certain good/technology may increase with the number of users and, relatedly, with the size and quality of the associated network), informational increasing returns (i.e., as the number of early adopters increases, so does the popularity of the technology and the steepness of the adoption curve) and technological interrelatedness (i.e., as the diffusion of a certain technology accelerates, the same is likely to happen to complementary ones) may further stimulate the adoption of low-carbon technologies (Katz and Shapiro, 1986; Chen and Shi, 2021).

Innovation system and evolutionary theories, in turn, underline the importance of knowledge generation and diffusion; pointing to the pivotal role of key actors such as universities, research institutes, firms, standardisation agencies (Fagerberg and Srholec, 2008). The interactions among these entities may ease knowledge diffusion, learning and technology transfer, stimulating the adoption of innovations, including environmental ones (Cainelli et al., 2012).

While the relative cost of green goods and technologies vis-à-vis dirtier ones is a major driver, the irreversibility (i.e., sunk costs and technology-specific investments that may constrain agents' future decisions) and path-dependency of technological change are likely to produce diverging patterns concerning the adoption of low-carbon technologies, as well as competitive performance in key markets (e.g., PV panels, electric vehicles).

Irreversibility and path-dependency also characterize preferences, cultural habits, and institutional configurations: early adopters can reach 'positive tipping points' (thresholds related, for example, to the share of adopters of a specific technology, after which self-reinforcing positive feedback kicks in, further stimulating adoption) further favouring acceleration (Lenton et al., 2022); the opposite holds if specific investment or prevailing demand and institutional configurations relate to old or, even worse, brown goods and technologies.

Path-dependency could then turn out to be either a barrier to adoption and acceleration or instead a driver rewarding first mover commitments (Turnheim and Sovacool, 2020). Therefore, incumbents can not only affect the pace of the transition (e.g., lobbying to delay the deployment of new technologies and protect markets for older/dirtier ones), but also shape the characteristics of low-carbon technologies during the diffusion phase. More specifically, there could be a tension between pursuing deeper architectural changes that lead to broader societal and institutional transformations – and thus more sustained acceleration – and the resistance of incumbents, who favour less-radical, modular substitution pathways that allow them to preserve their technological and market leadership (Sovacool et al., 2025).

Technological heterogeneity also plays a crucial role. Learning processes (e.g., local vs. global), the relevance of formal and tacit knowledge (e.g., formal research through lab R&D, learning-by-doing, -using, and -interacting), customization needs (i.e., the extent to which technological artifacts must be adapted for different use environments), and the nature of institutions that facilitate technology transfer: all these elements may vary substantially across sectoral, technological, and product domains. This variation can lead to either linear or accelerated/exponential diffusion patterns and help explain heterogeneous dynamics across countries and regions with different industrial and technological specialisations (Malerba, 2005; Nelson, 2003).

Since decarbonisation largely depends on the perceived potential of low-carbon technologies and their relative cost vis-à-vis dirtier alternatives, expected demand flows, related uncertainty, and supporting policies may play a fundamental role. Here again, heterogeneity abounds (Costantini et al., 2017). Regulatory interventions (e.g., ban on the circulation of combustion engines vehicles, standards and mandates promoting the implementation of technologies with a low environmental impact) can have a systemic effect, reshaping production and consumption choices; as well as stimulating change in infrastructure, institutional and regulatory frameworks (Costantini and Mazzanti, 2012; Costantini and Crespi, 2008). On the demand side, adoption is promoted through subsidies and tax incentives, whose main aim is to increase the relative affordability of green goods (e.g., electric vs. combustion-engine vehicles) (Tchórzewska et al., 2022), as well as through green public procurement, which directs public demand towards industries and products that may help accelerate the transition (Cheng et al., 2018). Technology-push policies, in turn, seek to accelerate the transition to low-carbon technologies and to strengthen the associated knowledge base and capabilities. Instruments range from R&D incentives (Adomako and Tran, 2024) to policies supporting firms' patenting activities (Fabrizi et al., 2018), and from institutions that promote technology transfer to subsidies for training aimed at developing green skills.

Policies are never implemented in isolation and, particularly in the context of the net-zero transition, alignment between heterogeneous instruments, complementarities and coordination could make a difference in accelerating/slowing-down the transition itself (Edmondson et al., 2019).

However, designing a policy mix capable to accelerate the transition is a complex task often affected by time inconsistencies, conflicts, information asymmetries and bad coordination between government levels, weakening the ability to effectively integrate policies (Flanagan et al., 2011; Rogge and Reichardt, 2016; Roberts et al., 2018; Kern et al., 2019). Nonetheless, learning and self-reinforcing policy feedback may help fine-tune policy mixes, strengthening supportive coalitions and institutional arrangements that facilitate multi-level cooperation (Lockwood, 2022).

The existing literature thus identifies a complex set of interacting drivers and barriers shaping the net-zero transition, from cost dynamics and innovation systems to institutional structures, policy mixes, and technological trajectories. Yet, the operation of these mechanisms cannot be analysed in a vacuum. The global landscape in which the transition is unfolding has changed dramatically in recent years, reshaped by a series of overlapping crises and geopolitical disruptions. These developments not only influence the speed and direction of the transition but also challenge the assumptions underpinning established transition pathways. In what follows, we explore how the current era of polycrisis reconfigures the balance between environmental targets, economic competitiveness, and technological sovereignty.

2.2 The net-zero transition in the era of polycrisis

Before entering the era of 'polycrisis' – a term coined by historian Adam Tooze referring to upheaval induced by the interaction between financial crises, the COVID-19 pandemic, and the ongoing wars (Tooze, 2022) – accelerating decarbonisation seemed the only way forward. Despite resistance from incumbents and vested interests (e.g., oil and gas industries), the growing salience of climate change and closing window of opportunity for structural change provided significant impetus for action (Sovacool et al., 2025). Most economies set ambitious climate targets and adopted environmental regulations (e.g., reducing emissions below increasingly demanding thresholds, limiting the circulation of internal combustion engines cars); as well as demand-pull and technology-push policies aimed at stimulating the diffusion of green goods and technologies.

The polycrisis is changing this landscape. The dynamics of the net-zero transition and the role played by the factors driving/hindering it are dramatically reshaped by the ongoing trade and technology wars that are disrupting a large number of industries and supply chains (Crespi et al., 2021; Johnstone and McLeish, 2022; Crespi et al., 2025). The Russia-Ukraine war and, more recently, the tariffs imposed by the US on virtually all their trade partners have highlighted the issue of the coercive use of trade/industrial policies, as well as of CRMs and technologies (Baldwin and Evenett, 2024). Combined with geographical polarisation and market concentration, these developments risk jeopardizing policy agendas aimed at accelerating decarbonisation (Edler et al., 2023; Caravella et al., 2024).

The search for the cheapest goods and components on international markets, or the widespread use of off-shoring strategies as a way to reduce the relative cost of green goods and thus speed-up the transition, is now at odds with the need to avoid becoming overly dependent on foreign suppliers — especially when political relations are subject to instability and geopolitical risk (Johnstone and Schot, 2023). Indeed, the latter may have an ambivalent effect on acceleration. In order to escape the dependency on geopolitically risky oil and gas suppliers, countries may want to increase the pace of the net-zero transition by stimulating the deployment of green goods and technologies (Guarascio et al., 2025). Yet, without the necessary domestic production and technological capacity, they risk falling into a new dependency on countries dominating green supply chains, while facing uncertainty, sector-specific inflation, and aggressive trade policies (Guarascio et al., 2024; Dachs et al., 2025).

A complex policy trade-off comes to the fore. On the one hand, decarbonisation may help reduce the dependency on a highly concentrated and geographically polarised (and exposed to geopolitical risks) fossil fuel industry (e.g., the EU accelerating decarbonisation to reduce its reliance on Russian gas and oil), hence increasing the momentum for acceleration. On the other hand, economies accelerating their net-zero transition path risk moving from being dependent on a few gas and oil suppliers to a similarly dangerous dependency on those dominating the markets for CRMs, technologies, intermediate and final goods needed to achieve decarbonisation (Li et al., 2024). In other words, there is a potential trade-off between accelerating decarbonisation and facing the risk of increasing trade and technological dependency in a context of growing uncertainty and disruptions along critical supply chains. In particular, rising concerns on these latter issues may lead to a slowing down in the transition due to the diffusion of protectionists and industrial policies to strengthen strategic autonomy and technological sovereignty (Crespi et al., 2021; Kivimaa and Entsalo, 2026).

Three crucial elements must be considered to avoid slowing – or even halting – the transition, while simultaneously preventing the emergence of an unsustainable dependency. First, the pace of the transition matters. In the new global context, a certain degree of productive and technological self-sufficiency, at least in some specific segments of the supply chain, is necessary. Since autarchy is neither a plausible nor a desirable option (Edler et al., 2023), policies should be aimed at avoiding the emergence of unilateral dependencies. Acording to this perspective, the development of technological and productive leadership in specific segments can help to build relationships along the supply chain characterised by mutual dependencies, which are certainly preferable in terms of security and resilience. Second, demand-pull measures, essential for adoption, must be complemented by technology-push interventions, key to pursuit technological upgrading, and, if necessary, by targeted import substitution policies allowing to protect domestic industries (Costantini et al., 2015; Nunez-Jimenez et al., 2022). Third, the cost-related benefits stemming from the international division of labour and cooperation, especially in R&D and innovation, cannot be foregone. Sustainable trade relationships are in fact the result of a proper combination of specialisation (i.e., identifying industries and supply chain stages where economies of scale and scope can be maximised), diversification (i.e., spotting stages where the risk of unilateral dependency is stronger and intervene accordingly) and cooperation (Stephan et al., 2019; Crespi et al., 2025).

In this context, carrying out a granular mapping of relevant supply chains is crucial, as this will help identifying stages and products where it is necessary to strengthen domestic capabilities, as well as those where it continues to be convenient and sustainable to rely on external suppliers. Heterogeneity matters, though. For instance, the photovoltaic supply chain is structurally different from the wind turbine or the lithium-ion battery ones. Technological characteristics, degree of product- and industry-level fragmentation, geographical distribution of activities, concentration/competition in markets and relevant players: all these elements are supply-chain specific and need to be thoroughly assessed in order to properly design the policy mix. (Caravella et al., 2024).

2.3 The case of the lithium-ion battery supply chain

During the past decade, technological advances have led to a notable decrease in production costs of LBSC, facilitating the adoption and diffusion of this technology. Today, LBSC represent the most used technology for electric mobility, which in turn is crucial to decarbonise the transport sector, accounting for nearly 21% of global greenhouse-gas (GHG) emissions (Capliez et al., 2025). In this context, batteries are becoming increasingly strategic not just to increase competitiveness and vertical integration in the automotive industry, but also and foremost as a primary target of industrial policy and national sovereignty concerns in the pursuit of value-chain resilience and strategic autonomy. While these objectives are valuable, especially amid increasing geopolitical uncertainty, implementing such policies remains challenging and carries the risk that inward-looking approaches and zero-sum perspectives may increase costs or slow the pace of cost reductions, partially offsetting the benefits of technological advances and capacity building in certain locations. This is not only a theoretical possibility but a practical concern with immediate implications for the timing and costs of technology adoption and net-zero transition. For instance, tariffs or export restrictions to specific battery inputs can have large impacts on final prices or create bottlenecks along the supply chains, while uncertainty about supply and costs may delay private investment. This concern particularly applies to raw materials: e.g., while graphite is the most quantitatively relevant raw material for li-ion batteries, cobalt and nickel cover a large share of costs due to high prices. Furthermore, their prices are also very volatile: nickel prices rose by 41% between 2021 and 2022, then declined by 18% in 2023, including a monthly peak drop of 43% between January 2023 and January 2024; subsequently, in 2024, prices followed an upward trend, increasing by approximately 20% between February and May (Capliez et al., 2025; Wietschel et al., 2025).

In balancing environmental policy objectives and industrial competitiveness, countries have taken heterogeneous approaches. China adopted an early expansionary strategy that was primary concerned with industrial competitiveness and technological leadership. The "Go Global" policy in the early 2000s and the Belt and Road Initiative from 2013 (Damoah et al., 2022) can be seen as internationalized industrial policies carried out through mining and infrastructural projects, foreign direct investment, M&As and the internationalization of State-owned enterprises (Clò et al., 2023). In the case of batteries, lithium and cobalt are prominent examples of this strategy: through investments in Australia, Argentina and Chile, China gained control of most of the global lithium production; similarly, more than half of cobalt production in Congo, is under Chinese control (Capliez et al., 2025). The result is that China became firstly a dominant player in upstream stages, but then also moved into downstream stages quickly overcoming earlier primary actors such as Japan, the US and EU.

The US and EU took a different, more defensive, approach in reaction to the emergence of the dominant position of China. Both the US's Inflation Reduction Act (2022) and the European Net Zero Industry Act (2024) explicitly address electric vehicles in their productive or trade dimensions to reduce import dependency and counter China's dominance. The EU lithium-ion batteries policy framework, in particular, seems to be moving consistently with the open collaborative supply chain approach depicted above, although with some delay given the competitive setting. A key European goal is to increase its production capacity sixfold by 2030, while the Critical Raw Materials Act (2024) aims at securing the supply of critical raw materials. The EU also aims at strengthening international partnerships (e.g., with the Democratic Republic of Congo and Australia). It recognizes the importance of improving the monitoring framework, and stresses that data collection on batteries and raw materials should be based on a sound methodology and continuous updates, particularly concerning trade flows, demand and supply, concentration of supply, and production capacities at different stages of the value chain. The European Commission even introduced the idea of battery supply chain stress tests for large companies, while planning to provide EU funding for research on battery technologies (European Commission, 2023).

Yet, the ambitious EU industrial goals are not only hard to meet but also imply a high economic cost, long implementation periods, and may conflict with the environmental preferences of EU citizens thus risking low political support. Specifically, Europe's critical metal reserves are insufficient. Moreover, exploration and commercial production of mines requires substantial investment and may take up to 15-20 years while mines face a strong local opposition in the population due to environmental degradation and "nimby" attitudes (Capliez et al., 2024). Lastly, even if these obstacles were overcome, EU production would likely remain uncompetitive for quite some time due to high wages, costs of materials and energy.

The trade-off between the search for autonomy and reducing dependencies versus accelerating the net-zero transition is not only apparent, but of crucial practical relevance in the case of lithium-ion batteries, which illustrates how inward-looking strategies can backfire, raising costs, delaying adoption, and fragmenting innovation. To avoid these pitfalls, a more balanced and collaborative approach is needed, while a granular and timely mapping of the value chain, trade and technological advantages represent the necessary informative base (Caravella et al., 2024; Crespi et al., 2025).

3 Analytical framework and research questions

To analyse the relationship between acceleration, strategic dependency and technology in the LBSC, different perspectives and related strands of literature are combined.

We adopt a long-term, granular approach. In complex and highly internationalised supply chains, competitive positions and the international division of labour (e.g., market shares and product- and technology-related specialisation) may take considerable time to change (Syrquin, 1988). Yet, major discoveries, radical innovations, and policy shocks can trigger discontinuities capable of reshaping hierarchies and equilibria (Lee and Malerba, 2017). More broadly, in an era of overlapping geopolitical, environmental, and pandemic shocks, GVCs are being reshaped, calling for a renewed set of conceptual and empirical tools (Cipollina and Bruno, 2026). At the same time, the various stages of the supply chain (e.g., raw materials, intermediate inputs, and finished products) follow different production, technological, and market logics (e.g., relative stability, stronger market concentration upstream; greater dynamism, competition, and the relevance of incremental innovations downstream), which is crucial to consider (Bontadini, 2021).

Therefore, we build on Caravella et al. (2024) by developing a long-term mapping (20 years) of the LBSC, achieving the highest possible level of granularity in inspecting the supply chain. This allows identifying, for each stage and product component, major discontinuities (e.g., spikes in global demand), shifts in competitive hierarchies (e.g, changeover from one market leader to another), and country-specific trajectories (e.g., economies consolidating their position or becoming marginalised). Such granularity also enables a product-level intelligence (Caravella et al., 2021; Edler et al., 2023) highlighting critical areas where industrial policy and/or supplier diversification strategies can help reconciling two potentially conflicting objectives: accelerating the net-zero transition while reducing unilateral dependencies (Baldwin and Freeman, 2022). This leads us to our first two research questions:

RQ1 — Which structural changes have characterised the global LBSC over the past twenty years?

RQ2 — What are the areas of the LBSC (i.e., stages, product components) where the competitive gap has widened the most?

In mapping the LBSC, we integrate both trade and technology dimensions. This allows us to test one of the core hypotheses of evolutionary theory (Dosi and Nelson, 2010), namely whether – and to what extent – the strengthening of technological capabilities in a specific domain (e.g., machinery, cells and components, batteries) could translate into greater competitiveness and help reduce import dependency. Economies with stronger technological capabilities are more likely to possess the skills and assets necessary to enhance their production capacities in strategic stages, thereby reducing the risk of facing strong import dependency (Fagerberg and Srholec, 2008; Dosi et al., 2015).

However, heterogeneity and time also matter. Whether technological capabilities – partially captured through indicators such as R&D and patent data – are a key driver of competitiveness depends on the nature of activities conducted within different stages of the supply chain (Sovacool et al., 2025). Accordingly, we do not expect technology to play the same role across the up, mid and downstream stages, nor across different product components. Moreover, the accumulation of technological capabilities is an inherently path-dependent process which may lead to wide and hard-to-close technology gaps. Hence, the ability to exploit such capabilities to strengthen their competitive position may depend on how close or far economies are from the technological frontier (Guarascio et al., 2017).

