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Trade and Industrial Policy in Supply Chains: Directed Technological Change in Rare Earths

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Trade and Industrial Policy in Supply Chains: Directed Technological Change in Rare Earths

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Abstract

Trade and industrial policies, while primarily intended to support domestic industries, may unintentionally stimulate technological progress abroad. We document this mechanism in the case of rare earth elements (REEs) – critical inputs for manufacturing at the knowledge frontier, with low elasticity of substitution, inelastic supply, and high production and processing concentration. To assess the importance of REEs across industries, we construct an input-output table that includes disaggregated REE inputs. Using REE-related patents categorized by a large language model, trade data, and physical and chemical substitution properties of REEs, we show that the introduction of REE export restrictions by China led to a global surge in innovation and exports in REE-intensive downstream sectors outside of China. To rationalize these findings and quantify the global impact of the adverse REE supply shock, we develop a quantitative general-equilibrium model of trade and directed technological change. We also propose a structural method to estimate sectoral input substitution elasticities for REEs from patent data and find REEs to be complementary inputs. Under endogenous technologies and with complementary inputs, input-supply restrictions on REEs induce a surge in REE-enhancing innovation and lead to an expansion of REE-intensive downstream sectors.

Keywords: Trade Restrictions, Industrial Policy, Global Value Chains, Rare Earths, Directed Technological Change, Input-Output Linkages, Downstream Sectors, Innovation
JEL Codes: F13, F14, F42, O33, O47

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1 Introduction

Governments traditionally use industrial policies to selectively promote economic activity in specific industries. While industrial policy can aim at correcting market imperfections that misalign private and social benefits, its effects are complex when industries are interconnected through global value chains. This concern is particularly relevant for industries that provide essential, hard-to-substitute inputs for other sectors. Rare earth elements (REEs) are a leading example: they are critical for a range of advanced manufacturing goods, their supply is inelastic and heavily concentrated in China. These features have made REEs central to debates on supply-chain vulnerabilities in the context of geopolitical tensions and the green transition.

In this paper, we provide an empirical and quantitative analysis of the effects of China's policy that unexpectedly restricted the global supply of REEs in 2010. We advance both reduced-form causal evidence and a general-equilibrium analysis based on a novel quantitative trade model with directed technological change and input-output (IO) linkages. Our key finding is that policies that create an adverse supply shock of essential inputs can trigger a strong positive response of innovation and economic activity in foreign downstream industries that intensively use these inputs. Intuitively, when inputs are complements (i.e. elasticity of substitution below one), a surge in the price of an input endogenously creates technological change that is directed at increasing the efficiency of input use, potentially leading to an expansion of downstream industries abroad that intensively use the input at the expense of other sectors. This endogenous productivity response significantly mitigates the effect of restrictive policies that would otherwise severely hamper foreign industries. We show that REEs, because of their particular characteristics, are susceptible to this mechanism.

REEs, crucial inputs in many manufacturing products due to their chemical properties, are economically interesting due to at least four characteristics. First, REEs have broad and diverse applications at the knowledge frontier across various industries, including electronics, lighting, aerospace, defense, automotive, medical, and clean energy.[1] Second, in many applications, REEs are difficult to substitute with other inputs due to the high specificity of their applications (USGS, 2002), even though their input quantities are oftentimes tiny. Third, their supply over time tends to be inelastic due to their nature as byproducts as well as their toxic processing requirements (Nassar et al., 2015; EPA, 2012) and long time-to-build in mining and processing. Fourth, the supply for REE mining and processing is highly concentrated. Notably, China controls approximately 60% of the mining and 90% of the post-mine processing of these elements (BIS, 2023), distinguishing them from most other critical minerals whose production is geographically dispersed, such as lithium.

[1] Critical uses include permanent magnets, which are present in electronic devices as well as vehicle motors and wind turbines, and various chemical catalysts, which are essential for energy efficiency, environmental protection, and renewables production, USGS (2022).

An important challenge in assessing the importance of REE inputs for downstream industries is that detailed information on REE-producing and -using industries is not explicitly available in standard industry data and IO tables. Therefore, the first contribution that this paper makes is the construction of a novel IO table that maps the use of REEs across industries into the U.S. Bureau of Economic Analysis supply-use table. This IO table combines quantity information on the REE content of all key applications of REEs at the level of individual chemical elements that we obtain from the U.S. Geological Survey with element-level price information taken from industry sources. This augmented IO table allows us to calculate total REE requirements for each 4-digit SIC manufacturing industry.

Our second contribution is an empirical investigation of an adverse REE supply shock on REE-using industries across the world. We exploit the rare earth crisis of 2010 as a quasi-natural experiment. Following a territorial dispute with Japan in 2010, China increased restrictions on its exports of REEs to the rest of the world. With China being essentially a monopolist in the extraction and sales of most REE minerals at that time, this negative REE supply shock caused a surge in international REE prices amid sourcing uncertainties. Global REE unit prices spiked by factors of 10 to 45, remaining high for about five years, as export restrictions were in place. In March 2012, the U.S. brought a case to the World Trade Organization (WTO) Dispute Settlement Body against these export restrictions on REEs. Following a WTO ruling, China relaxed its export restrictions on REEs in 2015, restoring access to these critical materials on the global market. Thus, while the shock ultimately turned out to be temporary, the duration of Chinese supply restrictions was ex ante unclear. Moreover, China's actions revealed its willingness to weaponize export restrictions, and it became clear that it could potentially repeat similar measures.[2]

Using data on manufacturing industries across countries, we provide evidence for the impact of Chinese export restrictions on REEs on downstream industries. Our analysis emphasizes directed technological change by investigating the impact of an REE supply shock on innovation in downstream industries, in contrast to existing literature, which typically examines the restricted inputs directly. We employ difference-in-differences estimates with continuous treatment intensity, where the exposure of each downstream industry to the contractionary REE supply shock depends on its total REE input requirement by chemical element and the substitutability of each element as determined by their physical-chemical properties (Graedel et al., 2015). To measure innovation activities downstream, we obtain the universe of granted patents across countries that mention REEs, chemical compounds of REEs, or REE-specific technologies from the Google Patent Research Database. We use a large language model (LLM) to identify those patents within the corpus

[2]China eventually did reimpose restrictions on six REEs and rare earth permanent magnets in April 2025 as a response to the second Trump administration's new tariffs (Bradsher, 2025). This was an escalation from an earlier ban on the exports of gallium, germanium, antimony, and superhard materials to the U.S. in late 2024 (Pierson et al., 2024).

that describe key improvements of REE-using technologies and to link each patent to its using industry.

Our evidence supports the hypothesis that the supply shock triggered directed technological change in REE-using industries: we find a surge of patenting activity outside of China for technologies that improve the efficiency of REE use, including through substitution.[3] This surge in REE-related patents exceeds the overall growth in industry patenting.[4] In line with this finding, auto companies in Japan (e.g. Toyota and Honda) and abroad (e.g. Tesla, Renault, GM), as well as electronic companies (e.g. Hitachi and Phillips), announced efforts as soon as 2010 to create new products using less or no REEs (Banner, 2022; Reuters, 2021; Bomgardner, 2018; Owano, 2018; Halvorson, 2022; Houser, 2023).[5]

Having shown that the REE supply shock triggered an increase in REE-enhancing innovation in downstream industries, we assess the impact on the competitiveness of downstream industries by studying the evolution of exports. We find that REE-intensive manufacturing industries outside China expanded their exports compared to less REE-intensive industries in the same country. On average, manufacturing industries that are one standard deviation more REE-sensitive than the cross-sectoral average experienced a 0.35 percentage point (p.p.) higher annual growth rate in exports between 2010 and 2018 compared to the period 2002-2009. The effect on export growth was particularly large for manufacturing industries located in Europe or Japan. By contrast, similar export growth of REE-intensive industries did not occur within China, where access to REEs was abundant. Aside from element-level variation, we also consider country-level variation in the exposure to the REE supply shock. Here, we consider either historical REE sourcing shares from China or country-specific spikes of REE import unit values. In line with our previous results, we find that REE-intensive industries outside of China expanded their REE-related patenting and export growth relative to other industries.

Our third contribution is to quantify the impact of China's REE export restrictions on downstream industries using a novel quantitative general-equilibrium (GE) trade model featuring comparative

[3]We consider inventing REE-free substitutes to be an extreme form of REE-saving technological change. Our model interprets both efficiency increases and inventing REE-free substitutes as increases in the effective productivity of the REE input bundle.

[4]We also complement our patent analysis with panel evidence on total factor and labor productivity. While relative productivity increased in REE-intensive downstream industries outside of China in response to the adverse REE supply shock, we see relative productivity declines in China's REE-intensive industries following the REE supply shock.

[5]In January 2011, GM filed a patent for a powder coating process that reduced dysprosium and terbium usage in REE magnets by at least 20% preserving their magnetic properties, noting supply constraints in the filing. In July 2011, Skyworks Solutions patented a yttrium substitute in synthetic garnets for electronic microwave devices, citing rising costs due to restricted yttrium supply. By 2016, Toyota cut dysprosium in the Prius and, in 2018, reduced neodymium in electric motor magnets by 20%. Volkswagen followed, while Nissan and BMW unveiled magnet-free motor prototypes in 2022-2023. Other industries also sought REE reductions, such as catalysts using less cerium (Machida et al., 2017). See Appendix B.3 for other examples.

advantage based on factor abundance and directed technological change. The model integrates a structural multi-sector gravity model of trade with a detailed IO structure (see Caliendo and Parro, 2015; Fadinger et al., 2024) with a two-factor Heckscher-Ohlin model (Chor, 2010; Burstein and Vogel, 2017; Morrow and Trefler, 2022) and a static variant of Acemoglu's (2002) model of directed technological change. In this framework, industry-level goods are differentiated by origin, and perfectly competitive firms produce output using a combination of intermediate inputs and a value-added bundle. The value-added bundle aggregates REE inputs and equipped labor using a CES function with industry-specific substitution parameters. REE inputs are traded internationally, with China acting as the sole supplier, thus allowing it to impose export taxes unilaterally.

We examine two model variants. In the short-run version, technology is held fixed and comparative advantage is determined by factor abundance. Under this scenario, a Chinese export tax on REEs raises input costs for downstream industries outside of China — especially for those industries where the elasticity of substitution between REE inputs and labor is low and for those that are more dependent on REEs. This leads to a contraction of REE-intensive industries relative to labor-intensive ones in the rest of the world, while China's relative production of REE-intensive goods expands.

By contrast, in the long-run version of the model, technology is endogenous, and its factor bias is shaped by firms' targeted innovation efforts in the REE or labor input layers. A key determinant of the direction of technological change in response to a Chinese REE export tax are each industry's REE intensity as well as its elasticity of substitution between REEs and equipped labor. If REEs and equipped labor are complements in a given industry, a negative supply shock to REEs shifts the direction of innovation toward REE-saving technologies. Moreover, this effect is stronger the more REE intensive an industry is. In this case, rising global REE prices increase the profitability of innovations that improve REE efficiency. When negative innovation externalities are sufficiently strong, this technological response can more than offset the direct cost increase resulting from higher REE prices, leading to a decline in downstream production costs of REE-intensive industries relative to labor-intensive ones. As a result, REE-intensive industries may expand relative to labor-intensive industries outside China.

We calibrate our model using trade and production data. Central to the calibration are the industry-level elasticities of substitution between REEs and labor, as well as each industry's reliance on REE inputs. Due to the absence of comprehensive international data on REE expenditure shares, standard estimation techniques for substitution elasticities are not applicable. As a fourth contribution, we thus develop a novel structural estimation method for the elasticity of substitution between REEs and labor. This approach exploits observable differences in innovation activity —

measured by the relative number of patents aimed at improving REE input efficiency — and relates them to variation in relative REE prices. Our estimates reveal that the elasticity of substitution between REEs and labor is well below unity in many industries. Given these estimates, we calibrate industry-specific REE input intensities using U.S. data. We find that industries with higher REE intensity also exhibit lower substitution elasticities, providing empirical support for our proposed theoretical mechanism.

The model qualitatively and quantitatively replicates the patterns observed in our reduced-form evidence. When technology adapts endogenously, an increase in global REE prices — triggered by the export restriction — induces a sufficiently strong directed technological response, causing REE-intensive industries to expand relative to other industries outside of China. While the policy yields a modest welfare gain for China, the negative impact on GDP and welfare in other countries is mitigated almost entirely by the endogenous technological adjustment, which significantly reduces global demand for REEs and thereby China's ability to extract rents from other countries via export taxes. We further demonstrate that directed technological change is crucial for these outcomes. In the short-run version of the model with fixed technologies, global production and exports in REE-intensive industries shift markedly in favor of China. In this scenario, China experiences a substantial economic boom and large welfare gains from export taxes due to its high degree of monopoly power, whereas other countries suffer considerable declines in real GDP and welfare. Overall, our analysis links the quantitative effects of export restrictions on REEs to their distinctive technological and institutional features — namely low substitutability, inelastic supply and high market concentration — in a highly policy-relevant context.