Long-term technological specialisation patterns are another key determinant of countries' relative positioning within supply chains. A strong degree of specialisation can reflect their strategic orientation towards specific technological domains (and corresponding policy objectives), while also serving as a proxy for established technological capacity (Archibugi and Pianta, 1992; Archibugi and Iammarino, 1999; Malerba, 2005). Consequently, economies with a strong specialisation in LB-related technologies are expected to experience lower levels of import dependency and/or to be more capable of reducing such dependency in stages where it had previously increased.

This leads us to our third and fourth research questions:

RQ3 — Does the strengthening of technological capabilities enhance the competitive position of economies, potentially reducing their import dependency?
RQ4 — Are economies that specialise in the technologies underlying key LBSC product components less likely to experience import dependency?

To address these questions, we analyse in depth both the LBSC as a whole; as well as its stages (i.e., up, mid and downstream), in order to account for the specific structural and technological characteristics of each stage. Moreover, to account for institutional heterogeneity and diversity in terms of industrial, innovation and trade policy strategies, we test the relationship between competitiveness, technological capabilities, and specialisation separately for each country.

Finally, we investigate the complex relationship between net-zero acceleration, dependency, and technological capabilities. On the one hand, following the approach first advanced by Porter and van der Linde countries that are subject to more stringent environmental regulations may become net exporters of environmental technologies via induced technological change mechanisms (Porter, 1991; Porter and van der Linde, 1995). On the other, more stringent environmental policies oriented to accelerate decarbonisation, might result in stronger dependency when the relative positioning of economies in terms of technological and industrial competitiveness is weak.

Hence, our final research question asks:

RQ5 — Does environmental policy stringency lead to greater import dependency?

In this case, the expectation is that more stringent policies may trigger structural dependencies when there is a lack of internal technological and industrial capacities, while the opposite might hold for countries holding strong position in the supply chain, as for instance, by boosting domestic demand, stronger restrictions on internal combustion engines could help companies that already dominate the LBSC to further strengthen their position.

4 Data and Methodology

To analyse the intersection between trade and technology along the LBSC, two data sources are employed: trade data are retrieved from the BACI-UNComtrade database (Gaulier and Zignago, 2010), while patent data from the OECD Regpat database (Maraut et al., 2008).[1]

The unit of analysis is the triad country-product-technology, where products are reported at the sixth digit of the HS classification, and technology is proxied by full-digit CPC patent classes. We identify 26 product-technology combinations which in turn are grouped into five stages of the value chain: ”Raw Materials”,

[1]OECD, REGPAT database, January 2024.

roughly corresponding to the up-stream; ”Refined Materials” and ”Machinery”, which jointly form the mid-stream; ”Battery Materials/Cell Components” and ”Battery”, which mainly refer to chemical compositions and the final product, constituting the down-stream.[2]

Our analysis covers the 2002–2022 period to provide a long-term view of the LBSC's evolution and structural changes. The data includes a large number of countries, covering the entire global trade of LBCS-related products. Nevertheless, most countries participate only marginally in this sector, with both trade and patenting activity highly concentrated among a few key players. For this reason, the analysis below focuses on the five leading economies in the field: the US, the EU, Japan, the Republic of Korea, and China. These five economies offer a comprehensive representation of the main dynamics of the LBSC, since they account for the vast majority of trade and innovation in this sector.

4.1 The trade and technological dimension

The time frame and the sample of countries selected raise three concerns for data management. First, during the period considered, the Harmonized System (HS) classification of traded goods has changed several times, from HS 2002 to HS 2012, HS 2017, and finally HS 2022. This might generate inconsistency in the selection and tracking LBSC-related products over time. Problems arise when inputs of the LBSC are divided or merged with products unrelated to the value chain, introducing bias into the figures. A careful analysis of each product's time series was developed to identify problematic products and correct the time series through interpolation (see Appendix A for the detailed procedure).

Second, the patent database should be carefully selected to avoid home bias, due to applicants being more likely to file patents at their home country office. Because of this home bias, considering data from a unique national office inflates the figures for domestic innovation.
In order to overcome this issue and adopt a reliable cross-country perspective, we consider only patents that have followed the international route according to the Patent Cooperation Treaty (PCT). This solves country-specific biases, but reduces the number of patents considered, since the international route implies higher costs (Aklilu et al., 2025). However, the selection of more expensive – and potentially more protected – patents ensures that only high-quality innovation is being selected, reducing the noise generated by less-relevant innovation.

Third, patents are often associated with multiple inventors and technological classes. We apply a double-fractional counting, which consists of partitioning each patent by inventor and technology, and collaps-

[2]Given the relevance of circular procedures to accelerate the net-zero transition and reduce dependency on CRMs, waste and exhausted batteries have also been mapped and included in the ”Recycling” stage of the value chain. However, the stage is omitted from the analysis due to difficulties in distinguishing waste of LBSCs from other types of batteries and due to peculiarities that make comparison with other stages more complex.

ing the information at the country-CPC level. This procedure allows us to identify the value of patents ($PatentValue_{i,CPC,t}$) filed by inventors from country i, concerning the technological class CPC, in year t.

Because our research interest regards technological capabilities, i.e. competencies accumulated over time, rather than annual innovation, we consider the stock of patents, applying a standard yearly discount factor of 15%.[3] The adopted procedure is the following:

$$PatentStock_{i,CPC,t} = PatentValue_{i,CPC,t} + \sum_{t=0}^{t} PatentValue_{i,CPC,t-1} * 0.85$$

4.2 Mapping trade and innovation along the LBSC value chain

The methodology employed to identify the HS product codes and CPC technological classes associated with the LBSC components involves a systematic and multi-stage approach composed of five main steps.

1. HS 6-digit product codes identification. In the first step, an extensive literature review[4] was carried out to identify the HS 6-digit codes associated with the main LBSC inputs. The use of keyword-based research on HS product descriptions validated the completeness of the list.

2. CPC patent classes identification. Secondly, we proceeded to select the associated CPC classes. For each product, we used the HS description as input to the EPO search engine[5], retrieved the top 50 patents, and extracted the associated CPC classes.

3. CPC patent codes filter and selection. Third, in order to reduce the probability of including false positives, we filter the CPC classes to be included on a predetermined pool of LBSC-associated technological classes. These codes were either mentioned in the literature[6] or associated with the patenting activities of leading firms in the industry[7]. If this procedure did not match any CPC code to the targeted HS product, the pool of LBSC-related technological classes was explored accurately through keyword-based search. The final choice for inclusion was also based on frequency analysis, to highlight the most commonly reported CPC classes, and qualitative assessments, to ensure their relevance. As an illustrative example, this procedure led to the association of product *"253090 - Minerals n.e.c."* (mainly including lithium ores) to the technological class *"C22B26/12 – Obtaining lithium"* identified by Moïsé and Rubínová (2023). Once a

[3]The stock is computed starting from the first available year, namely 1977.

[4]The literature review for the identification of HS products included McMahon (2022); Tsuji (2022); UNCTAD (2023); Sun et al. (2021); LaRocca (2020); Cheng et al. (2024); Hao et al. (2022); Tian et al. (2021); Matthews (2020); Scott and Ireland (2020).

[5]`https://worldwide.espacenet.com/patent/`

[6]Relevant contributions for the identification of CPC codes are Moïsé and Rubínová (2023); Malhotra et al. (2021); Peiseler et al. (2024); Stephan et al. (2017); Wagner et al. (2013); Mueller et al. (2015); Wali et al. (2024).

[7]Leading firms include key players in production - such as Contemporary Amperex Technology, Byd Company Limited, Northvolt AB, Tesla Motors, Inc., LG Energy Solution - and innovation - LG Chem, Ltd., LG ENERGY SOLUTION, LTD., Samsung SDI Co., Ltd., Contemporary Amperex Technology Co., Limited, Zeon Corporation, SK Innovation Co., Ltd. The CPC classes identified in this way are filtered to include an explicit reference to critical raw materials, namely graphite, lithium, manganese, nickel, or cobalt.

Table 1: LBSC mapping into stages and products.

Stage	Product description
1. Raw Materials	Graphite, natural
	Lithium ores
	Manganese ores
	Nickel and Cobalt ores
	Lithium carbonates
2. Refined Materials	Manganese oxides
	Lithium oxides
	Nickel and Cobalt oxides
	Nickel chlorides
	Chlorides (including lithium)
	Nickel sulphates
	Sulphates (including manganese)
	Nickel and Cobalt waste and scrap
	Manganese waste and scrap
3. Machinery	Machines, including roll manufacturing
4. Cell Components	Fluorides (including lithium)
	LMO
	LCO
	LFP,NCA,NCM,LNO
	Phosphides, precursors for NCA and NCM
	Graphite, artificial
	Plastics, in roll
	Aluminium foil
	Cells
	Electrodes
5. Battery	Li-ion Batteries
6. Recycling	Waste and scrap of batteries

Note: see Table A.7 in the Appendix for detail on related HS and CPC patent codes.
Source: authors' elaborations.

CPC class is identified as relevant, all its subordinate levels are also included and assigned to the same HS product.

4. Matching into product-technology combinations. Fourth, since HS codes and CPC classes are connected by many-to-many correspondence, the data is aggregated according to product similarity[8].

5. Experts validation. Finally, the overall mapping and aggregation were subject to external validation through consultations with experts in the field.

This procedure leads us to select 44 HS 6-digit product codes, 153 CPC patent classes spanning over 45,104 patents in the whole Regpat database. The resulting 27 HS-CPC combinations, corresponding to meaningful product-technology combinations, are reported in Table 1.

Compared to standard classification methods based on text analysis of patent descriptions, our procedure offers a key practical advantage: it provides a manageable unit of analysis —- CPC classes —- that can be feasibly reviewed and validated by an expert, while maintaining a low risk of type II errors. It is a conservative method that deliberately excludes broader classes likely to contain both LBSC-related and unrelated patents, to focus on specific, product-linked technologies.

[8] For instance, product *"380110 - Graphite; artificial"* is merged with *"380190 - Graphite or other carbon based preparations; in the form of pastes, blocks, plates or other semi-manufactures"*.

4.3 Measuring strategic dependency and technological capabilities

The rich and detailed information collected is employed to build indicators of import dependency and technological specialisation. Import dependency is measured with a composite indicator as in Gehringer (2023); Caravella et al. (2024). This is made of three components, each one grasping a different aspect of uneven trade relationships. For each country i, product k (with k belonging to the 26 HS-CPC combinations identified), and year t ($t \in \{2002, ..., 2022\}$), the first component is the Normalized Trade Balance (NTB) computed as:

$$NTB_{i,k,t} = \frac{Im_{i,k,t} - X_{i,k,t}}{Im_{i,k,t} + X_{i,k,t}}$$

This is standardised to vary between 0 and 1, and grasp the dominant or dependent position of country i in the international arena, concerning production k, and taking the size of the country into consideration.

The second component is the import share of country i from its main supplier (IMP_MS) of product k. While NTB tells if the country is in a dependent position, the IMP_MS accounts for the magnitude of dependency on the main supplier (j):

$$IMP\_MS_{i,k,t,j} = \frac{Im_{i,k,t,j}}{Im_{i,k,t}}$$

Finally, the index includes the global export share of the main supplier in production k, assessing the magnitude of its market power:

$$EXPSH_{k,t,j} = \frac{X_{k,t,j}}{X_{k,t,.}}$$

The three components are combined in a unique indicator providing a proxy of strategic dependency at the product level:

$$IDEP_{i,k,t} = NTB_{i,k,t} \frac{(IMP\_MS_{i,k,t,j} + EXPSH_{k,t,j})}{2}$$

On the technological side, to grasp countries' technological specialisation in each LBSC input, we build a Balassa-type Revealed Technological Advantage (RTA) index (Balassa, 1965):

$$RTA_{i,k,t} = \frac{\frac{PatentStock_{i,k,t}}{PatentStock_{i,.,t}}}{\frac{\sum_{i=1}^{N} PatentStock_{i,k,t}}{\sum_{i=1}^{N} PatentStock_{i,.,t}}}$$

As previously noted, most countries hold few or no patents related to the LBSC. To avoid excessively compressing the denominator of the RTA, the aggregate share is therefore computed using only the top 14 innovating countries, which together account for approximately 99% of LBSC-related patents over the entire period considered.[9]

4.4 Environmental policy stringency

As argued above, policy plays a crucial role in accelerating decarbonisation. As pressure from climate change kept growing, virtually all economies, albeit with a high degree of heterogeneity in terms of policy strategy and intensity of the effort, have introduced measures to limiting the use of polluting goods and technologies while encouraging the adoption of green ones (Borrás and Edquist, 2013; Albulescu et al., 2022; Martínez-Zarzoso et al., 2019). LBSCs are strongly affected by these measures, as they compete directly with polluting technologies; and are subject to a significant number of direct (e.g., incentives to promote the diffusion of EVs) and indirect (e.g., regulations setting strict deadlines to phase out from fossil fuel) intervention aimed at speeding up their diffusion. However, a greater policy stringency does not guarantee effectiveness in accelerating the net-zero transition. If subsidies become more generous and regulations stricter in contexts where supply is unable to adequately meet demand or where import dependency drives up costs or creates unmanageable macroeconomic and geopolitical imbalances, the outcome may be sub-optimal. Policy effort could be relaxed, leading to a slowdown rather than accelerating the transition. On the other hand, if environmental stringency continue to be pursued despite production/trade imbalances, import dependency may get worse, paving the way for further instability and future crises.

To account for the role of policy stringency, we include a specific country-level proxy provided by the OECD (Kruse et al., 2022). The Environmental Policy Stringency (EPS) index is a composite indicator embedding different types of supply-side and regulatory policies, such as the tax rate for CO2 emissions, emission limit values, and public R&D expenditure aimed at climate objectives. Stringency refers to the degree to which environmentally harmful behavior or pollution incurs a higher, either explicit or implicit, cost. This concept is easy to apply to instruments like environmental taxes, where a higher tax per unit of pollution directly reflects greater stringency. Similarly, stricter (i.e., lower) emission limit values also signal increased stringency. For policy tools such as subsidies—including feed-in tariffs or funding for research and development—a higher level of financial support is likewise considered indicative of a more stringent environmental policy. These subsidies raise the opportunity cost of polluting activities and are generally funded by taxpayers or consumers, thereby creating a relative advantage for cleaner alternatives. As such, they can be viewed as a proxy for a blend of technology-push and broader systemic environmental policies (Botta and Koźluk, 2014).

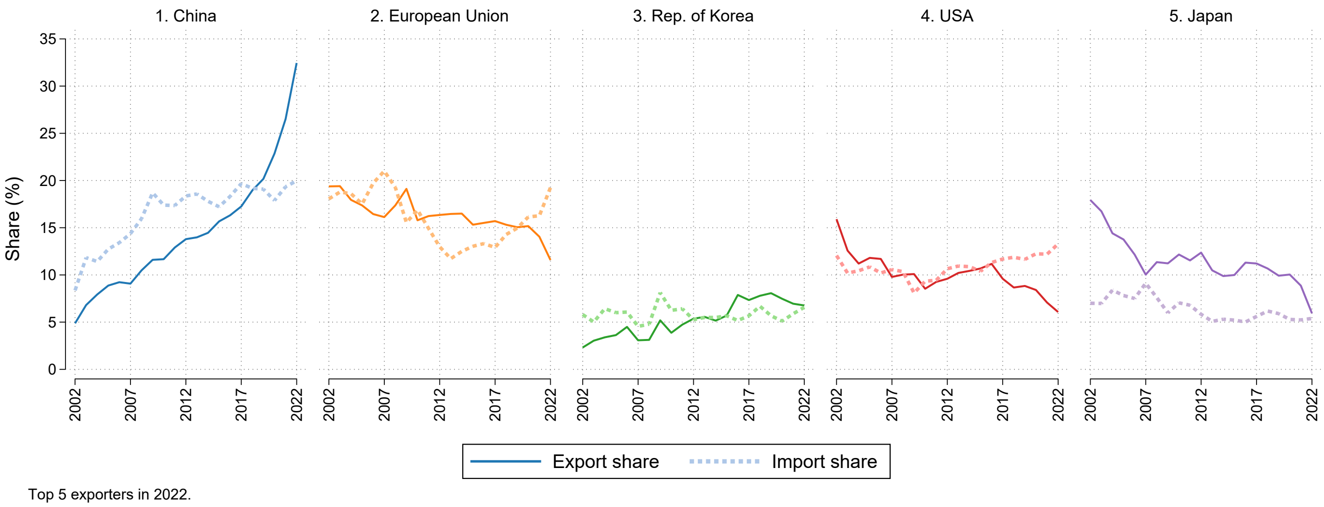
[9] Selected countries, in order of importance, are: Japan, United States, South Korea, China, European Union, Canada, United Kingdom, Australia, Switzerland, Singapore, Hong Kong, India, Russian Federation, Brazil, South Africa.

5 The Long-run Evolution of LBSC

5.1 Trade

World trade of LBSC-related products reached 300 billion US dollars in 2022. It was about 50 billion in 2002 and stayed around 150 in 2011-2016. This means that LBSC trade tripled during the period 2002-2011, and almost doubled again from 2017 to 2022. During the 21-year period of analysis, LBSC trade increased sixfold.[10]

Figure 1: Country shares in total LBSC trade.



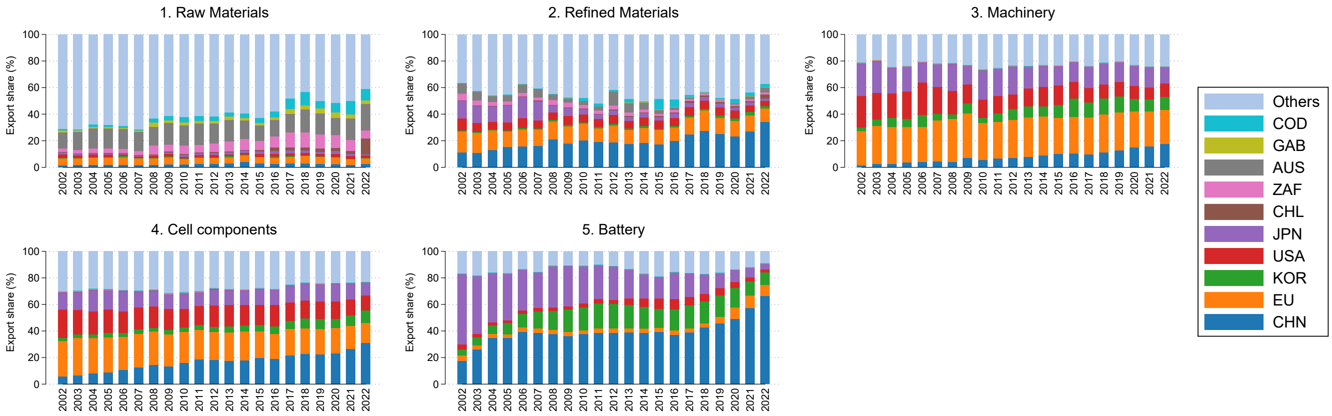
Source: authors' elaborations based on BACI data.

As Figure A.21 shows, the rapid increase in LBSC trade is driven by the emergence of China as world leader, with its overall export share moving from 5% in 2002 to 32% in 2022. The rise of China is followed by Korea, but on a different scale, since its share reaches only 7% in 2022. The other major exporters, the EU, the US, and Japan see a reduction in their export shares. At the same time, looking at imports, the EU and the US increase their import shares, especially in the most recent years, becoming major net importers, while Japan reduces its import share, suggesting disengagement from the industry.

While the aggregate figures provide a broad representation of the entire chain, they hide significant heterogeneity between LBSC stages. Three stages constitute the bulk of global LBSC trade, about 75% in 2022: battery (stage 5), cell components (stage 4), and raw materials (stage 1), each with about 75 billion USD trade.

[10]Concerning the EU, these numbers consider the region as an aggregate and therefore only capture extra-EU exports, while excluding intra-EU trade.

Figure 2: Country export shares by stage (main exporters).



Source: authors' elaborations based on BACI data.

LBSC stages are heterogeneous, and countries occupy different positions.

Exports concentration is very high in battery (stage 5) where the top 5 exporters – China, Korea, EU, US, Japan – account for approximately 90% of world exports (Figure 2). Concentration is also high in machinery (stage 3) and cell components (stage 4), where the same top 5 exporters cover 80% of exports. They also cover about 50% of exports in refined materials (stage 2), while their presence is limited in raw materials exports (stage 1).

The dominance of China is very strong in finished battery (stage 5) where its export share reaches 66%, with a dramatic increase in just 6 years from 2016 to 2022 (+30 p.p.). Japan's shares follow an opposite trend, with a fast decline from more than 50% in 2002 to about 5% in 2022. China's export position in finished batteries is even more striking compared to the dramatic collapse in its import shares since 2009, which closely matches Japan's drop in exports: in 2002, China essentially stops importing batteries and almost only exports them.

China reinforces its position and becomes the world's leading exporter also in cell components (stage 4; greater than 30% in 2022) and refined materials (stage 2; almost 35% in 2022). The EU remains a somewhat stable leader in the export of battery-related machinery (stage 3; 25% in 2022), followed by China, whose shares increase steadily, reaching approximately 17% in 2022. Not surprisingly, raw materials (stage 1) export shares are less concentrated, and the role of exporters is related to their endowments of natural resources. LBSC producers in mid or downstream stages need to import raw and refined materials for further processing.

On the imports side, while China stops importing finished batteries and becomes the main world producer, its need for materials increases rapidly: China alone imports almost 50% of battery-related raw materials and almost 30% of refined materials. The EU follows an opposite trend: while it increasingly relies on imported batteries (and cell components), its raw and refined material import shares rapidly shrink.

Table 2: Top LBSC products trade shares, exporters and importers (2022).

Rank	**Description**	**Share**	**Cum. share**	**Top exporter**	**Top exporter share**	**Top importer**	**Top importer share**
1	Li-ion Batteries	27.5	27.5	CHN	66.6	EU	33.3
2	Nickel and Cobalt ores	13.9	41.4	CAN	15.3	CHN	39.8
3	LFP,NCA,NCM,LNO	13.3	54.7	CHN	24.4	CHN	13.7
4	Machines, including roll manufacturing	13.2	67.8	EU	25.6	USA	15.8
5	Aluminium foil	5.9	73.8	CHN	37.8	EU	17.0
6	Lithium carbonates	3.3	77.1	CHL	83.3	CHN	63.8
7	Lithium ores	3.2	80.4	AUS	76.2	CHN	86.4
8	Nickel and Cobalt oxides	2.7	83.1	IDN	29.9	CHN	60.1
9	Manganese ores	2.7	85.8	ZAF	40.3	CHN	60.9
10	LCO	2.2	88.0	KOR	55.6	EU	59.0
11	Plastics, in roll	2.0	90.0	CHN	28.1	EU	13.0
12	Lithium oxides	1.8	91.9	CHN	79.5	KOR	67.2
13	Cells	1.8	93.7	CHN	32.6	USA	26.9
14	Graphite, artificial	1.0	94.7	CHN	50.4	EU	31.8
15	Electrodes	0.9	95.6	CHN	69.8	NOR	16.0
16	Manganese waste and scrap	0.7	96.4	CHN	79.2	EU	22.9
17	Nickel and Cobalt waste and scrap	0.7	97.1	USA	19.9	USA	23.9
18	Sulphates (including manganese)	0.7	97.7	CHN	36.6	CHN	18.2
19	Fluorides (including lithium)	0.4	98.2	CHN	43.0	USA	18.0
20	Waste and scrap of batteries	0.4	98.6	USA	53.4	KOR	32.0
	Others	1.4	100				

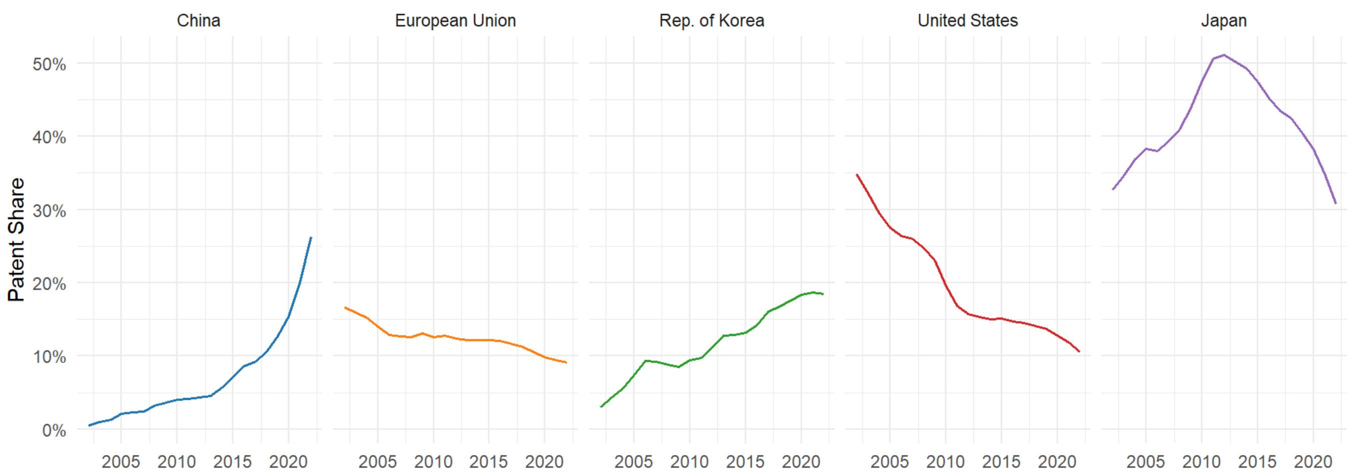
Source: authors' elaborations based on BACI data.

Increasing detail to the product level, batteries and the next three top products make up more than two-thirds of the world LBSC trade: batteries represent 27.5% of LBSC trade; Nickel and Cobalt ores 13.9%; LFP, NCA, NCM, LNO 13.3%; battery-related machines 13.2%. The latter is the only product where the EU still plays an important role as an exporter.

5.2 Technology

Concerning the efforts to strengthen technological capabilities, as proxied by patents, LBSC faced increasing attention at the global level. The total number of LBSC-related patents that has taken the international route was 575 in 2002 and jumped to 4427 patents in 2021, showing a 669.9% increase. Innovation initially took off in 2007, slowed down between 2012 and 2015, and then started rising again with renewed vigour. Innovation anticipated and enabled the rise in exports (see Figure A.17).

Figure 3: Countries' patent share in LBSC-related products.



Source: authors' elaborations based on Regpat data.

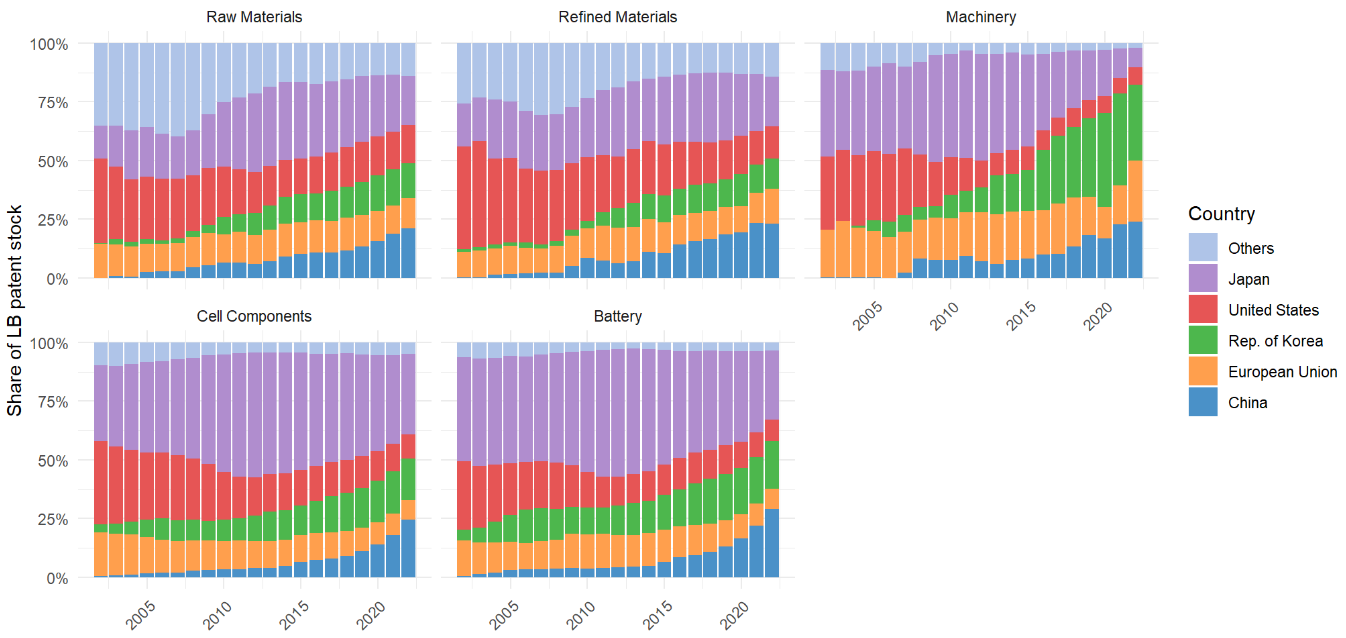
While the global rise in exports is driven by the rise of China, on the technological side other actors have also played a significant role in different periods. Figure 3 reports the global share of patents by country. It shows that Japan was primarily responsible for the initial surge in patenting activity, while the more recent increase since 2015 has been driven by China and South Korea.

Japan is still the main player in terms of patented innovations, accounting for more than one-third of global patents, but since 2011, has significantly scaled back its efforts (from 50% to 35% approximately). The US and the EU are also reducing their shares, with the former having declined the most (-35 pp. from 2002 to 2021) and the latter showing a historical low presence in the value chain (always below 20%). Innovative activity has steadily shifted from the Western Bloc to Asia, with Japan initially taking the lead, later overtaken by China and South Korea.

This dynamics is also evident when examining innovation across different stages of the value chain (Figure A.18). Cell components, which embed the diverse chemical compositions that differentiate battery types, are the most heavily targeted by patent activity. They are followed by the battery stage itself, highlighting the strategic importance of downstream stages in shaping overall performance and competitiveness.

In terms of products, most of the patents targeted the final product, and the innovative activity has concentrated over time. Li-ion Batteries accounted for more than 20% of all LBSC patents in 2002, but the share has increased to almost 30% by 2022. The second most targeted products are electrodes, accounting for almost 20% of patents in 2022. It is worth emphasising that different chemical combinations (LCO, LMO, LFP and others) moved from middle rankings (8th, 10th, 4th, respectively) to the top rankings (3rd, 4th, 5th) in the period considered, suggesting that innovation was leveraged to overcome existing bottlenecks.[11]

Figure 4: Countries' patent share in different stages of the LBSC.



Source: authors' elaborations based on Regpat data.

These aggregate trends in the LBSC reflect heterogeneous dynamics across the supply chain. Disaggregating the data by value chain stage, Figure 4 illustrates the decline of Western countries, the inverted-U trajectory of Japan, and the rise of the Far East. Notably, the EU has maintained a stable technological presence in Machinery, holding a consistent 25% share. Japan remains the leading player in Cell Components and Battery stages, but has lost ground in Machinery. South Korea's growing share is largely driven by its specialisation in Machinery, while China's figures are primarily supported by its dominance in Refined Materials, consistent with its historical export strength in this area. Nonetheless, China's rise is evident across all stages of the LBSC.

[11] Indeed, innovative chemical compositions, besides increasing the battery performance, can also reduce demand of CRMs and, therefore, import dependency (IEA, 2024).

5.3 Product/Technology Strategic Intelligence Analysis

This paper operationalizes the concept of product-level intelligence (for a discussion of the analytical rationale, see Edler et al., 2023; Caravella et al., 2024) by jointly analyzing countries' positions within the IDEP and RTA distributions and how these have evolved over time. Figure 5 focuses on the LBSC as a whole, depicting each country's trajectory between 2002 and 2022. The graph is divided into four quadrants by two dashed lines serving as reference points: the horizontal line represents the median IDEP value, and the vertical line marks an RTA equal to 1 —– representing the global average. Each quadrant reflects a distinct structural positioning.

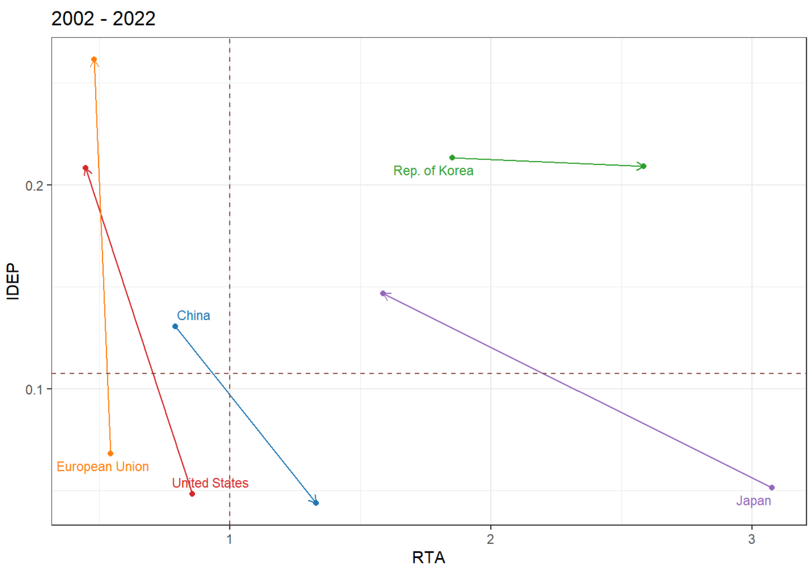
SE quadrant – Strong position. Countries in the southeast quadrant are structurally well positioned to compete in the LBSC, exhibiting low dependency and strong technological capabilities.

SW quadrant – Marginal players. Countries with low participation in the value chain (low dependency but also marginal innovation) cluster in the southwest quadrant.

NW quadrant – Critical position. The northwest quadrant signals problematic positions and priority areas for improvement, as it includes countries with high dependency and low technological competitiveness.

NE quadrant – Structural transformation. Finally, the northeast quadrant includes countries undergoing structural transformation – characterised by high RTA values but still significant dependency.

Figure 5: Countries' dependency and technological specialisation across the LBSC.



Source: authors' elaborations based on Regpat and BACI data.

The evolution of countries' positions within the LBSC reveals distinct trajectories of structural change and strategic repositioning. In 2002, the EU was located in the southwest quadrant and has since moved toward a position of greater dependency, while maintaining a relatively stable level of technological competitiveness. The US followed a similar trajectory, but on top of increasing their import dependency they also experienced a significant loss in technological capabilities. This pattern suggests that the Western bloc had a limited presence in the LBSC when the technology began to expand globally. As Western countries (particularly the EU) scaled up their engagement to accelerate the net-zero transition, their insufficient technological and production capacity translated into growing reliance on external markets.