Related Literature: Our theoretical approach builds on the literature on modern quantitative trade models. Seminal contributions include Eaton and Kortum (2002), Costinot and Rodríguez-Clare (2014), and Caliendo and Parro (2015). Caliendo and Parro (2022) provide a comprehensive overview of trade policy in this class of models, while Ossa (2014) analyzes strategic trade policy, and Lashkaripour and Lugovskyy (2023) examine the interaction between trade and industrial policies in settings with scale economies. We contribute to this literature by incorporating directed technological change into a quantitative trade model. While the existing literature largely examines import tariffs, our focus is on export taxes and quantity restrictions.

In the field of innovation, our work relates to studies such as Acemoglu (1998, 2002), Acemoglu et al. (2012), and Aghion et al. (2016) on directed technological change. The latter authors find that firms in the auto industry innovate relatively more in clean technologies when they face higher tax-inclusive fuel prices but document path dependence in the type of innovation (firms' history and aggregate spillovers). In terms of a global economy, Acemoglu et al. (2015) highlight the complex relationship between direction of technological progress and offshoring, which can both drive skill-biased technological change and spur innovations favoring unskilled labor. More generally, a series of papers on biased technological change, document how innovation favors a particular input due to its relative supply or price, with Kennedy (1964) being one seminal work. In a historical context, Hanlon (2015) finds that the blockade on cotton from the Southern U.S. during the U.S. Civil War spurred technological progress in the use of cotton inputs from India in a context where inputs are gross substitutes. Popp (2002) finds that higher energy prices induced more innovation in energy-saving technology, proxied by patents. Hassler et al. (2021) model energy-saving technological change to estimate the elasticity of substitution between energy and labor or capital inputs. Relatedly, Blum (2010) documents empirically for a large sample of countries that changes in countries' relative factor endowments do not only lead to Heckscher-Ohlin forces by shifting the output mix of economies' but also change factor returns in the long run, which leads to directed technological change, shifting producers' isoquants in the long run.

In contrast to existing work, we emphasize the propagation effects of a deliberate industrial-policy intervention targeting an essential and concentrated input – characterized by low substitutability and inelastic supply – on downstream innovation and productivity in a modern setting. Furthermore, our quantitative general-equilibrium analysis of REE export taxes provides a detailed welfare assessment of their impact on downstream innovation.

The academic literature on industrial policy is vast, as summarized in Harrison and Rodríguez-Clare (2010) and Juhász et al. (2024). Empirical evidence on the effect of industrial policy is mixed, fueling the debate. Criscuolo et al. (2019), for example, find positive effects on incumbent firms' investment and employment but not TFP for regional policies. Bartelme et al. (2025) explore the theoretical and empirical evidence of industrial policy subsidies based on external economies of scale, finding limited empirical support. The analysis reveals significant variation in economies of scale across manufacturing sectors. However, despite this variation, in highly open economies, the impact of such policies appears to be minimal and not transformative. Studying industrial policy in high-tech sectors, Barwick et al. (2024) find that targeted subsidies increase firm-level innovation but have modest spillover effects on industry productivity. The authors highlight risks of resource misallocation, questioning the efficiency of such interventions. Kee and Xie (2025) examine Indonesia's export restrictions on nickel and highlight the unintended negative impact on Indonesia's own downstream industries as lower domestic nickel prices enable the entry of smaller, less efficient steel-using firms. In contrast, Juhász et al. (2024) offer a more nuanced and generally positive perspective on industrial policy, highlighting its potential to drive structural economic transformation. Liu (2019) finds that targeted industrial policies can enhance efficiency by correcting distortions in upstream sectors.

Equally rich is the literature on supply chains and trade restrictions, with a recent overview by

Fajgelbaum and Khandelwal (2022) and significant works by Grossman et al. (2024), and Bown et al. (2023). A vast number of papers document the effects of trade restrictions on global supply chains. Barattieri and Cacciatore (2023) show that protectionist trade barriers disrupt production networks, harming downstream firms through higher input costs and job losses. Recent studies focusing on U.S. tariffs document a "great reallocation" of import sourcing away from China, documenting widespread reallocation and negative effects on prices and welfare (Amiti et al. 2019, Fajgelbaum et al. 2020, Flaaen et al. 2020, Grossman et al. 2024, Alfaro and Chor 2023, Alfaro et al. 2025).

The paper also relates to the growing literature on the role of sanctions and geoeconomics more broadly (Hirschman, 1945; Felbermayr et al., 2020). A large portion of this literature has analyzed financial effects (e.g., Cipriani et al., 2023; Eichengreen et al., 2023; Itskhoki and Mukhin, 2022), while our paper focuses on downstream production and innovation implications. Juhász (2018), for example, finds increased mechanized cotton spinning in French regions more exposed to British Blockage. Bachmann et al. (2024) and Moll et al. (2023) highlight the different ways in which German firms and households adopted to the restricted imports of energy through demand reduction, increase efficiency, and diversification to alternative sources. Our analysis stresses and quantifies the role of directed technological change in adjusting to adverse shocks in a modern context and highlights that in an environment of strongly complementary inputs sanctions may backfire by triggering foreign innovation.

The remainder of the paper is organized as follows. Section 2 describes the context and policies around REEs. Section 3 presents the data and describes the construction of the IO table and the REE-related patent data. Section 4 presents the empirical analysis of innovation and trade effects. We then set up the theoretical model in Section 5. In Section 6, we quantify the model and present the results of various counterfactuals. The last section concludes.

2 Background: Rare Earth Elements

2.1 Differentiating Characteristics

The U.S. Geological Survey (USGS) defines the REEs as a group of 17 elements composed of scandium, yttrium, and the lanthanides.[6] We note four characteristics of REEs that distinguish them from other minerals.

[6]The lanthanides include the following elements: lanthanum (La), cerium (Ce), praseodymium (Pr), neodymium (Nd), promethium (Pm), samarium (Sm), europium (Eu), gadolinium (Gd), terbium (Tb), dysprosium (Dy), holmium (Ho), erbium (Er), thulium (Tm), ytterbium (Yb), and lutetium (Lu).