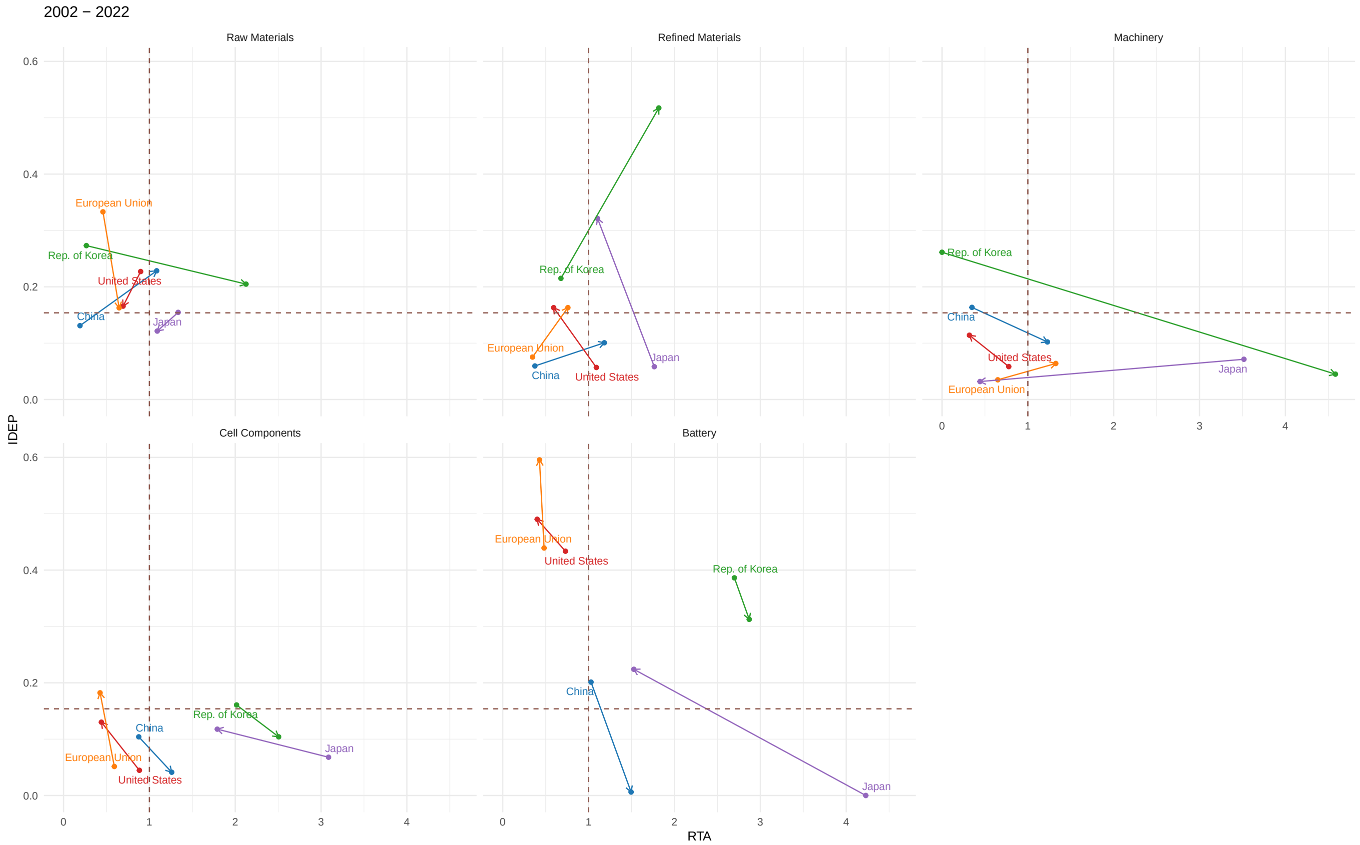
In contrast, China made a notable shift from the southwest to the southeast quadrant, reflecting rapid improvements in both productive and technological specialisation. Despite being more dependent on foreign suppliers than the US and EU in 2002, China has since upgraded to a structurally robust position. The starkly different outcomes among countries starting from similar positions highlights the central role of policy approaches in shaping dependency.

Concerning South Korea, it emerges as a player in active structural transformation. It has consistently remained in the northeast quadrant, but has moved significantly along the x-axis, indicating a strong increase in technological specialisation, while still exhibiting some dependency. This might reflect a strategic positioning into GVCs as innovation hub — also considered the dominance of China in production stages — or an ongoing process of transformation, still in the phase of capabilities accumulation.

Japan, positioned in the structurally advantageous southeast quadrant, has remained there over time but experienced a substantial shift toward the northwest. While it retains relatively low dependency and strong technological capabilities, this trajectory is the most pronounced structural repositioning among the countries considered. This movement may indicate that Japan is falling behind in the value chain, similar to Western countries. However, this trend could also be the result of strategic disengagement from the LBSC. The latter interpretation is supported by the trade data shown in Figure A.21: unlike the US and EU, whose increased dependency reflects a deteriorating trade balance (rising imports and declining exports shares), both Japanese imports and exports shares have declined.[12]

[12] A possible explanation is that Japan's mobility transition strategy has prioritized competing technologies — such as hydrogen engines — leading to a reallocation of resources away from the LBSC. However, this possibility needs further exploration.

Figure 6: Countries' dependency and technological specialisation in different LBSC stages.



Source: authors' elaborations based on Regpat and BACI data.

Because the aggregate LBSC can mask significant heterogeneity between stages, Figure 6 explores countries' strategic positioning in different areas by disaggregating the previous graph into the five distinct stages of the LBSC.

It is evident that the US and the EU have not experienced a uniform decline across all stages of the LBSC. The deterioration in their overall positions is largely driven by the downstream stages —- specifically, Cell Components and Batteries. This negative trend is clear in both areas; however, while these countries appear only marginally engaged in Cell Components (low IDEP and low RTA), they exhibit very high levels of dependency in Battery production. In the midstream stage, which includes Machinery and Refined Materials, the US has seen a decline in its position, whereas the EU shows a dual trend of increasing dependency alongside a modest rise in technological specialisation. In the upstream stage – namely, Raw Materials – IDEP is declining for both actors, while RTA does not change much. The IDEP reduction in the upstream stage is not surprising considering the broader context: US and EU show a general absence from the LBSC, whereby the low and declining levels of production in the mid and downstream stages (reflected in rising import dependency) reduce their need for upstream inputs.

China's trajectory aligns with this broader reasoning, but follows an opposite direction. The country has strategically invested in the final product stage, gaining a strong position. It has also followed an upgrading path in both Cell Components and Machinery, although it remains relatively underspecialised in these areas. To support the development of these stages and accelerate the net-zero transition, China has relied heavily on the international market for Raw and Refined Materials, but at the same time, it appears to be addressing its growing dependencies by leveraging its technological capabilities, as shown by its movement toward the northwest quadrant in these stages. Overall, China's strategy appears to prioritise downstream stages while accepting higher exposure in upstream inputs.[13]

South Korea's ongoing structural transformation becomes more evident at a more granular level. Overall, the country is progressing toward the southeast quadrant, though at varying speeds across different stages. By 2022, it had secured a strong position in three out of four stages, including a remarkable upgrade in the Machinery sector, where it now plays a leading global role. However, in the final battery stage, South Korea remains highly dependent on China. The only deviation from this overall improving trend is in Refined Materials, where both IDEP and RTA are increasing, indicating growing engagement but also rising dependency.

Finally, Japan is retreating from all stages of the LBSC, especially in Machinery and the final product.

The structure of the dataset enables an even deeper, product-level analysis, identifying specific products where countries face particular difficulties. This is reported, for 2022, in Figures A.19 and A.20 and confirms the broader analysis. Such detail also allows the identification of areas for policy action that countries should target to reduce their dependence.

This product/technology-intelligence approach can prove valuable in informing industrial policy and, in particular, in supporting strategies aimed at (realistically) pursuing acceleration. The US and the EU, for example, have the preliminary urgency to reduce their dependency on final products (batteries). However, the analysis have shown how both have weakened their position all across the supply chain also losing most of their former technological advantages.[14] One possibility, for the EU, could be to exploit its technological strength in Machinery to reinforce its position also in the downstream.

China sets on a positive upgrading trajectory, but is developing dependencies in the upstream. Moreover, it is only marginally involved in Cell Components, which is the crucial step where active salts are chemically synthesised. While the critical raw material dependency is being addressed through innovation and inter-

[13] As a complement to this analysis, it must be acknowledged that our data do not allow firm-level analysis, and therefore accounting for the nationality of exporting firms. In this respect, it is worth mentioning that China's growing dependency in Raw Materials is likely driven by imports of Chinese firms directly investing in CRM-rich countries.

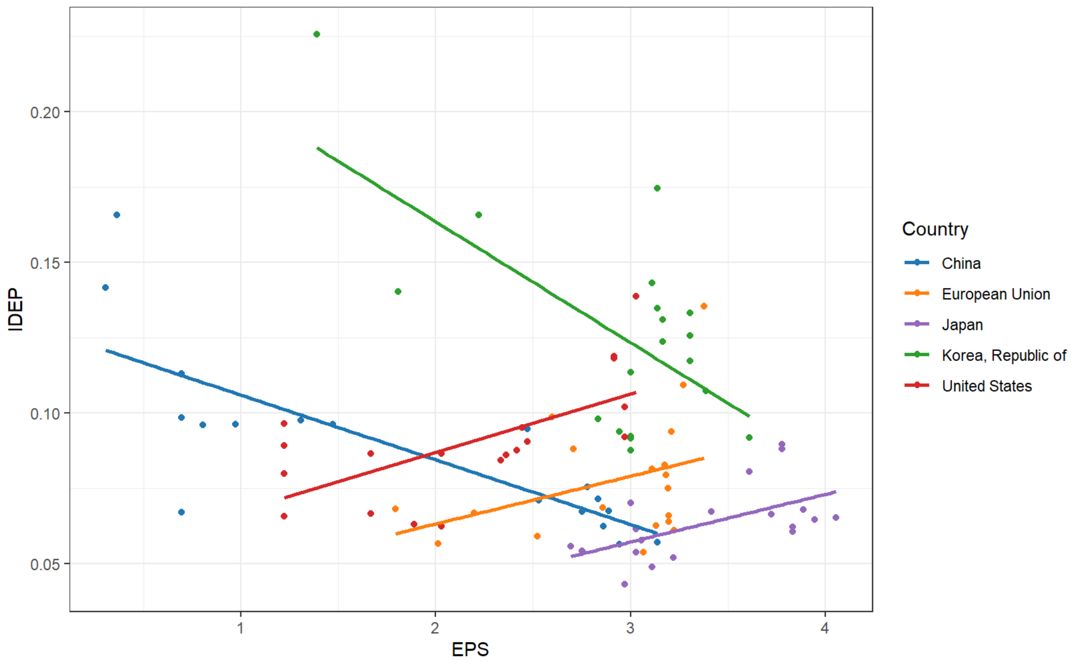
[14] Interestingly enough, this finding stands in sharp contrast to the Draghi Report released in September 2024, which portrayed Europe as a strong innovation hub and argued that its accumulated technological capabilities could be leveraged to build a competitive LBSC. This claim was based primarily on the number of patents filed at the European Patent Office, regardless of the applicant's origin. A more accurate analysis reveals that LBSC-related innovation filed by European applicants remains very limited, casting doubt on the possibility of relying on domestic knowledge to drive industrialisation in this sector.

national diplomacy, cell component capabilities need to be prioritised. Innovation in Cell Components can reduce the content of CRMs in the batteries and, hence, reduce dependency also in the upstream stages. The evidence presented above shows that countries' positions in the LBSC are highly heterogeneous and shaped by distinct patterns of technological specialisation and strategic dependency. These configurations are the result not only of industrial structures and past trajectories, but also of deliberate policy choices. Among these, the stringency of environmental policy represents a key dimension that can either accelerate or constrain transitions. In the following section, we explore how differences in environmental policy stringency correlate with countries' levels of import dependency, offering a first empirical look at how environmental targets may or may not align with external vulnerabilities along the LBSC.

5.4 Dependency vs. Environmental Policy Stringency

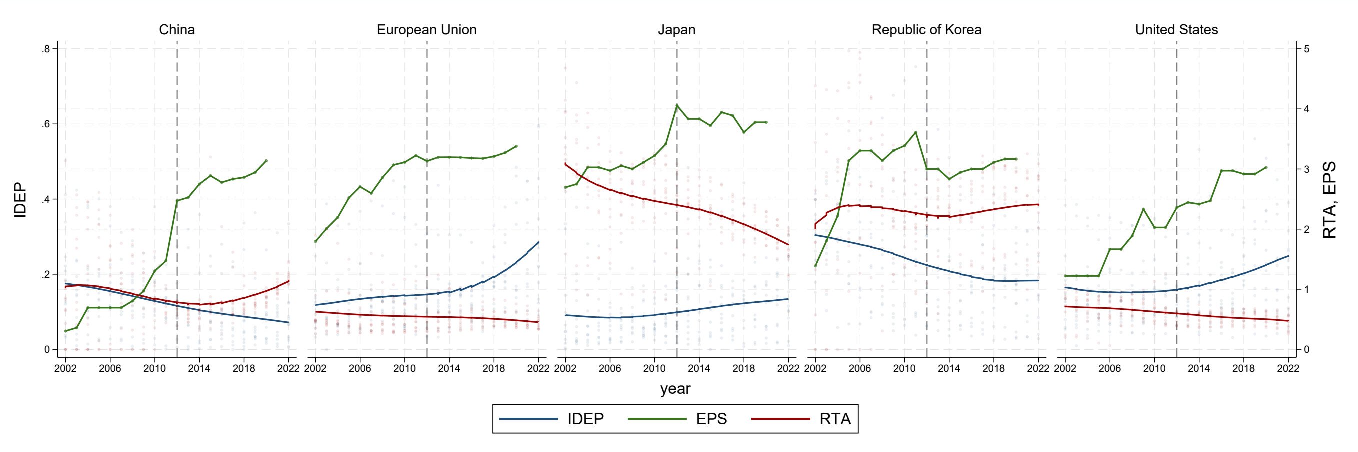
Building on the structural trajectories outlined above, we now examine how countries' import dependency correlates with environmental policy stringency. As discussed, we expect heterogeneous dynamics to materialize, reflecting countries's uneven positions to jointly pursue acceleration and balanced trade relationships in the LBSC. Figure 7 reports the joint distribution of IDEP over the whole supply chain, on the one hand; and the EPS index, on the other. Linear correlation is reported to provide an idea of the direction of the relationship.

Figure 7: Correlation between IDEP and EPS, 2002-2020.



Source: authors' elaborations based on BACI and OECD data.

Figure 8: Countries' trends in IDEP, EPS, and RTA - Downstream sector



Source: authors' elaborations based on BACI, Regpat, OECD data. Curves are estimated with the lowess method.

The evidence aligns with the hypotheses sketched in Section 3. In fact, all countries display an increase in the stringency of their environmental policies over time. However, when it comes to the relationship with our dependency indicator (IDEP) two distinct blocs emerge. A negative correlation is detected in China and South Korea; while more environmental stringency is associated with increasing dependency in the EU, the US and Japan. Such divergent patterns are confirmed when the dynamics over time of our key indicators (RTA, IDEP and EPS) are analysed over time (Figure 8). In particular, it is worth noting the opposite dynamics after 2012 of RTA and IDEP in China on the one hand, and in EU and US on the other. Moreover, data highlight the different timing of the increase in the EPS in China with respect to EU, US and Japan, suggesting heterogeneous policy strategies: a combination of demand-pull, technology-push and aggressive industrial policies in China followed by an acceleration in EPS promoting the fast diffusion of green goods and technologies including LBSC, and commercial leadership at the global level. In contrast, a different pattern characterises EU, US and Japan as growing environmental stringency goes hand in hand with skyrocketing dependency and waning technological efforts (particularly in the EU and the US). Hence, these figures suggest that while for these latter economies the acceleration towards the green transition might encounter limitations due to the emergence of unsustainable structural dependencies, this does not hold for countries like China, where internal productive and technological capabilities allow for an increasing pace of net-zero transition.

From a theoretical perspective, the heterogeneous cross-country trajectories of environmental policy stringency, import dependency, and technological capabilities call for a re-examination of the seminal 'Porter hypothesis'—namely, the proposition that stringent environmental regulations can stimulate innovation, enhance efficiency, reduce costs, and ultimately strengthen competitiveness (Porter, 1991; Porter and van der Linde, 1995). In the specific context of the LSBC, our findings provide an important qualification to this hypothesis. The anticipatory role of regulation and its capacity to foster technological upgrading and competitiveness appear to be effective only under particular structural and policy conditions. Specifically, positive outcomes are more likely when stringent environmental policies are complemented by coherent industrial, innovation, and trade strategies explicitly designed to reinforce productive and technological capabilities in targeted sectors. By contrast, the introduction of stricter environmental regulations without a parallel expansion of domestic production capacity in relevant industries may run counter to Porter's expectations, potentially increasing external dependency and slowing the transition process.

6 Econometric Strategy and Results

While the previous section documented key empirical regularities, this section investigates whether these patterns reflect systematic relationships that can be identified econometrically. In particular, to assess the extent to which technological capabilities and environmental policy can be leveraged to overcome bottlenecks, reduce external dependency, and accelerate the net-zero transition, we consider the following dynamic panel specification:

$$\mathrm{IDEP}_{i,k,t} = \beta_0 + \rho\,\mathrm{IDEP}_{i,k,t-1} + \beta_1\,\mathrm{RTA}_{i,k,t-1} + \beta_2\,\mathrm{EPS}_{i,k,t-1} + c_{i,k} + \lambda_t + \varepsilon_{i,k,t} \tag{1}$$

where i indexes countries, k products within the LBSC, and t years. The dependent variable is the level of dependency, $\mathrm{IDEP}_{i,k,t}$, which takes values in the $[0, 1)$ interval. The specification includes a dynamic component, $\mathrm{IDEP}_{i,k,t-1}$, to capture persistence arising from the path-dependent nature of productive structures. The main covariates of interest are the countries' relative technological specialisation, $\mathrm{RTA}_{i,k,t-1}$, and the environmental policy stringency index, $\mathrm{EPS}_{i,k,t-1}$. Both variables are lagged by one period, as the descriptive analysis suggests that changes in technological capabilities and policy tend to precede adjustments in dependency. This lag structure also contributes to alleviating potential endogeneity concerns. The dependency indicator is further allowed to be affected by unobserved country–product heterogeneity $(c_{i,k})$, reflecting the fact that countries have pursued different strategies across inputs, as well as on common time-specific shocks (λ_t). The effect of remaining unobservable determinants is captured by the idiosyncratic error term $\varepsilon_{i,k,t}$, which is assumed to be mean independent of the included regressors, conditional on fixed effects.
Given the complexity of the underlying data-generating process, we refrain from a causal interpretation of the estimated coefficients and focus instead on the identification of systematic empirical relationships. Consistent with the descriptive evidence, we expect $\rho > 0$ due to persistence, $\beta_1 < 0$ insofar as higher technological specialisation strengthens domestic productive capabilities and reduces dependency, and a heterogeneous effect of environmental policy stringency across countries, reflecting differences in policy

design and implementation. In order to capture cross-country heterogeneity, we augment the baseline specification by introducing an interaction term between the variable of interest and a country-specific dummy variable that equals one for a given country and zero otherwise. Using EPS as an illustrative example, and denoting the dummy variable by D_i, the model is specified as follows:

$$\mathrm{IDEP}_{i,k,t} = \beta_0 + \rho\,\mathrm{IDEP}_{i,k,t-1} + \beta_1\,\mathrm{RTA}_{i,k,t-1} + \beta_2\,\mathrm{EPS}_{i,k,t-1} + \beta_3\,(\mathrm{EPS}_{i,k,t-1} \times D_i) + c_{i,k} + \lambda_t + \varepsilon_{i,k,t} \quad (2)$$

Because the analysis relies on high-quality and costly patents filed at WIPO and defined at a highly disaggregated technological level, many countries do not file patents in several technologies and therefore exhibit a null RTA. Since this may obscure the role played by innovation in shaping dependency patterns, we restrict the analysis to the five countries examined in the previous section. For the same reason, the European Union is treated as a single geopolitical entity. This choice also avoids capturing dependencies across countries that belong to the same industrial ecosystems, are subject to a common regulatory framework, and are likely targeted by the same policy initiatives, as is the case of the EU. While the estimates should be interpreted as capturing systematic relationships among major industrial economies, the inclusion of consistently low innovators (the EU and the US), catching-up countries (Korea), and recently emerged leaders (China) allows us to derive insights that may be relevant for other countries as well.

The resulting dataset is a balanced panel with a relatively large cross-sectional dimension and a limited time dimension, comprising 130 country–product combinations (five countries and 26 products) observed over 19 years (2002–2020).[15]

The linear specification reported in Equation 1 is estimated using alternative estimators commonly employed in dynamic panel settings with bounded dependent variables.

We begin with a standard two-wat fixed effects (TWFE) estimator, which removes time-invariant unobserved heterogeneity and common time shocks through a within transformation. Due to its transparency and ease of interpretation, this approach provides a useful benchmark for the empirical analysis. However, it is subject to two well-known limitations in the present context. First, the inclusion of a lagged dependent variable alongside fixed effects may induce bias in the estimated coefficients (Nickell bias[16]). Second, linear models do not explicitly account for the bounded nature of fractional response variables. As a result, they may generate predicted values outside the admissible $[0, 1)$ interval and fail to account for the accumulation of observations at boundary values. While these issues are potentially problematic in principle, in our application, they are mitigated by the relatively large time dimension of the panel and by the very limited

[15] The sample is limited to 2020 due to the availability of the EPS index.

[16] This so-called Nickell bias (Nickell, 1981) arises because the within transformation, while removing time-invariant heterogeneity, mechanically introduces correlation between the lagged dependent variable and the transformed error term. However, this bias vanishes as the time dimension grows.

presence of corner solutions (accounting for approximately 0.5% of the whole sample). For these reasons, we retain the fixed-effects estimates as a benchmark.

To address these limitations, we complement the fixed-effects analysis with a random-effects Tobit estimator (Wooldridge, 2005; Loudermilk, 2007). The Tobit approach postulates that the observed outcome $\text{IDEP}_{i,k,t}$ is generated by an underlying latent variable $\text{IDEP}^*_{i,k,t}$, which follows the linear specification reported in Equation 1, but is only observed within the admissible bounds of the fractional support. Observations at the boundaries, therefore, arise naturally as corner solutions. By explicitly accounting for this feature, the Tobit model accommodates the bounded nature of the dependent variable.
In addition, to deal with the individual heterogeneity while avoiding the incidental parameters problem, we adopt a correlated random-effects approach. Using a simplified notation in which $y_{i,t}$ denotes the dependent variable and $x_{i,t}$ the vector of covariates, the unobserved effect is modelled as $c_i = \psi + \xi_0 y_{i0} + \bar{x}_i \xi + a_i$, where $\bar{x}_i = \frac{1}{T}\sum_{t=1}^{T} x_{i,t}$ denotes the time average of the covariates, y_{i0} is the dependent variable in the first period observed, and a_i captures the remaining unobserved heterogeneity. We further assume that a_i is well-behaved conditional on the initial condition y_{i0} and the time averages $\bar{x}_i$, that is $a_i|y_{i0}, \bar{x}_i \sim \mathcal{N}(0, \sigma_a^2)$, which implies $c_i \sim \mathcal{N}\left(\psi + \xi_0 y_{i0} + \bar{x}_i \xi,\ \sigma_a^2\right)$. Under these assumptions, a_i can be treated as a random effect, and the model can be consistently estimated by maximum likelihood as a random-effects Tobit, augmented with the initial condition and the time averages of the regressors. The resulting estimating equation is therefore given by:

$$\text{IDEP}_{ikt} = \theta + \rho\, \text{IDEP}_{ikt-1} + \beta_1\, \text{RTA}_{ikt-1} + \beta_2\, \text{EPS}_{it-1} + \xi_0 \text{IDEP}_{ik0} + \xi_1 \bar{\text{RTA}}_{i,k} + \xi_2 \bar{\text{EPS}}_{i,k} + a_i + \lambda_t + \varepsilon_{ikt}. \quad (3)$$

Although these assumptions are stronger than those required by the linear fixed-effects estimator, the random-effects Tobit provides a complementary framework that jointly accounts for unobserved heterogeneity, dynamic persistence, and the bounded nature of the dependency indicator.
Last, standard errors are clustered at the country–product level to allow for arbitrary serial correlation and heteroskedasticity within panels.

Table 3 reports the results of the TWFE estimation. To account for heterogeneity across the LBSC, we split the sample in upstream, midstream, and downstream, in line with the definition reported in Section 4. Three main patterns emerge. First, the lagged dependency indicator ($IDEP_{i,k,t-1}$) is positive and highly significant across all specifications, reflecting strong path-dependence in countries' positions within the LBSC. Second, in the upstream sector, both the RTA and EPS coefficients are positive and significant. This pattern likely might be due to three mechanisms: (i) countries that are leaders in downstream production often possess advanced technological capabilities or supportive policies, enabling innovation upstream as well;

	Full	UP	MID	DOWN
	(1)	(2)	(3)	(4)
Constant	0.0670***	0.0863**	0.0829***	0.0562***
	(0.0123)	(0.0389)	(0.0176)	(0.0173)
$IDEP_{i,k,t-1}$	0.645***	0.562***	0.654***	0.670***
	(0.0265)	(0.0726)	(0.0405)	(0.0339)
$RTA_{i,k,t-1}$	0.000974	0.00912***	0.000813	-0.00828**
	(0.000815)	(0.00235)	(0.000884)	(0.00357)
$EPS_{i,k,t-1}$	0.00341	0.0307**	-0.000882	-0.00173
	(0.00476)	(0.0115)	(0.00727)	(0.00698)
Panel FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	2468	473	950	1045
Groups	130	25	50	55
Within R^2	0.426	0.408	0.448	0.454
F-statistic	41.86***	80.07***	37.83***	54.42***

Standard errors clustered at the country-product level in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Least-squares dummy variable estimates by LBSC segment. Each column reports a different subsample: full, upstream (UP), midstream (MID), and downstream (DOWN) sectors.

however, if they lack sufficient resource endowments, they will still rely on imports; (ii) the coefficients may capture an ongoing adjustment process, in which countries actively leverage innovation to reduce rising dependency (e.g., China in Figure 6); (iii) it may reflect foreign direct investment in resource extraction, whereby countries establish subsidiaries abroad to secure raw materials while continuing to patent domestically. In such cases, imported raw materials inflate the IDEP even though the resources remain under the country's control.[17] Third, in the downstream sector, technological capabilities play a more pronounced role (RQ3, RQ4). The negative and significant coefficient on $RTA_{i,k,t-1}$ in column (4) suggests that higher technological specialization reduces dependency in complex stages, such as cell components and final assembly, consistent with evidence that most innovation occurs in these stages (see Figure A.18). These results further validate our approach of examining heterogeneity across the value chain, as they show that the role of technological capabilities differs across segments.

The CRE Tobit results, reported in Table 4, are fully consistent with the fixed-effects estimates. The coefficients on $IDEP_{i,k,t-1}$ is positive and significant, the $RTA_{i,k,t-1}$ is negative and significant in the downstream, while both $RTA_{i,k,t-1}$ and $EPS_{i,k,t-1}$ are positive and significant in the upstream sector. The inclusion of $IDEP_{i,k,0}$ (initial condition) and the time-averaged regressors ($R\bar{T}A_{i,k}$, $E\bar{P}S_{i,k}$) accounts for

[17]Further research efforts will be needed to properly verify these hypotheses.

	Full	UP	MID	DOWN
	(1)	(2)	(3)	(4)
Constant	-0.0259*	-0.0163	-0.0287	-0.0191
	(0.0139)	(0.0436)	(0.0227)	(0.0139)
$IDEP_{i,k,t-1}$	0.749***	0.645***	0.756***	0.793***
	(0.0197)	(0.0420)	(0.0314)	(0.0328)
$RTA_{i,k,t-1}$	0.00116	0.00894***	0.00105	-0.00820**
	(0.000860)	(0.00330)	(0.000939)	(0.00367)
$EPS_{i,k,t-1}$	0.00287	0.0278***	0.000058	-0.00229
	(0.00343)	(0.00830)	(0.00560)	(0.00495)
$IDEP_{i,k,0}$	0.224***	0.291***	0.265***	0.0932***
	(0.0245)	(0.0623)	(0.0427)	(0.0243)
$\overline{RTA}_{i,k}$	-0.00187	0.00782	0.000149	0.00249
	(0.00249)	(0.0129)	(0.00303)	(0.00459)
$\overline{EPS}_{i,k}$	0.00950*	-0.00661	0.0121	0.0130**
	(0.00573)	(0.0162)	(0.00943)	(0.00650)
σ_u	0.0264***	0.0381***	0.0268***	0.00567
	(0.00299)	(0.00760)	(0.00489)	(0.00573)
Time FE	Yes	Yes	Yes	Yes
Observations	2468	473	950	1045
Groups	130	25	50	55
Log-Likelihood	3268.3	607.1	1241.6	1488.8
Chi-squared	4728.8***	677.1***	2427.2***	1974.4***

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Correlated Random Effects (CRE) Tobit estimates by LBSC segment

individual heterogeneity and avoids the incidental parameters problem, following the correlated random effects approach. The panel-level variance σ_u is small but significant in most segments, suggesting that country–product-specific unobserved factors play a non-negligible role.

Interestingly, in the downstream segment, the time-averaged environmental policy variable is positive and significant, while the estimated variance of the random effect is not statistically different from zero. This suggests that cross-country heterogeneity in downstream dependency is largely captured by differences in environmental policy stance, leaving limited residual unobserved variation. Moreover, Figure 7 suggest that the relationship between EPS and IDEP may vary significantly across countries.

To delve deeper into this aspect, we estimate the specification reported in Equation 2 through both the TWFE and CRE Tobit, restricting the sample to the downstream stage, where technological capabilities and environmental policy appear to play a more prominent role. The interaction term included in the specification allows the effect of EPS to vary across countries, thereby capturing national-level heterogeneity in the relationship between environmental policy, technology and dependency. This exercise is particularly relevant for the debate on acceleration, as we can explicitly highlight the potential trade-off between greater policy stringency, as a way to pursue acceleration and external constraints, as proxied by our IDEP. Furthermore, we can distinguish among different policy strategies, as proxied by the selected countries.

	China	EU	Japan	Korea	USA
Constant	0.0359*	0.0466**	0.0447**	0.0566***	0.0569***
	(0.0193)	(0.0175)	(0.0190)	(0.0185)	(0.0177)
$IDEP_{i,k,t-1}$	0.647***	0.658***	0.663***	0.662***	0.657***
	(0.0332)	(0.0345)	(0.0329)	(0.0378)	(0.0363)
$RTA_{i,k,t-1}$	-0.00974***	-0.00919**	-0.00756**	-0.00669*	-0.00870**
	(0.00338)	(0.00362)	(0.00337)	(0.00368)	(0.00354)
$EPS_{i,t-1}$	0.0170*	-0.0000900	-0.000794	0.00277	-0.00418
	(0.00894)	(0.00706)	(0.00706)	(0.00787)	(0.00706)
$EPS_{i,t-1} \times D_{China}$	-0.0221***				
	(0.00790)				
$EPS_{i,t-1} \times D_{EU}$		0.0294***			
		(0.00822)			
$EPS_{i,t-1} \times D_{Japan}$			0.0190		
			(0.0115)		
$EPS_{i,t-1} \times D_{Korea}$				-0.0291**	
				(0.0110)	
$EPS_{i,t-1} \times D_{USA}$					0.0233***
					(0.00635)
Panel FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Observations	1045	1045	1045	1045	1045
Within R^2	0.461	0.459	0.456	0.461	0.460
F-statistic	54.45***	49.19***	52.47***	45.23***	47.62***

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Fixed-effects estimates with country-specific interactions for EPS (Downstream segment). Standard errors clustered at the country–product level.

From Table 5, two divergent patterns can be highlighted. Greater environmental policy stringency is associated with lower levels of the IDEP indicator only in China and South Korea; while a positive and significant correlation is detected in the EU and US cases. This result aligns with our expectations regarding

RQ5: countries experiencing a strong and generalised upgrading regarding both production (as reflected by trade performances) and technology – as in the case of South Korea and, especially, China – seem to be able to reconcile acceleration and manageable trade relationships. On the contrary, economies that have lost substantial ground (see Section 4) like the EU and the US risk being trapped by the above-mentioned tradeoff: more environmental stringency could quite likely mean greater dependency.
In general, the CRE Tobit estimates, reported in Table 6, confirm the story sketched, but suggest caution. China presents a negative and significant coefficient for the interaction term, while the coefficient for Korea is not significant anymore. In line with fixed effects results, the US presents a positive and significant coefficient, while the EU, despite being still positive, is not significant anymore. Moreover, Japan shows a negative and only marginally significant coefficient.
Overall, the CRE Tobit results, reported in Table 6, broadly confirm the patterns emerging from the fixed-effects specifications, while suggesting a more nuanced picture. China exhibits a negative and statistically significant interaction term, confirming that tighter environmental policy is associated with reduced dependency in contexts characterised by intense technological dynamics. In contrast, the interaction term for the US remains positive and statistically significant, indicating that this is not a general rule. This is also true for the EU, for which the interaction term is positive, albeit not significant. Korea and Japan instead present an opposite sign compared to the fixed effect, calling for deeper analysis.

To further explore country-level heterogeneity, we replicate the downstream analysis by interacting the RTA with country dummies (see Tables A.9 and A.10). As argued above, cross-country differences may shape the way technological capabilities translate into trade performance and dependency outcomes. In particular, heterogeneity in industrial policy strategies, institutional frameworks, and the structure and quality of National Innovation Systems can influence the extent to which technological specialisation effectively reduces dependency within the LBSC (Fagerberg and Srholec, 2008). The fixed-effects estimates do not reveal statistically significant country-specific differences in the effect of the RTA. However, the CRE Tobit specification detects a negative and mildly significant interaction for China, suggesting that technological upgrading is more important in this case than the average. By contrast, as already noted in the descriptive statistics, the interaction term for Korea is positive and weakly significant, pointing to a more complex relationship between technological specialisation and dependency. For the remaining countries, no robust differential patterns emerge.
Finally, our findings are not sensitive to the definition of the dependency indicator. In the Appendix, we report robustness checks using an alternative measure of dependency that uses Herfindahl-Hirschman's concentration indexes (HHIs) instead of the main supplier trade shares. This alternative dependency indicator is closer to the approach proposed by the European Commission (2021) and Arjona et al. (2023) that

	China	EU	Japan	Korea	USA
Constant	0.0272	-0.0133	-0.0268*	-0.0180	-0.0272*
	(0.0211)	(0.0151)	(0.0143)	(0.0140)	(0.0144)
$IDEP_{i,k,t-1}$	0.771***	0.789***	0.795***	0.793***	0.785***
	(0.0331)	(0.0329)	(0.0323)	(0.0326)	(0.0331)
$RTA_{i,k,t-1}$	-0.00919**	-0.00830**	-0.00819**	-0.00819**	-0.00852**
	(0.00366)	(0.00367)	(0.00367)	(0.00367)	(0.00366)
$EPS_{i,t-1}$	0.00799	-0.00214	-0.00248	-0.00249	-0.00283
	(0.00602)	(0.00494)	(0.00495)	(0.00496)	(0.00494)
$EPS_{i,t-1} \times D_{China}$	-0.0121***				
	(0.00409)				
$EPS_{i,t-1} \times D_{EU}$		0.00263			
		(0.00251)			
$EPS_{i,t-1} \times D_{Japan}$			-0.00346*		
			(0.00200)		
$EPS_{i,t-1} \times D_{Korea}$				0.00121	
				(0.00205)	
$EPS_{i,t-1} \times D_{USA}$					0.00534**
					(0.00253)
$EPS_{i,k,0}$	0.0973***	0.0941***	0.0820***	0.0891***	0.0963***
	(0.0240)	(0.0244)	(0.0237)	(0.0247)	(0.0244)
$\overline{RTA}_{i,k}$	0.00638	0.00546	0.00419	0.00174	0.00408
	(0.00478)	(0.00539)	(0.00462)	(0.00475)	(0.00465)
$\overline{EPS}_i$	-0.0104	0.00907	0.0165**	0.0132**	0.0156**
	(0.0101)	(0.00751)	(0.00675)	(0.00648)	(0.00666)
σ_u	0.00690	0.00611	0.00397	0.00515	0.00613
Time FE	Yes	Yes	Yes	Yes	Yes
Observations	1045	1045	1045	1045	1045
Log-Likelihood	1493.7	1489.3	1490.2	1488.9	1491.2
Chi-squared	2038.7***	1972.5***	2143.8***	2021.5***	2027.3***

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Correlated random-effects Tobit estimates with country-specific interactions (Downstream segment).

precisely considers import HHIs as well as world export HHIs among the core indicators used to identify critical products.[18] The overall results remain unchanged across specifications and methods, confirming

[18]The alternative IDEP is calculated replacing the main supplier import share in total country imports of a given product and the world export share of that main supplier on total world exports of the product with the corresponding Herfindahl-Hirschman's

the stability of the main conclusions.