First, these elements are collectively known for their unique magnetic, catalytic, and luminescent properties, making them *essential* in a broad variety of high-tech and strategic applications (USGS, 2014). These include electronics, lighting, aerospace, defense, medical and green technologies. These diverse applications arise from chemical properties that are similar across all REEs, hence their classification as a group, although slight differences in electronic configurations give individual elements specific specializations.[7]

Second, their applications usually involve small quantities but they are challenging to substitute due to their high specificity (USGS, 2002; Graedel et al., 2015). For example, no other known elements could replace europium as a red phosphor for monitors or erbium in laser repeaters for fiber optics. Meanwhile, in principle, REE permanent magnets in electric-vehicle motors can be substituted with ferrite magnets, but this would make them about 30% heavier (Adamas Intelligence, 2023). This characteristic contributes to their *low elasticity of substitution* as an input, which informs economic responses to shocks on their supply.

Third, REEs have a relatively *inelastic supply* due to their nature as byproducts (Nassar et al., 2015) along with their toxic processing and handling (EPA, 2012). Despite their name, most REEs are geologically relatively abundant. However, due to their high reactivity, REEs do not occur as individual metals in nature the way copper and silver do, but instead as constituents of ores and minerals (Balaram, 2019). For example, lanthanum (from Greek *lanthanein*, 'to lie hidden') commonly occurs with cerium. These same deposits were later found to also contain praseodymium (from Greek *prasinos*, 'leek-green', and *didymos*, 'twin') and neodymium (*neos*, 'new twin'). High similarity in their chemical configuration, or their "chemical coherence", makes them particularly difficult to separate from each other (The Geological Society of London, 2011). Consequently, mining and processing REEs involve steps that are relatively lengthy, complex, and costly (Hurst 2010). Other chemical properties, such as radioactivity, complicate the process and add regulatory costs.[8]

Finally, REE production and processing are one of *the most concentrated* across mineral resources, with China controlling more than 90% of post-mining processing (BIS, 2023). China possesses

[7]Salient examples of REE use are for permanent magnets (e.g., neodymium and samarium), as found in products ranging from electronic speakers and medical equipment to wind turbines; catalysts (e.g., cerium, lanthanum) used in petroleum refining and automobile exhausts; and medical treatments (e.g. gadolinium for magnetic resonance imaging, yttrium for radiation therapy). See Voncken (2016) for a list of applications by element as related to their properties.

[8]Most REE mines have thorium, for example, which is radioactive. Cerium, lanthanum, and dysprosium, like the other lanthanides, react easily with oxygen (corroding quickly), are highly reactive to water, highly pyrophoric (igniting spontaneously in the air), and are powerful irritants requiring particular handling protocols. REEs have substantial metabolic effects: skin exposure can result in irritation, ulceration, delayed healing, and granuloma formation; ocular contact can lead to conjunctivitis and corneal damage, scarring, and opacity. Inhalation of REE dust can induce acute irritative bronchitis and pneumonitis. Most REEs are classified as mildly to moderately toxic (Harbison and Johnson 2015).

abundant REE resources, including the only developed ion-adsorption clay deposits, which are the most low-cost source for heavy REEs (Packey and Kingsnorth, 2016; USGS, 2002). This natural endowment was compounded by China's long history of REE promotion policies.

2.2 China's REE Policies and Production

In 1975, China sought to promote the REE mining industry (Shen et al., 2020). Policy tools included export-tax reimbursements starting in 1985, which coincided with China's REE market share growth. In 1990, the Chinese government designated REEs as a strategic resource, barring foreign investors from ownership of mines and limiting their involvement to REE smelting and separation projects unless through joint ventures with Chinese companies. Every REE mining or smelting project and joint venture required approval from the state, and additional export quotas were introduced in 1999 to address illegal production (Tse, 2011).

In the early 2000s, China emerged as the dominant player in the global production and processing of REEs, driven by several factors including abundant reserves, low labor costs, lax environmental regulations, and economies of scale (Morrison and Tang, 2012). Not long before, REE processing plants in advanced economies such as France and Japan began shutting down, culminating in the closure of California's Mountain Pass, the primary source of REEs before the mid-1980s (USGS, 2002). Between 1990 and 2000, China's production grew by more than 356%, from 16,000 to 73,000 metric tons (Tse, 2011). During this same period, production from other countries dropped by nearly 60%, from 44,000 to 16,000 metric tons. China's share of global REE output surged from 27% in 1990 to over 90% by 2008, supplying the vast majority of the world's REEs in the form of concentrates, intermediate products, and chemicals. In 2009, China's market share in global REE mine production reached 98% (see Figure A.2 in the Data Appendix).

2.3 The 2010 REE Supply Shock

We exploit the extreme and unprecedented 2010-2011 REE price surge by a factor of 10 (terbium and europium) to 45 (cerium) as a negative supply shock for our empirical analysis (see Figure 1).[9] The price jump was triggered by new Chinese export restrictions that tightened supply and heightened uncertainty amid geopolitical tensions. Beyond the extreme price spike, the main impact of China's export restrictions was supply uncertainty. The episode demonstrated China's

[9]REE markets are highly illiquid, making yearly price changes more discernible than higher-frequency movements, which tend to be extremely noisy. For comparison, the factor price increase from the 1974 OPEC shock was around 300%, while the REE shock was between 1000% and 4500%.

ability—and willingness—to weaponize REEs. Concerns over China's near-monopoly on REEs had been minimal before 2010, as reflected in the scarcity of official reports and business discussions.

The 2010 crisis made the risk of future disruptions evident, creating a lasting shock to REE supply uncertainty, which we focus on in our analysis. In July 2010, China drastically reduced the REE export quota for the second half of the year by 72%, with a stated motive of combating illegal mining and environmental pollution (Müller et al., 2016).[10] Then on September 7, 2010, a Chinese trawler collided with Japanese coast guard boats in the Senkaku-Diaoyu waters, triggering a diplomatic dispute. Immediate reports emerged of a ban as China halted all shipments of REEs in retaliation for Japan's detention of a Chinese fishing-boat captain. The restrictions were soon followed by increased export tariffs on certain REE products in January 2011, and higher taxes on REE mining and new export quotas on REE ferroalloys by May 2011 (WTO 2012, OECD 2024). REE market prices jumped at an unprecedented rate, peaking in mid to late 2011 before gradually declining. Global REE supply dropped by about 30,000 mt as China tightened production (Figure A.2).