7 Conclusion

This work explores a central tension in today's fractured global economy: the trade-off between the need to accelerate the net-zero transition and the national efforts to reduce foreign strategic dependencies. The structural geopolitical shifts of the past two decades have led countries to revise their approach towards free international trade and devise policies to address dependencies and preserve autonomy. However, in a highly interconnected and globalized world economy, these objectives may conflict with environmental goals. The risk is even higher considering that the desire to preserve autonomy and maintain sovereignty can be easily misrepresented politically as protectionist or nationalistic. In this paper we argue that sovereignty must not be confused with autarky and, while countries should legitimately safeguard sovereignty, inward-looking policies are both unlikely to succeed and potentially harmful to the net-zero transition.

The lithium-ion battery supply chain exemplifies this tension as it represents one of the leading technologies for the net-zero transition but it is also characterized by a supply chain particularly exposed to strategic dependencies, and for which many specific policies have been devised internationally.

By focusing on the LBSC, this work provides a methodological, empirical and policy-oriented contribution to the debate on the need to reconcile net-zero acceleration and the pursuit of strategic autonomy. From a methodological point of view, we provide an analytical framework that can be applied to any supply chain in order to identify stages where industrial and trade policies are most urgent and necessary. By the same token, the granular mapping proposed here could be useful to support the design of policy mixes directed to complex and critical supply chains, such as those relevant to the net-zero transition.

Concerning the empirical contribution, we highlight the emergence of China's leadership in terms of both trade and technology; as well as the parallel decline of the EU, the US and Japan, while Korea perform comparatively better than Western counterparts. These evidence, combined with information related to policy stringency suggest that while for some economies (in particular EU and US) the acceleration towards the green transition might encounter limitations due to the emergence of unsustainable structural dependencies, the same constraint may not apply for countries like China, where internal productive and technological capabilities allow for an increasing pace of net-zero transition.

The econometric analysis confirms that enhancing technological capabilities can help mitigate import dependency, primarily in the downstream sector. This result confirms the hypothesis that while China has been particularly able to leverage technological capacities to increase international competitiveness, the de-

indexes. This alternative formulation, rather than taking the trade shares of the main supplier only, considers the entire distribution of trade shares across all suppliers as well as across all available world exporters. Therefore, it is more comprehensive and addresses possible concerns regarding neglecting other relevant suppliers in the baseline formulation of the IDEP.

clining technological specialization observed in EU and US appears to be a relevant driver of their external dependencies in the scrutinized sector.

Overall, our results reveal significant dependency among countries along the entire value chain, fueled by an asymmetric distribution of technological capabilities. This may exacerbate critical bottlenecks and geopolitical tensions, fostering more protectionist trade attitudes and inward-looking industrial policies, potentially increasing in the costs of the net-zero transition and delaying decarbonisation efforts.

The broader policy implication of the proposed analysis is that accelerating towards the net-zero transitions does not necessarily come at the cost of reducing technological sovereignty and increasing structural dependencies. However, the pace of net-zero transition and the related policy mix should be designed in accordance with the degree of structural dependencies and the level of development of domestic capabilities Hence, a well-designed policy mix that integrates environmental targets with innovation and industrial policy can enhance both resilience and acceleration towards net-zero transition. In this respect, our findings provide indications on the importance to integrate in the design of policy mix considerations related to technological and productive asymmetries, as well as trade and geopolitical obstacles that may hamper the faster achievement of net-zero targets.

In this perspective an important step to devising well-designed policies balancing these two apparently conflicting objectives is to recognize the production and technical complexities of modern technologies, acknowledging that international collaboration is likely to be more successful than a race to national supply chain autonomy. To this end, a mixed policy scenario seems preferable (Rogge and Reichardt, 2016; Costantini et al., 2017).

Policies should subsequently aim to: i) prevent strong unilateral dependencies, developing a monitoring framework and implement timely actions to address them; ii) accept mutual rather than unilateral dependencies, that is strengthen the international linkages pointing towards specialisation and division of labor; iii) use industrial policy selectively to reinforce key stages, moving away from a costly search of self-sufficiency along the entire supply chain towards the identification and targeting of the specific stages that can be effectively reinforced.

This approach points towards a collaborative technological sovereignty framework (Lee et al., 2024; Crespi et al., 2025) grounded in the recognition that modern complex technologies are characterized by interconnected components embedded within global innovation networks (Leoncini et al., 1996; Singh, 1997; Dosi and Nelson, 2010). In this context, national innovation systems are more likely to succeed by leveraging their specific essential critical technologies in a mutually complementary way. However, the strategic management of a collaborative supply chain approach requires detailed information on the key stages of the supply chain. In this respect, the present paper provides a methodology to develop a trade and technology product intelligence analysis that can be applied in different sectors in order to identify risks, opportunities and areas of policy intervention able to foster the acceleration to the net-zero transition without falling into unsustainable strategic dependencies.

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Appendix A LBSC mapping with HS and CPC pantent codes and data validation

Table A.7 shows how we mapped the selected 6-digit HS codes into LBSC products and stages and the correspondence with the relevant CPC patent codes.

The LBSC mapping is based on an accurate selection of 6-digit product codes from the Harmonized System classification. The identification of LBSC HS codes is based on the latest revision of HS 2022 (HS22), which more accurately represents recent technological developments. However, to track trade values back in time, previous HS revisions must be used, such as the HS 2002, 2007, 2012 or 2017 (HS02, HS07, HS12, HS17). Unfortunately, for some products, older HS revisions may be less suitable than more recent ones to provide an accurate representation of the LBSC. Therefore, in order to study the evolution of the LBSC, it is necessary to balance the accuracy from the latest revisions with the historical perspective provided by previous HS revisions. To this end, ensuring that the right flows are tracked required a precise code-by-code inspection of HS concordances and traded values.

Quoting from the United Nations Statistical Division: "The data conversions from HS 2022 to earlier HS versions developed by UNSD assign one single code (subheading) of an earlier HS edition to each HS 2022 subheading. Yet, users should be aware that the very nature of a revision of a classification does not allow the establishment of a clear 1:1 correspondence for all codes (subheadings) of a new to the codes of previous versions of classification and should bear in mind the potential shortcomings (different contents than indicated, break in series) for certain subheadings when using converted instead of original data." (p. 1 from UNSD, *Correlation and conversion tables used in UN Comtrade*, available at https://unstats.un.org/unsd/classifications/Econ)

Table A.8 provides detail on the correspondences between HS revisions adding information on the consistency of the trade data.

Figure A.9 shows trade values by 6-digit code across HS revisions (raw BACI data). Inspection allows to spot possible inconsistencies that may require intervention. Fortunately, there are only few cases that require attention:

- HS 282200: HS17 data shows suspect spikes;
- HS 284800 and 285100: these codes must be taken together as they are partially merged into code 285390 in HS17 and HS22 (n:n relationship between HS02 and HS22);
- HS 382490: the HS02 series is above the HS12/17/22 ones, the latest ones being more reliable;
- HS 847989: the HS02 series shows a stronger upward trend, then a downward jump in 2012, then it becomes aligned with other revisions between 2012 and 2016, and finally it rises above the HS12/17/22 revisions after 2016; the latest HS revisions are instead all aligned and more reliable;

- HS 854810: partially mapped into 854913 since HS22, which is the most relevant for lithium-ion batteries; previous HS revisions capture several other types of battery-related waste, implying that the values under HS22 code 854913 are much smaller than those under HS02/12/17 code 854810.

To address inconsistencies due to classification revisions affecting the above few products, we constructed a harmonized time series to ensure that the adjusted series extending back to 2002 provide the most accurate representation of LBSC product codes. Specifically, the adjustments are conducted by either accounting for code splits/groupings according to HS concordance tables or by extrapolating 2002-2012 values from interpolated HS12 and HS17 classifications onto the HS02 framework so to give prevalence to the most recent and reliable revisions whenever possible. This ensures consistency across revisions while preserving underlying data trends.

The final (adjusted) data use the HS02 revision when it is aligned with more recent ones, while making the following adjustments on the spotted inconsistent trends:

- HS 282200: HS02 series until 2016, HS17 series since 2017. Fully reliable.
- HS 284800: HS22 285390 groups HS02 codes 284800 and 285100, and HS12 codes 284800 and 285300 until 2016. Highly reliable.
- HS 382490: extrapolates 2002-2012 data based on linear interpolation of HS12 and HS17 series for 382499 on the HS02 for 382490. Highly reliable until 2012, fully reliable after.
- HS 847989: extrapolates 2002-2012 data based on linear interpolation of HS12 and HS17 series on the HS02 one. Highly reliable until 2012, fully reliable after.
- HS 854810: HS02-17 code 854810 is then split into many codes in the HS22 revision. Amon the new codes, HS22 code 854913 is best suited for lithium batteries. However, with one data point (2022 only), the series cannot be reasonably adjusted for previous years. Values from HS02-17 code 854810 are therefore used with the caveat that it may include other types of battery waste. Low reliability.

Figure A.10 superimposes the adjusted data series on the raw data from Figure A.9, showing how the adjustment ensures the representation of LBSC products more precisely identified in the more recent HS revisions, while allowing to go back to 2002 without inconsistencies in the data series. The only caveat applies to HS code 854810 as detailed above. However, the values traded under this HS code are so small that the aggregate representation of the LBSC is virtually unaffected in any case.

For the aggregate LBSC, Figure A.11 shows the comparison between the adjusted series and the raw data according to different HS revisions. The adjusted series is consistent with the HS12/17/22 revisions and thus looks very reliable, while the HS02 overestimation of LBSC trade is mostly due to HS codes 382490 (chemicals and salts of inorganic acids) and 847989 (machines).

Table A.7: LBSC mapping and correspondence with HS codes and CPC patent codes.

Stage	Product description	HS product code (rev. 2022)	CPC patent code
1. Raw Materials	Graphite, natural	250410, 250490	C01B32/20, C01B32/21, C01B32/215, C01B32/22, C01B32/225, C01B32/23, H01M4/625
	Lithium ores	253090	C22B26/12, H01M4/382, H01M4/405
	Manganese ores	260200	C22B47/00, C22B47/0018, C22B47/0027, C22B47/0036, C22B47/0045, C22B47/0054, C22B47/0063, C22B47/0072, C22B47/0081, C22B47/009
	Nickel and Cobalt ores	260400, 260500, 750110, 750210, 750220, 750400, 810520	C22B23/00, C22B23/005, C22B23/02, C22B23/021, C22B23/023, C22B23/025, C22B23/028, C22B23/04, C22B23/0407, C22B23/0415, C22B23/0423, C22B23/0438, C22B23/0446, C22B23/0453, C22B23/0461, C22B23/0469, C22B23/0476, C22B23/0484, C22B23/0492
	Lithium carbonates	283691	C01D15/08
2. Refined Materials	Manganese oxides	282010, 282090	C01G45/02, C08K2003/2262, C25B1/21, H01M4/50, H01M4/502
	Lithium oxides	282520	C01D15/02
	Nickel and Cobalt oxides	282200, 282540, 750120	C01G51/04, C01G53/04, H01M4/52, H01M4/521, H01M4/523
	Nickel chlorides	282735	C01G53/09
	Chlorides (including lithium)	282739	C01D15/04
	Nickel sulphates	283324	C01G53/10, C22B23/043
	Sulphates (including manganese)	283329	C01G45/10
	Nickel and Cobalt waste and scrap	750300, 810530, 810590	C01G51/003, C22B23/06, C22B23/065, C25C1/08
	Manganese waste and scrap	811100	C25C1/10, C25C3/30
3. Machinery	Machines, including roll manufacturing	847989	H01M10/0404, H01M10/0409, H01M4/0435
4. Cell Components	Fluorides (including lithium)	282619, 282690	C01B25/455, C01D15/005
	LMO	284169	C01G45/1228, C01G45/1235, C01G45/1242, C01G45/1257, H01M4/505
	LCO	284190	C01G51/42, H01M4/525
	LFP,NCA,NCM,LNO	284290, 382499	C01B25/375, C01G51/44, C01G51/50, C01G51/52, C01G51/54, C01G51/56, C01G51/58, C01G51/60, C01G51/62, C01G51/64, C01G53/42, C01G53/44, C01G53/50, C01G53/52, C01G53/54, C01G53/56, C01G53/58, C01G53/60, C01G53/62, C01G53/64, H01M10/4242, H01M4/485, H01M4/58, H01M4/581, H01M4/5815, H01M4/582, H01M4/5825
	Phosphides, precursors for NCA and NCM	285390	C01B25/08, C01B25/081, C01B25/088, H01M4/5805
	Graphite, artificial	380110, 380120, 380190	C01B32/205, C04B35/52, C04B35/521, C04B35/522, C04B35/524, C04B35/528, C04B35/532, C04B35/536, H01M4/583, H01M4/5835, H01M4/587
	Plastics, in roll	391910	B29C53/581, B29C53/582, B29K2023/12, B29K2623/12, B32B2323/10, H01M50/403, H01M50/406, H01M50/417, H01M50/449, H01M50/451, H01M50/454, H01M50/457
	Aluminium foil	760720, 761699	B21B1/40, B21B2003/001, B32B15/20, H01M4/661, H01M4/662, H01M4/667
	Cells	850790	H01M4/0404, H01M4/366, Y10T29/49115
	Electrodes	854519	H01M4/13, H01M4/131, H01M4/1315, H01M4/133, H01M4/136, H01M4/137, H01M4/139, H01M4/1391, H01M4/13915, H01M4/1393, H01M4/1397, H01M4/1399
5. Battery	Li-ion Batteries	850760	H01M10/052, H01M10/0525
6. Recycling	Waste and scrap of batteries	854913	H01M10/54, Y02W30/84

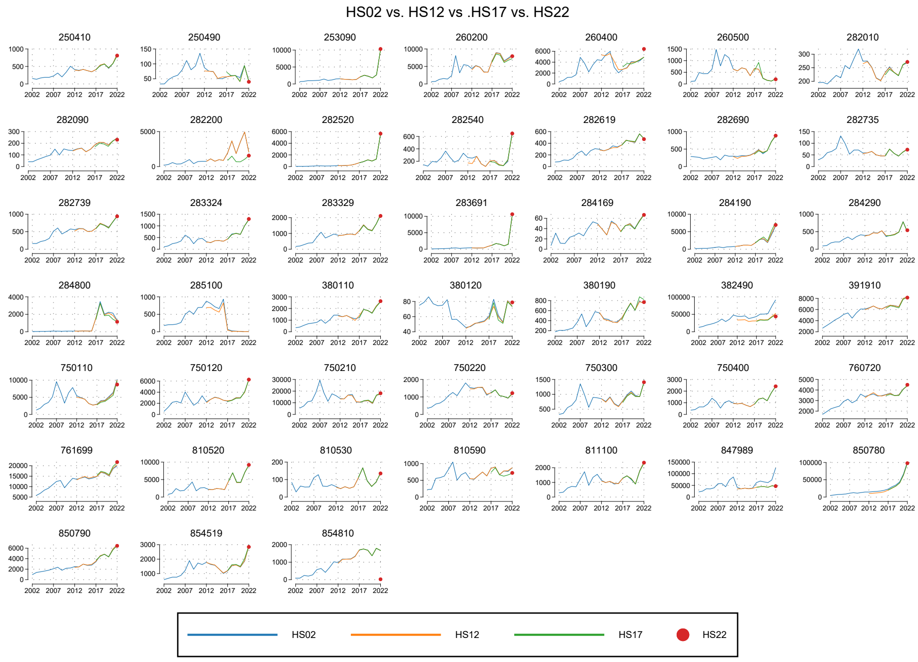
Source: authors' elaborations.

Table A.8: LBSC product codes and correspondences between HS revisions.