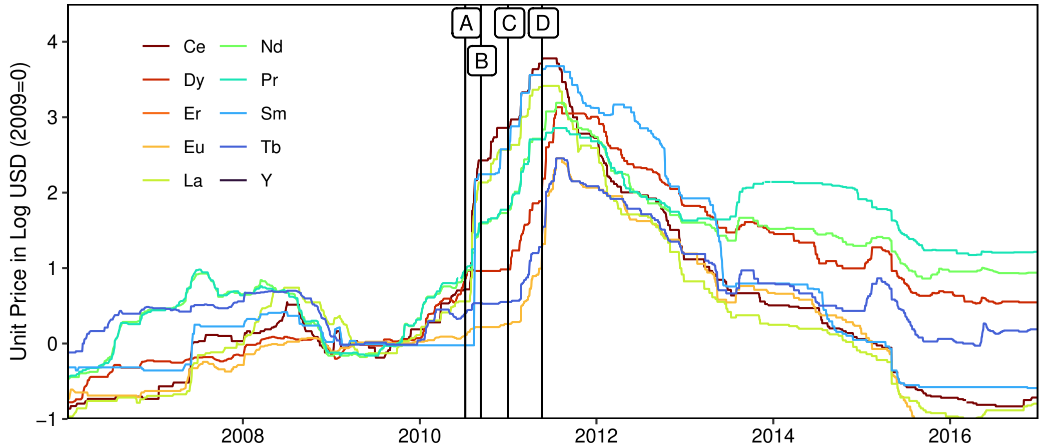
On March 13, 2012, the U.S., joined by Japan, the E.U. and Canada, requested WTO dispute settlement consultations. A WTO panel dismissed China's exemption argument based on conservation of an exhaustible natural resource and determined that the quotas were intended for industrial policy objectives (WTO, 2015) and in 2014 ruled in the plaintiff's favor. China removed its export quotas on REEs in 2015, replacing the quota with an export license and the export tax with a resource tax based on value (Mancheri et al., 2019).

Limited Supply Responses: Although the price spike spurred efforts to explore alternative sources of REEs, including new mines and processing facilities, progress was slow and limited, hinting at the low supply inelasticity of REEs.[11] As a consequence, mining and processing remained reliant on China (see Figure A.2 in Appendix A). Some firms held REE inventories but were unwilling to release those, fearing depletion of their stocks without fresh imports from China (Gholz and Hughes, 2021). Given that many applications only use very small quantities of REEs, large-scale recycling was economically nonviable (Hurst, 2011).

[10]In August 2009, China had issued a draft policy to cut the annual export quota with potential export bans on certain heavy REEs and reduced annual REE export quotas by around 12% each year from 2005 to 2009 (see Shen et al. 2020; Packey and Kingsnorth 2016; Pritchard 2009; Bradsher 2009, 2010). The domestic REE production quota was also cut by 20% in 2010 (Tse, 2011).

[11]Mining expanded somewhat in Australia, while firms in the U.S. continued previously ongoing efforts to reopen Mountain Pass. However, it took several years for new supply to reach markets, and these mines operated below planned capacity. Mountain Pass, sold to Molycorp in 2009, reopened in 2015 but soon shut down due to bankruptcy. It resumed operations in 2018 under MP Materials, with Chinese REE miner Leshan Shenghe holding a non-voting minority stake (Topf, 2017; Brickley, 2017). Lynas's plant in Malaysia commenced light REE oxides production in 2013 after the Malaysian government approved its development in 2007 (Gholz, 2014; Lynas, 2007).

Figure 1: Unit Prices of Selected Rare Earths



Notes: The figure plots indices of REE log unit prices using data from Asian Metal. The select elements are those with complete requirement data in the USGS report (Bleiwas and Gambogi, 2013). The vertical lines denote relevant episodes: A=Export quota cut by China; B=Senkaku-Diayou boat collision; C=Select export tariffs hike by China; D=New export quotas on ferro-alloys by China.

3 Data Sources and Descriptive Statistics

In this section, we describe our data sources and the construction of the key variables. Additional details are provided in the Data Appendix (Appendix A).

3.1 Input-Output Table with Rare Earths

To construct an IO table with REEs, we combine data from different sources. In particular, we capture the use of REEs from USGS and prices from BCC and Asian Metal. In Appendix A.1, we provide details on the imputation process of REE use into the standard supply-use table.

Use of REEs: We start with the 2012 supply-use table from the Bureau of Economic Analysis, the closest available to the time of the supply shock. The supply-use table comprises 405 BEA industry groups, which are a slightly more aggregated version of the 6-digit 2012 NAICS codes. This table reports the value of inorganic chemicals used by each industry—a broad category that includes REEs. To zoom in on REEs, we augment this table with data from a USGS report on REE inputs consumed by the U.S. in 2010 (Bleiwas and Gambogi, 2013). This report combines secondary data on REE inputs from various sources as well as primary data from disassembling and analyzing the manufacturer labels of numerous products. Total use of each element is computed by multiplying the amount of each REE contained in a product by the total quantity of the product consumed in the U.S. as obtained from consumption and trade statistics. It is the most comprehensive REE-content data available for the time around the supply-shock episode. REE use is available for seven "General Application" categories, namely magnets, alloys, batteries, automobile catalysts, fluid catalyst cracking, phosphors and diodes, and solutions.[12] These categories are the most upstream available for our purpose. We focus on estimates of the use of five broadly used REEs: lanthanum, cerium, praseodymium, neodymium, and dysprosium.

REE Price Data and Total Requirements: As the estimates are in metric tons, we convert them into USD million using a combination of prices from BCC (2015) and Asian Metal, both at the element level. Finally, we use the supply-use table, augmented with imputed REE data, to compute the total requirements matrix (Leontief inverse). The entries of this matrix indicate the amount of input each industry receives from every other industry, accounting for both direct and indirect linkages. Table A.1 in the Data Appendix lists the most REE-intensive industries. The top using industry by total requirement is SIC 3691 (Storage Batteries), which uses lanthanum. Another REE-intensive industry is SIC 3625 (Relays and Industrial Controls), which employs neodymium, praseodymium, and dysprosium.

3.2 Patent Data

Our primary measure for shifts in the direction of technological change is based on patent data. We obtain the universe of granted patents related to REEs from the Google Patent Research database.

REE Patents: We identify patents as related to REEs when their title or abstract contains specific keywords that include either the name of the elements themselves, their chemical compounds, or some key related technologies, such as technologies related to permanent magnets (Table A.4 in the Data Appendix lists the keywords). By the end of the sample period, around 30,000 distinct REE patents had been granted worldwide. We assign each patent to a country based on the location of the patent assignee, focusing on the top 50 countries by GDP. These countries are grouped into the following regions: Europe, the United States and Canada, China, Russia, South Korea, Japan, Australia, and the Rest of the World. Table A.5 in the Data Appendix lists the

[12] We exclude phosphors and diodes due to the presence of europium and terbium, whose estimates in dollar value become highly uncertain when multiplied by their high per-unit prices, which are one to two orders of magnitudes larger than for the rest of the elements. We also exclude solutions because the report provides no precise point estimates for this category's input element use.

countries in the sample. In the next step, we link each patent in our sample to a corresponding industry. This task is non-trivial, as patents are classified by technological fields rather than by industries. Given the substantial share of patents filed by non-corporate entities and the absence of a comprehensive global patent–firm matching database, we employ an LLM to assign patents in our sample to industries. Specifically, we extract and parse the title and abstract of each patent, and prompt the LLM (GPT4 from OpenAI) to identify the SIC code that best corresponds to the described technology.

Furthermore, we refine the sample of REE-related patents by instructing the LLM to classify each patent according to whether it pertains to a technology that enhances the efficiency of using REEs or facilitates substitution away from REEs.[13]

As a consistency check of our patent classification, we regress the cross-section of patent stocks measured at the industry-element level on its total requirement share from our IO table, including a full set of SIC industry fixed effects. An industry with an REE requirement for a specific element that is one standard deviation above the sample mean has, on average, 8.5% more patents mentioning this REE. We present examples of such patents in Appendix A.4.

Non REE Patents: One concern with our approach to measuring directed technological change is that we might pick up overall innovation in the industry and not necessarily innovation that is directed explicitly towards increasing the efficiency of REEs. We address this concern by controlling for the overall stock of patents in a given region-industry. Since the number of patents by region-industry is not directly observable, we proceed as follows. First, we draw a large random sample of patents and let the LLM allocate them to SIC industry codes. We then scale these numbers across regions and years by the number of granted patents that each region has when considering the full sample of manufacturing patents for that year.

3.3 Trade and Industry Data

We use data on exports of 4-digit SIC level manufacturing industries for the 50 largest economies in the world from 2002 until 2018 from UN Comtrade. We build a country-industry panel of total factor productivity and labor productivity to measure the effect on productivity across countries and industries. For Japan and the U.S., we have productivity measures from the Japanese Manufacturing Census and the NBER CES manufacturing database, respectively. For the other

[13] As an illustrative example, consider U.S. patent US-8586678-B2 with the title "Blends of linear and branched neodymium-catalyzed rubber formulations for use in golf balls." The LLM classifies this patented technology as improving the usage of REEs and assigns it to SIC 3949 "Sporting and Athletic Goods, n.e.c." which includes golf equipments.

countries, we rely on data from the UNIDO Indstat database. Appendix A.3 provides details on the productivity data. To control for industry characteristics, we obtain the average capital and labor intensity from the NBER CES manufacturing database.

We construct a country-industry proxy of how strongly an industry is targeted by industrial policy using the subsidy database from the Global Trade Alert (GTA) for the pre-shock period. This proxy is the share of subsidies – counted as the number of policy measures – going to a given country-industry relative to the total number of subsidy policies worldwide. The global denominator is chosen to prevent within-country re-allocation artifacts.

3.4 Descriptive Patterns

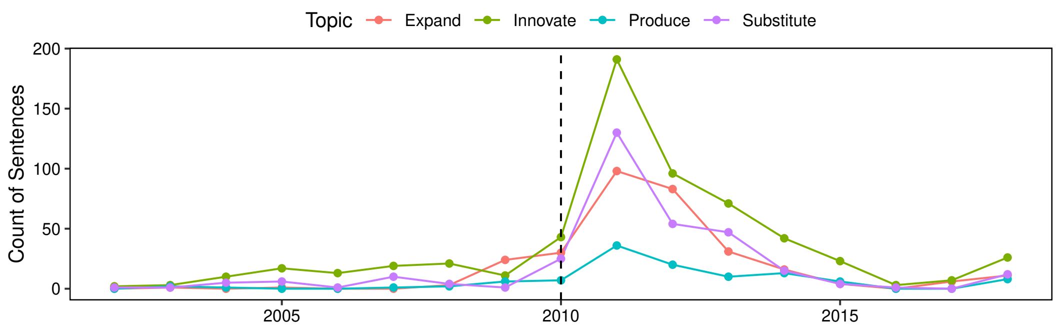
Figure 1 shows composite REE price indices (measured in USD in a log scale) over the sample period. Prices surged around 2010, peaked shortly after, then declined over the next several years and stabilized at a lower level. At the individual REE level, prices rose by a factor of 10 to 45. This spike reflects the global supply shock triggered by Chinese policy interventions in the REE market. Although prices did not remain elevated in the long run, their subsequent decline was driven by a medium-term increase in supply—primarily resulting from the relaxation of Chinese export restrictions and, to a lesser extent, limited entry by foreign producers—as well as a reduction in demand attributable to innovation. As we show in the empirical analysis below, the strong innovation response suggests that downstream industries considered China's export restrictions as permanent or likely to recur in the future.

Figure 2 depicts additional descriptive patterns. Panel (a) highlights how firms communicate about the negative REE supply shock. We scrape earnings calls of international firms and count sentences that mention REEs or related keywords. We then use an LLM to categorize those sentences. *"Expand"* denotes sentences about the expansion of REE production (including mining and refining), *"Innovate"* denotes innovations in REEs, which are further subdivided into production of REEs (*"Produce"*) or usage substitution (*"Substitute"*). The mentions rise sharply around the 2010 price spike, particularly for innovation-related topics. Within the innovation category, most mentions discuss substitution, highlighting a heightened focus on exploring alternatives in response to the price shock.

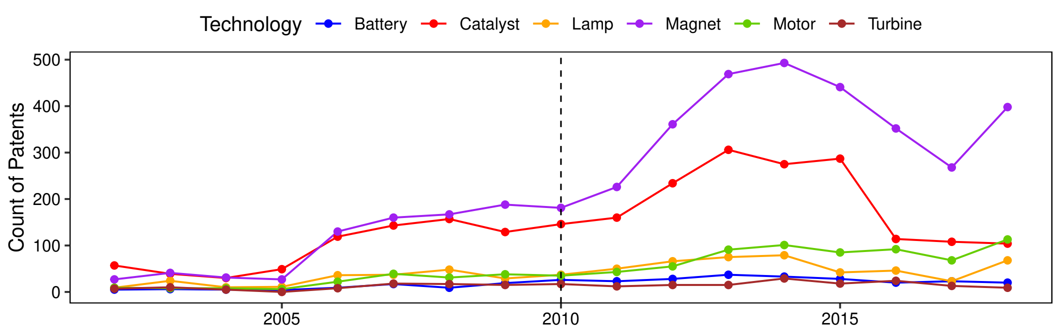
Panel (b) depicts the counts of newly granted patents on key technologies related to REEs. These patents generally increase over time, particularly in magnet and catalyst technologies, indicating a growing emphasis on innovation in these areas. However, the trend accelerates strongly after 2010, in line with the idea that the price spike may have catalyzed greater investment in technological development and innovation related to REEs. Overall, Figure 2 suggests that the sharp increase