Correspondences between HS revisions					HS22-HS02	Trade value
HS 2002	HS 2007	HS 2012	HS 2017	HS 2022	relationship[1]	consistency[2]
250410	250410	250410	250410	250410	1:1	***
250490	250490	250490	250490	250490	1:1	***
253090	253090	253090	253090	253090	1:1	***
260200	260200	260200	260200	260200	1:1	***
260400	260400	260400	260400	260400	1:1	***[3]
260500	260500	260500	260500	260500	1:1	***
282010	282010	282010	282010	282010	1:1	***
282090	282090	282090	282090	282090	1:1	***
282200	282200	282200	282200	282200	1:1	***[4]
282520	282520	282520	282520	282520	1:1	***
282540	282540	282540	282540	282540	1:1	***
282619	282619	282619	282619	282619	1:n	***
282690	282690	282690	282690	282690	1:n	***
282735	282735	282735	282735	282735	1:1	***
282739	282739	282739	282739	282739	n:n	***
283324	283324	283324	283324	283324	1:1	***
283329	283329	283329	283329	283329	n:n	***
283691	283691	283691	283691	283691	1:1	***
284169	284169	284169	284169	284169	1:1	***
284190	284190	284190	284190	284190	1:n	***
284290	284290	284290	284290	284290	n:n	***
285100	285300	285300	285390	285390	n:n	**[5]
284800	284800	284800			n:n	
380110	380110	380110	380110	380110	1:1	***
380120	380120	380120	380120	380120	1:1	***
380190	380190	380190	380190	380190	1:1	***
382490	382490	382490	382499	382499	n:n	**[6]
391910	391910	391910	391910	391910	1:1	***
750110	750110	750110	750110	750110	1:1	***
750120	750120	750120	750120	750120	1:1	***
750210	750210	750210	750210	750210	1:1	***
750220	750220	750220	750220	750220	1:1	***
750300	750300	750300	750300	750300	1:1	***
750400	750400	750400	750400	750400	1:1	***
760720	760720	760720	760720	760720	1:1	***
761699	761699	761699	761699	761699	n:1	***
810520	810520	810520	810520	810520	1:1	***
810530	810530	810530	810530	810530	1:1	***
810590	810590	810590	810590	810590	1:1	***
811100	811100	811100	811100	811100	1:1	***
847989	847989	847989	847989	847989	n:1	**[7]
850780	850780	850760	850760	850760	n:1	***
850790	850790	850790	850790	850790	n:1	***
854519	854519	854519	854519	854519	n:1	***
854810	854810	854810	854810	854913	n:1	*[8]

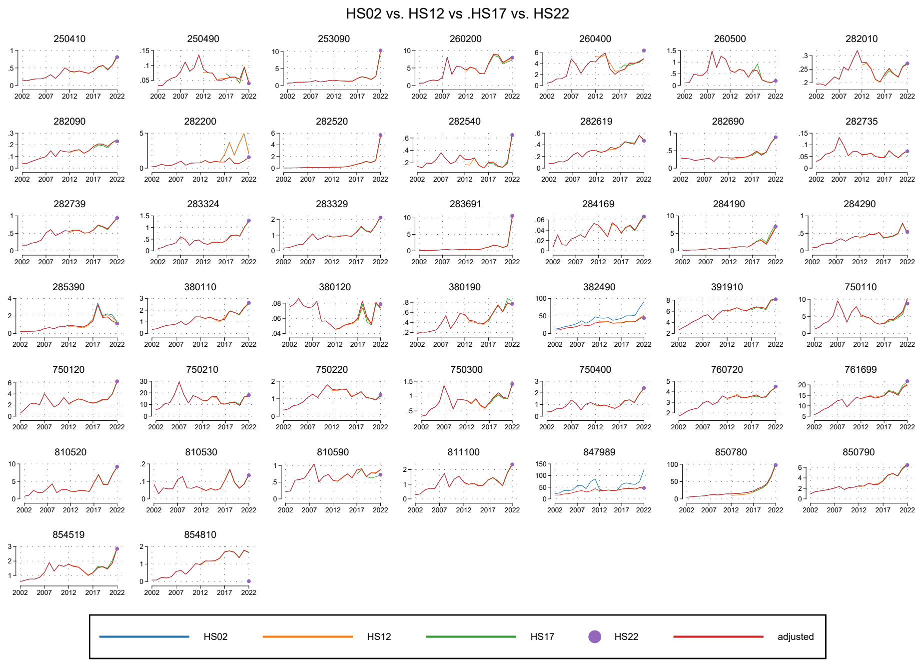
[1] Relationship legend: 1:1, the HS 2022 subheading is correlated with one and only one subheading in the previous HS; n:1, the HS 2022 subheading is a result of a split of one subheading in the previous classification into several subheadings; 1:n, the HS 2022 subheading is the result of merging several subheadings in the previous classification; n:n, the subheading is the result of a split and merge of several subheadings in the previous classification; [2] Trade value consistency between revisions: *, poor; **, good; ***, excellent; [3] HS rev. 2022 values slightly larger than previous classification revs; [4] HS rev. 2012 values between 2017 and 2021 larger than HS rev. 2017-2022 ones; [5] HS rev. 2002-2012 consistent before 2017, HS rev. 2012-2022 consistent after 2017; [6] HS rev. 2002 values larger than other revs. after 2012; [7] HS rev. 2002 values larger than other revs. since 2017; [8] HS rev. 2022 values much smaller than previous revs.
Source: authors' elaborations based on United Nations Statistics Division (UNSD) correlation and conversion tables and BACI data. Further documentation available at https://unstats.un.org/unsd/classifications/Econ.

Figure A.9: HS trade data consistency between HS revisions (raw data).



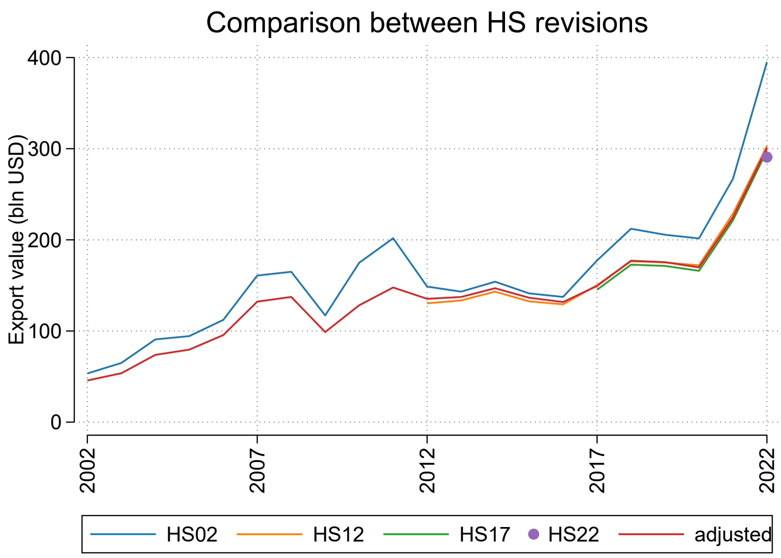
Source: authors' elaborations based on BACI data.

Figure A.10: HS adjusted trade data vs. raw data.



Source: authors' elaborations based on BACI data.

Figure A.11: Total LBSC adjusted trade data vs. raw data.

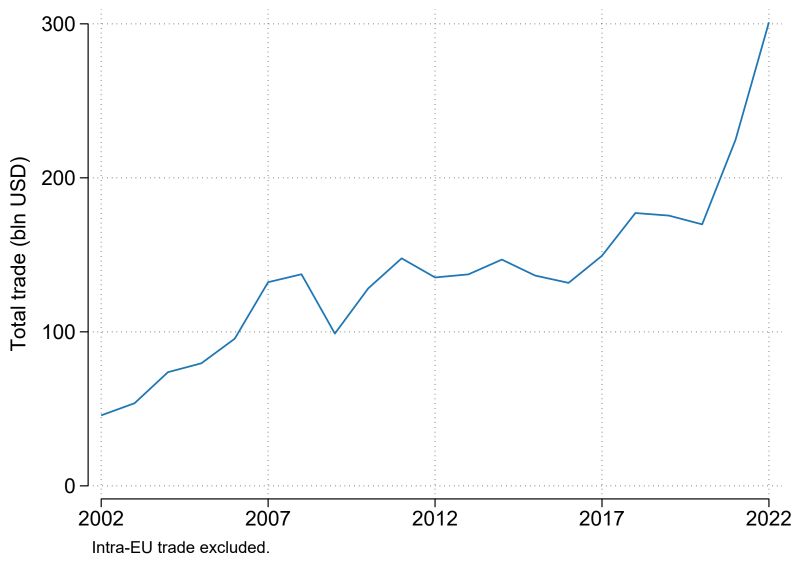


Source: authors' elaborations based on BACI data.

Appendix B Additional Descriptives

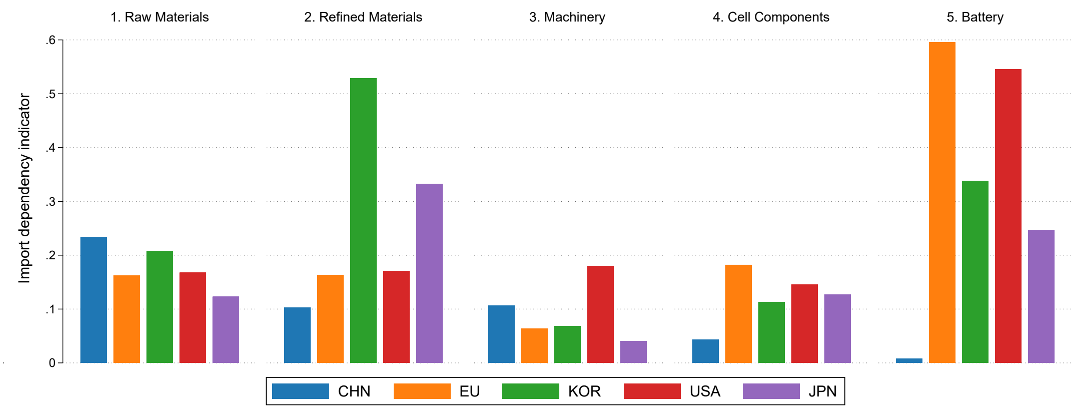
B.1 Trade

Figure A.12: World exports of LIB-related products.



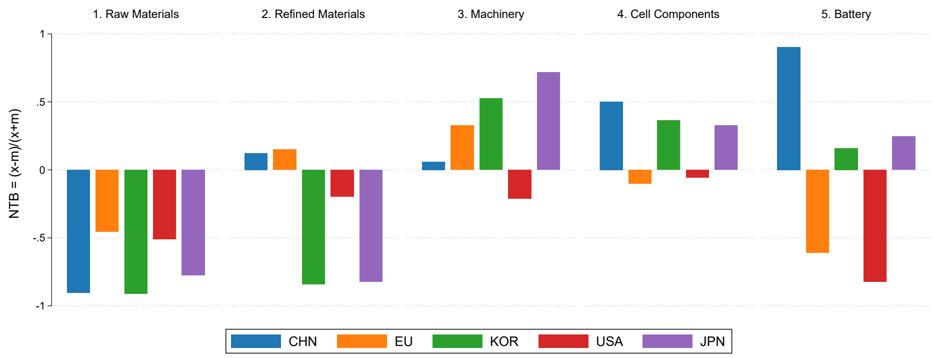
Source: authors' elaborations based on BACI data.
Note: the figures exclude intra-EU trade.

Figure A.13: Import dependency indicator (IDEP) by stage and country (2022).



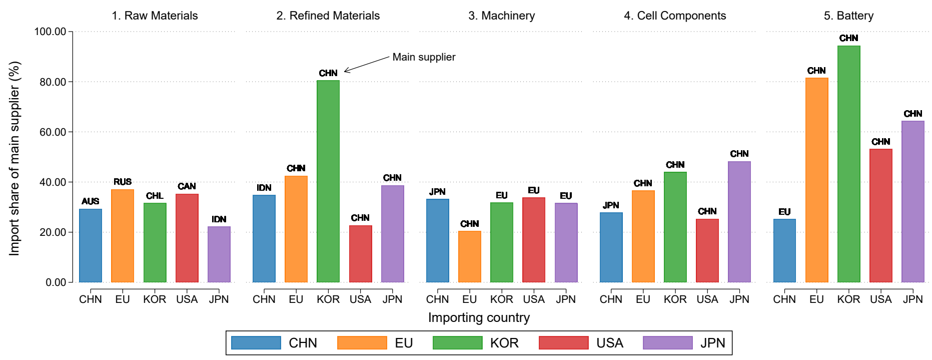
Source: authors' elaborations based on BACI data.

Figure A.14: Normalized trade balance by stage and country (2022).



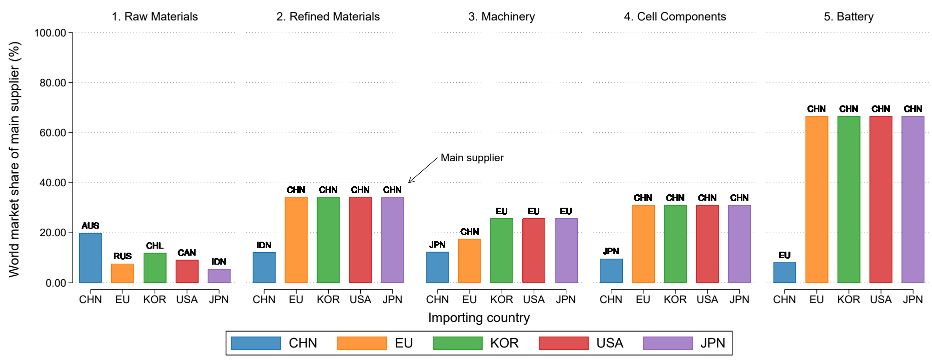
Source: authors' elaborations based on BACI data.

Figure A.15: Import share of main supplier by stage and country (2022).



Source: authors' elaborations based on BACI data.

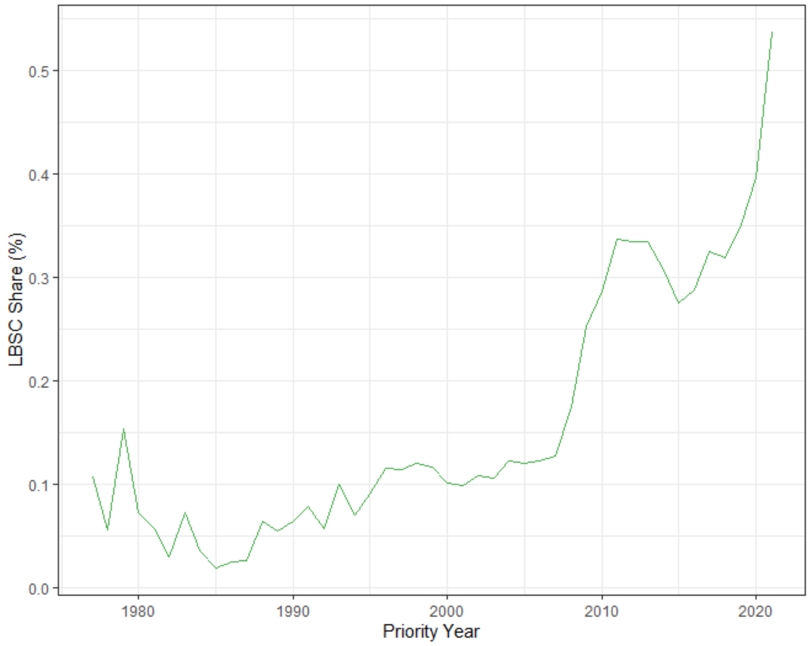
Figure A.16: World export share of main supplier by stage and country (2022).



Source: authors' elaborations based on BACI data.

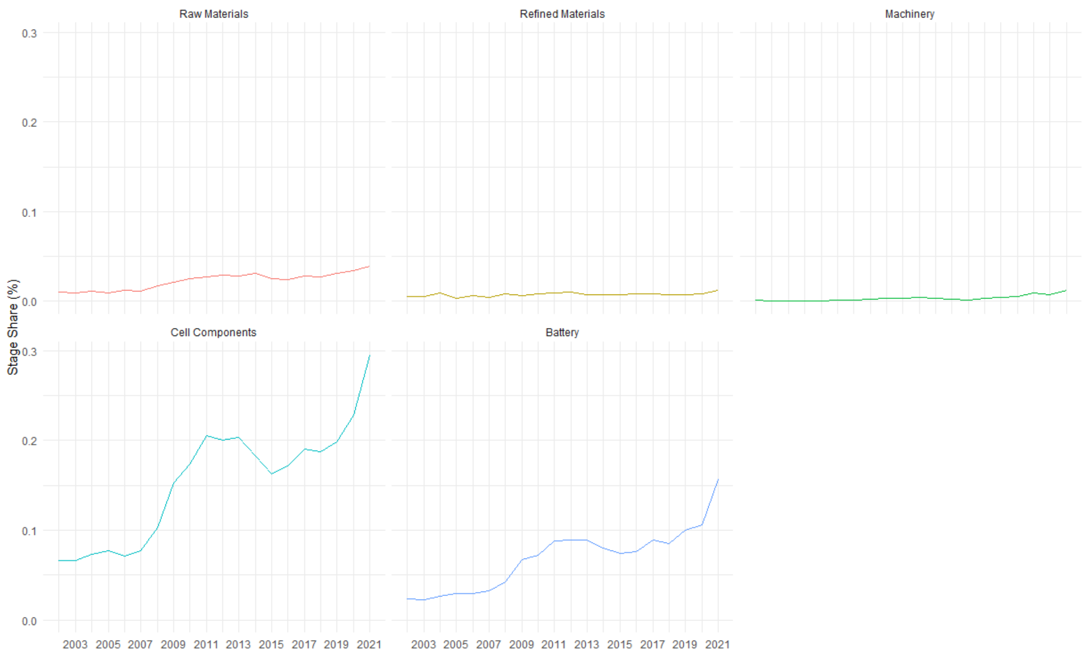
B.2 Patents

Figure A.17: World patent share in LIB-related products, globally filed at WIPO.



Source: authors' elaborations based on Regpat data.

Figure A.18: World patent share in different stages of the LBSC.



Source: authors' elaborations based on Regpat data.