Figure 2: The REE Supply Shock, Earnings Calls, and Innovation

(a) REE in Earnings Calls



(b) REE Patents



Notes: The figure presents mentions of REEs in firms' earnings calls *(a)*, and patents related to REEs *(b)*. Subfigure *(a)* depicts the count of REE mentions in global firms' earnings calls, categorized by topic using an LLM. Topics include *"Expand"* (expansion/diversification of REE production) and *"Innovation"* (innovations in REE production or usage). Innovation mentions are further split into *"Produce"* (innovating REE production) and *"Substitute"* (reducing/substituting REE use). Data is sourced from NL Analytics. Subfigure *(b)* shows the yearly count of new patents granted related to REE technologies, identified through keyword analysis in patent abstracts. Data is sourced from Google Patents.

in REE prices around 2010 significantly influenced producer behavior and innovation activities. In addition, the surge in patenting is hump-shaped and disappears after 2015, once Chinese export restrictions have been lifted. This indicates that it was not driven by a permanent sectoral shift towards green technologies, such as electric vehicles and wind turbines, but rather by a temporary price hike of REEs. Figure A.5 in the Appendix shows an example of a patent reducing REE use. Around one year after REE prices peaked, the Korean firm Daesung Electric Co filed a patent in South Korea for position sensors with a modified structure that removes the need for permanent REE magnets. The patent cites the positive price shock as its motivation, stating that "there is a cost problem due to the recent increase of the rare earth price". Position sensors have many downstream applications, from manufacturing processes to transport equipments, including automobiles.[14]

We construct a continuous measure of the exposure of each industry s to the REE supply shock. This measure combines element-level total requirements from our IO table with an index of element-level REE complementarity from Graedel et al. (2015). The complementarity index, based on expert assessments of the technologies available in 2008, reflects the physical and chemical substitutability of elements rather than economic factors. Dysprosium, for instance, is among the least substitutable elements, while samarium is among the most. Thus, between two industries using equal amounts of REEs, the one relying on harder-to-substitute elements is more exposed to supply shocks. For example, industries using dysprosium in permanent magnet motors—where substitutes are inadequate—are more exposed than industries using REEs in nickel–metal hydride batteries, which can be replaced by lithium-ion alternatives. We define industry exposure as

$$REE\ Sensitivity_s = \sum_e tr_{es} \times compl_e, \tag{1}$$

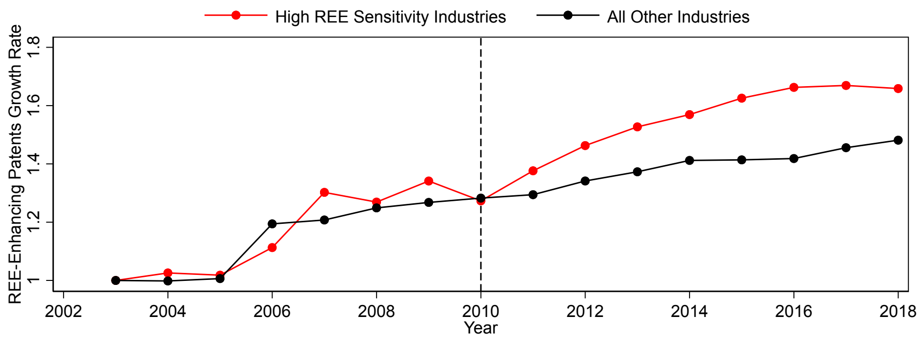
where tr_{es} denotes the total requirements of REE e in industry s and $compl_e$ is the complementarity index ranging from 0 (perfect substitutes available) to 100 (no substitutes).

Figure 3 shows industry-level trends in patents and exports for downstream industries outside China over the sample period, while Appendix Figure B.1 reports trends in productivity growth. We distinguish between industries that are highly sensitive to the REE supply shock and compare their trajectories with those of all other manufacturing industries. Industries classified as highly REE-sensitive are those above the 75th percentile of $REE\ Sensitivity_s$. In the pre-2010 period, trends in patenting and exports are closely aligned across both groups of industries, supporting the parallel trends assumption (panels a and b). After 2010, however, the patterns diverge: highly REE-sensitive industries exhibit a sustained acceleration in REE-enhancing patent stock growth,

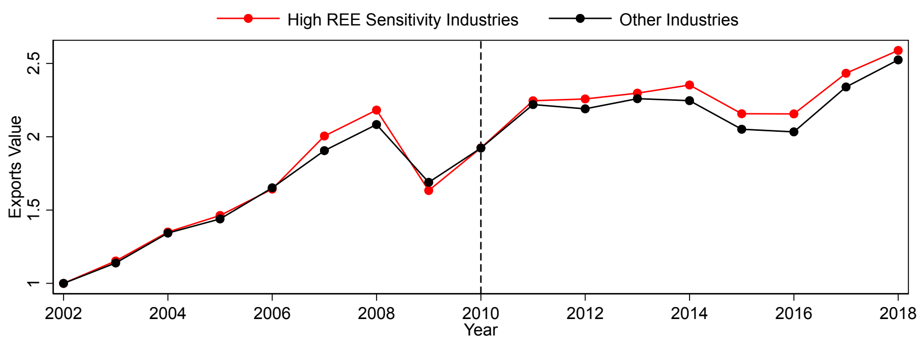
[14] Appendix A.4 provides further examples of REE patents.

Figure 3: High and Low REE Sensitivity Industries: Patents and Exports

(a) Patents



(b) Export Values



Notes: The figure plots the average of patents stock growth and export values of manufacturing industries (weighted by initial values in 2002-2004) that are classified above the 75th percentile of REE sensitivity (red) and for all other manufacturing industries (black). Growth rates are annualized growth calculated using the midpoint between t and $t-1$ as the denominator. The sample includes 4-digit SIC manufacturing industries from 2002-2018 across the 50 largest economies excluding China. REE sensitivity is constructed following equation (1).

with the gap widening relative to other industries through the mid-2010s.[15] Exports for both groups rise after 2010, but highly REE-sensitive industries generally outperform others following the supply shock (panel b).

[15]Similar parallel pre-trends up to 2010 and divergence after are visible in productivity growth (Appendix Figure B.1).