B.3 Product level intelligence

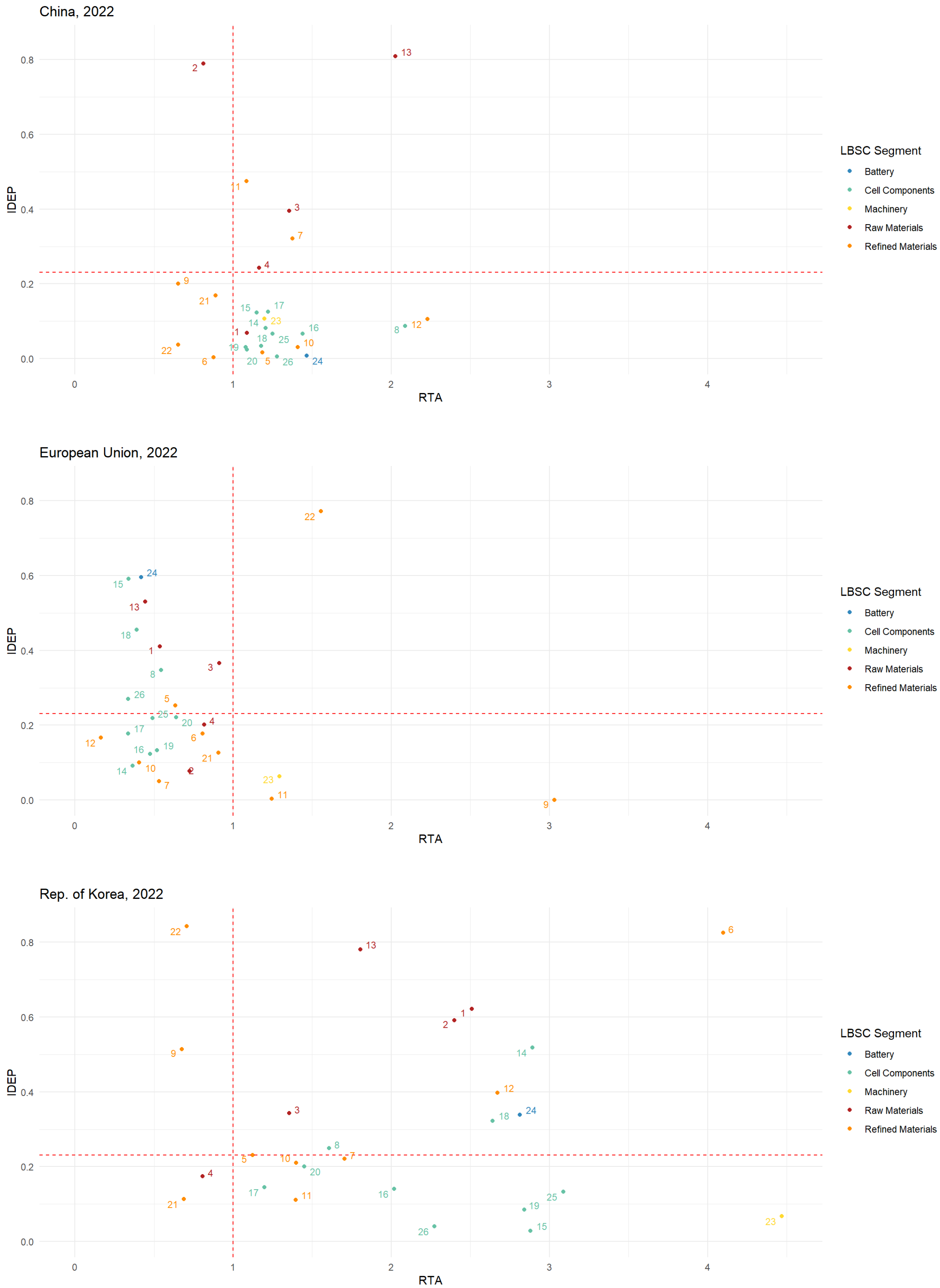
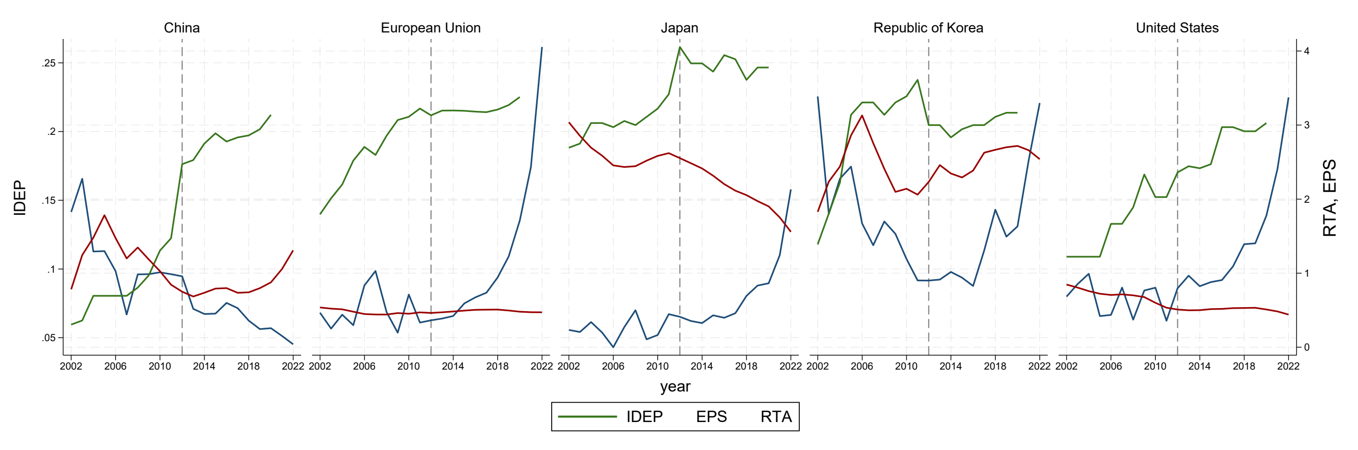


Figure A.19: Products labels correspondence below.

Figure A.20: Products labels correspond to: 1 - Graphite, natural; 2 - Lithium ores; 3 - Manganese ores; 4 - Nickel and Cobalt ores; 5 - Manganese oxides; 6 - Lithium oxides; 7 - Nickel and Cobalt oxides; 8 - Fluorides (including lithium); 9 - Nickel chlorides; 10 - Chlorides (including lithium); 11 - Nickel sulphates; 12 - Sulphates (including manganese); 13 - Lithium carbonates; 14 - LMO; 15 - LCO; 16 - LFP,NCA,NCM,LNO; 17 - Phosphides, precursors for NCA and NCM; 18 - Graphite, artificial; 19 - Plastics, in roll; 20 - Aluminium foil; 21 - Nickel and Cobalt waste and scrap; 22 - Manganese waste and scrap; 23 - Machines, including roll manufacturing; 24 - Li-ion Batteries; 25 - Cells; 26 - Electrodes

Figure A.21: Countries' trend in IDEP, EPS, and RTA.



Source: authors' elaborations based on BACI, Regpat, OECD data.

Appendix C Additional Estimates

C.1 RTA heterogeneity across countries

	China	EU	Japan	Korea	USA
Constant	0.0562***	0.0572***	0.0575***	0.0604***	0.0641***
	(0.0173)	(0.0174)	(0.0171)	(0.0167)	(0.0180)
$IDEP_{i,k,t-1}$	0.670***	0.670***	0.669***	0.668***	0.665***
	(0.0339)	(0.0340)	(0.0338)	(0.0337)	(0.0344)
$RTA_{i,k,t-1}$	-0.00825**	-0.00805**	-0.00765*	-0.0124**	-0.00745**
	(0.00392)	(0.00354)	(0.00396)	(0.00540)	(0.00349)
$EPS_{i,t-1}$	-0.00175	-0.00171	-0.00151	-0.00225	-0.00209
	(0.00687)	(0.00697)	(0.00707)	(0.00688)	(0.00697)
$RTA_{i,k,t-1} \times D_{China}$	-0.000113				
	(0.00916)				
$RTA_{i,k,t-1} \times D_{EU}$		-0.0123			
		(0.0218)			
$RTA_{i,k,t-1} \times D_{Japan}$			-0.00371		
			(0.00889)		
$RTA_{i,k,t-1} \times D_{Korea}$				0.00759	
				(0.00642)	
$RTA_{i,k,t-1} \times D_{USA}$					-0.0525
					(0.0326)
Panel FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Observations	1045	1045	1045	1045	1045
# Groups	55	55	55	55	55
Within R^2	0.454	0.454	0.454	0.455	0.456
F-statistic	52.58***	52.44***	52.34***	50.77***	52.63***

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.9: Fixed Effects Estimates with RTA Interaction — Downstream

	China	EU	Japan	Korea	USA
Constant	-0.00406	-0.0203	-0.0230	-0.0167	-0.0232
	(0.0155)	(0.0143)	(0.0141)	(0.0139)	(0.0143)
$IDEP_{i,k,t-1}$	0.802***	0.792***	0.789***	0.787***	0.798***
	(0.0340)	(0.0327)	(0.0324)	(0.0320)	(0.0338)
$RTA_{i,k,t-1}$	-0.00545	-0.00813**	-0.00744**	-0.0106***	-0.00840**
	(0.00393)	(0.00367)	(0.00371)	(0.00391)	(0.00368)
$EPS_{i,t-1}$	-0.00368	-0.00229	-0.00208	-0.00264	-0.00224
	(0.00501)	(0.00495)	(0.00495)	(0.00494)	(0.00496)
$RTA_{i,k,t-1} \times D_{China}$	-0.0112*				
	(0.00573)				
$RTA_{i,k,t-1} \times D_{EU}$		-0.00341			
		(0.00927)			
$RTA_{i,k,t-1} \times D_{Japan}$			-0.00376		
			(0.00285)		
$RTA_{i,k,t-1} \times D_{Korea}$				0.00481*	
				(0.00266)	
$RTA_{i,k,t-1} \times D_{USA}$					0.00756
					(0.00795)
$IDEP_{i,k,0}$	0.0850***	0.0940***	0.0861***	0.0844***	0.0906***
	(0.0243)	(0.0244)	(0.0239)	(0.0234)	(0.0244)
$\overline{RTA}_{i,k}$	0.00137	0.00175	0.00332	0.00154	0.00321
	(0.00452)	(0.00502)	(0.00461)	(0.00460)	(0.00460)
$\overline{EPS}_i$	0.00778	0.0140**	0.0152**	0.0144**	0.0137**
	(0.00684)	(0.00699)	(0.00670)	(0.00654)	(0.00646)
σ_u	0.00158	0.00571	0.00542	0.00553	0.00414
	(0.0190)	(0.00569)	(0.00579)	(0.00561)	(0.00766)
Time FE	Yes	Yes	Yes	Yes	Yes
Observations	1045	1045	1045	1045	1045
# Groups	55	55	55	55	55
Log-Likelihood	1490.6	1488.8	1489.6	1490.5	1489.2
Chi-squared	2162.7***	1976.9***	2047.2***	2086.5***	2048.0***

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.10: CRE Tobit Estimates with RTA Interaction — Downstream

C.2 Robustness Checks: Alternative Imports Dependency Indicator

	Full	UP	MID	DOWN
Constant	0.0515***	0.0498**	0.0651***	0.0479***
	(0.00781)	(0.0194)	(0.0132)	(0.0113)
$IDEP^{rob}_{i,k,t-1}$	0.683***	0.664***	0.688***	0.677***
	(0.0259)	(0.0397)	(0.0454)	(0.0345)
$RTA_{i,k,t-1}$	0.000375	0.00649***	0.000225	-0.00655**
	(0.000541)	(0.00142)	(0.000535)	(0.00314)
$EPS_{i,t-1}$	0.00153	0.0163**	-0.00232	0.000111
	(0.00324)	(0.00732)	(0.00548)	(0.00457)
Panel FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	2468	473	950	1045
# Groups	130	25	50	55
Within R^2	0.481	0.562	0.497	0.466
F-statistic	48.79***	423.2***	37.36***	53.42***

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.11: Fixed Effects Estimates by Stage (alternative IDEP)

	China	EU	Japan	Korea	USA
Constant	0.0357***	0.0420***	0.0396***	0.0489***	0.0490***
	(0.0125)	(0.0113)	(0.0119)	(0.0121)	(0.0116)
$IDEP^{rob}_{i,k,t-1}$	0.660***	0.669***	0.671***	0.663***	0.659***
	(0.0371)	(0.0347)	(0.0331)	(0.0366)	(0.0384)
$RTA_{i,k,t-1}$	-0.00750**	-0.00713**	-0.00606**	-0.00515	-0.00700**
	(0.00302)	(0.00321)	(0.00297)	(0.00319)	(0.00317)
$EPS_{i,t-1}$	0.0114*	0.00114	0.000821	0.00439	-0.00183
	(0.00604)	(0.00464)	(0.00460)	(0.00563)	(0.00463)
$EPS_{i,t-1} \times D_{China}$	-0.0132**				
	(0.00602)				
$EPS_{i,t-1} \times D_{EU}$		0.0175***			
		(0.00653)			
$EPS_{i,t-1} \times D_{Japan}$			0.0136		
			(0.00850)		
$EPS_{i,t-1} \times D_{Korea}$				-0.0270***	
				(0.00867)	
$EPS_{i,t-1} \times D_{USA}$					0.0196***
					(0.00538)
Panel FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Observations	1045	1045	1045	1045	1045
# Groups	55	55	55	55	55
Within R^2	0.470	0.469	0.468	0.476	0.474
F-statistic	57.79***	52.62***	56.59***	44.98***	54.63***

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.12: Fixed Effects Regression with Country Dummies in Downstream (alternative IDEP)

	Full	UP	MID	DOWN
Constant	-0.0154	-0.00667	-0.0227	-0.00286
	(0.00976)	(0.0270)	(0.0162)	(0.0102)
$IDEP^{rob}_{i,k,t-1}$	0.788***	0.748***	0.788***	0.800***
	(0.0193)	(0.0384)	(0.0303)	(0.0327)
$RTA_{i,k,t-1}$	0.000550	0.00648***	0.000416	-0.00582**
	(0.000618)	(0.00206)	(0.000701)	(0.00270)
$EPS_{i,t-1}$	0.000985	0.0142***	-0.00131	-0.00111
	(0.00246)	(0.00518)	(0.00419)	(0.00364)
$IDEP^{rob}_{i,k,0}$	0.222***	0.220***	0.285***	0.104***
	(0.0257)	(0.0541)	(0.0454)	(0.0267)
$\overline{RTA}_{i,k}$	-0.00126	0.00163	0.000158	0.00256
	(0.00174)	(0.00812)	(0.00209)	(0.00337)
$\overline{EPS}_{i,k}$	0.00671*	-0.00356	0.00982	0.00704
	(0.00404)	(0.0101)	(0.00670)	(0.00474)
σ_u	0.0182***	0.0237***	0.0179***	0.00413
	(0.00221)	(0.00512)	(0.00353)	(0.00425)
Time FE	Yes	Yes	Yes	Yes
Observations	2468	473	950	1045
Groups	130	25	50	55
Log-Likelihood	4083.5	831.4	1520.6	1811.2
Chi-squared	6435.1***	1168.1***	3666.5***	2335.4***

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.13: Random Effect Tobit by Stage (alternative IDEP)

	(1) China	(2) EU	(3) Japan	(4) Korea	(5) USA
Constant	0.0271*	0.000730	-0.00613	-0.00388	-0.0100
	(0.0151)	(0.0110)	(0.0106)	(0.0104)	(0.0106)
$IDEP^{rob}_{i,k,t-1}$	0.784***	0.798***	0.801***	0.799***	0.790***
	(0.0332)	(0.0329)	(0.0325)	(0.0330)	(0.0332)
$RTA_{i,k,t-1}$	-0.00653**	-0.00589**	-0.00581**	-0.00583**	-0.00614**
	(0.00270)	(0.00270)	(0.00270)	(0.00270)	(0.00269)
$EPS_{i,t-1}$	0.00564	-0.00101	-0.00121	-0.000952	-0.00151
	(0.00442)	(0.00364)	(0.00364)	(0.00365)	(0.00362)
$EPS_{i,t-1} \times D_{China}$	-0.00786***				
	(0.00289)				
$EPS_{i,t-1} \times D_{EU}$		0.00164			
		(0.00181)			
$EPS_{i,t-1} \times D_{Japan}$			-0.00156		
			(0.00154)		
$EPS_{i,t-1} \times D_{Korea}$				-0.000934	
				(0.00165)	
$EPS_{i,t-1} \times D_{USA}$					0.00466**
					(0.00190)
$IDEP^{rob}_{i,k,0}$	0.106***	0.105***	0.0959***	0.110***	0.111***
	(0.0263)	(0.0267)	(0.0269)	(0.0293)	(0.0269)
$\overline{RTA}_{i,k}$	0.00524	0.00444	0.00340	0.00308	0.00396
	(0.00351)	(0.00396)	(0.00345)	(0.00350)	(0.00342)
$\overline{EPS}_{i,k}$	-0.00831	0.00454	0.00858*	0.00695	0.00921*
	(0.00734)	(0.00548)	(0.00495)	(0.00476)	(0.00484)
σ_u	0.00444	0.00434	0.00363	0.00445	0.00453
	(0.00396)	(0.00411)	(0.00465)	(0.00411)	(0.00399)
Time FE	Yes	Yes	Yes	Yes	Yes
Observations	1045	1045	1045	1045	1045
Groups	55	55	55	55	55
Chi-squared	2411.5***	2331.2***	2415.8***	2300.6***	2412.7***

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.14: Random effect Tobit by country in the Downstream (interaction with EPS) (alternative IDEP)

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