4 Empirical Analysis

4.1 Directed Technological Change

Innovation in Downstream REE-Using Industries: As a starting point, we explore whether the negative REE supply shock had an impact on the direction of technological change in downstream manufacturing industries across the world and in China, using patent data. We consider a difference-in-differences specification with variable treatment intensity. We estimate the following count model for patents:

$$y_{rst} = \beta \mathit{REE\ Sensitivity}_s \times \mathit{post}_t + \gamma\Delta_{rst} + \eta_{rs} + \eta_{rt} + \epsilon_{rst}. \tag{2}$$

The outcome variable, y_{rst}, denotes the stock of granted REE patents in 4-digit SIC manufacturing industry s in region r and year t, over the sample period 2002–2018. Our coefficient of interest, β, is the estimate on the interaction between the industry's REE sensitivity measure, $\mathit{REE\ Sensitivity}_s$, described above, and a step dummy, post_t, which takes the value one from 2010 onward. This variable captures the period following China's initial implementation of export restrictions.

We include a full set of region-by-industry and region-by-year fixed effects to control for average patenting levels at the region-industry level and for region-specific shocks, respectively, along with a set of industry-region-period-specific control variables described below. Since region-industry fixed effects absorb average levels of patenting of each industry-region pair, identification relies on time variation in patent stocks within a given pair, effectively allowing us to examine the impact of the treatment on patent flows.

We estimate (2) using both Poisson pseudo-maximum likelihood (PPML) and linear regression. A key control variable included in all specifications is the (log) total patent stock of industry s in region r and year t, which proxies for overall innovation activity unrelated to REE-specific innovation. This helps ensure that our estimates do not simply capture region-industry-specific trends, such as a general surge in patenting in industries affected by the green transition.

To address further concerns that rising activity in REE-intensive industries may be driven by local subsidies or demand shifts (e.g., stemming from their relevance for the green transformation), we include additional controls. Specifically, we account for time-invariant industry-region-specific subsidy intensity (from the Global Trade Alert database) and the capital and labor intensity of each industry, each interacted with the post-treatment dummy post_t. We also include a time-varying demand proxy at the region-industry level, defined as the lagged, weighted midpoint GDP growth of the top 10 importing countries in year t. Finally, standard errors are clustered at the region-industry level, following Abadie et al. (2023).

Table 1: Patents in Rare-Earth Intense Manufacturing Industries

	NONCHN	USA	EUR	JPN	ALL	CHN
	PPLM: REE-Enhancing Patents					
	(1)	(2)	(3)	(4)	(5)	(6)
REE Sens. × Post	15.46***	17.91**	18.43***	25.65**	14.36***	2.886
	(4.943)	(7.227)	(6.026)	(11.05)	(5.155)	(19.35)
Observations	5,561	1,200	1,140	972	7,606	2,045
Clusters	387	81	74	66	531	144
	Linear: REE-Enhancing Patents					
	NONCHN	USA	EUR	JPN	ALL	CHN
	(7)	(8)	(9)	(10)	(11)	(12)
REE Sens. × Post	12.04***	20.52**	27.75***	15.19	7.334	-17.25
	(4.386)	(9.132)	(6.256)	(10.13)	(4.904)	(19.73)
Observations	4,865	1,101	966	893	6,185	1,320
Clusters	382	81	73	66	522	140
	Linear: Percent Difference in REE-Enhancing Patents to China					
	NONCHN	USA	EUR	JPN		
	(13)	(14)	(15)	(16)		
REE Sens. × Post	50.98***	62.59	66.08**	80.70**		
	(18.07)	(54.68)	(31.95)	(32.90)		
Observations	3,633	738	728	655		
Clusters	363	74	69	64		
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Region × Ind F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Region × Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table presents coefficient estimates of β from the regression: $y_{rst} = \beta\, REE\ Sens._s \times post_t + \gamma\Delta_{rst} + \eta_{rs} + \eta_{rt} + \epsilon_{rst}$ with Poisson pseudo-maximum likelihood estimation (upper panel) and OLS estimation of a linear regression model (middle and lower panels). The outcome y_{rst} represents granted REE-related patents that improve the efficiency of REE or help find ways to substitute REE usage. For the linear model with the count of REE-enhancing patents (middle panel), we take logs of the outcome variable. The sample includes 4-digit SIC manufacturing industries (with at least one REE-related patent) from 2002-2018 across 8 regions. Regions capture the location of the patent assignee and include Australia, China, European Union, Korea, Russia, Japan, U.S. and the Rest of the World. The treatment intensity $REE\ Sens._s$ is a weighted sum of an REE element-specific complementarity index (ranging from 0 to 100), with weights based on total requirement shares for industry s: $REE\ Sens._s = \sum_e tr_{es} \times compl_e$. $post_t$ is a dummy variable set to 1 for 2010 and later years (post-China's REE export restrictions). Region subsamples include non-China, the U.S., European economies, Japan, all regions, and China. All regressions include region-industry and region-year fixed effects. The control vector Δ_{rst} includes time-invariant measures of industry s's capital and labor intensity from the NBER CES manufacturing database, and subsidy fractions from the GTA database, all interacted with $post_t$ as well as the log of the total stock of granted patents in region-industry rs in year t. It also includes a lagged demand control at the region-industry-year level, constructed by taking the log of the weighted yearly real GDP of the top 10 importer countries for that region-industry. The top 10 importer countries are identified by ranking importer countries by trade value in the period 1996-2009. For the linear model with REE-enhancing patents as percent difference to China, we winsorize the outcome variable at the 1% level to take care of outliers and exclude industry-year observations where the patent count is zero. Standard errors (in parentheses) are clustered at the region-industry level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 1 reports the estimates from (2). The upper panel presents results from the PPML specification (including zeros), the middle panel from the linear model (restricted to positive counts, with the outcome in logs), and the lower panel from a linear model where the outcome is defined as the percentage difference in patents relative to China. The latter specification differences out industry-specific shocks.[16] The sample includes only those patents identified by the LLM as either improving the efficiency of REEs or substituting for their use. Column (1) covers all regions except China, columns (2)-(4) report results for the U.S., Europe, and Japan, column (5) adds China, and column (6) covers China individually. We find that, outside China, industries more sensitive to the REE supply shock increased their innovation activity during the treatment period relative to less affected industries. In specification (1), a one-standard-deviation increase in REE sensitivity is associated with 7.4% more REE-related patents after the 2010 supply shock. This effect is particularly pronounced in Europe, the U.S., and Japan, as shown in columns (2)-(4). In China, by contrast, more REE-sensitive industries also patented slightly more REE technologies in the treatment period (column (6)), but the effect is much weaker than in other economies and statistically indistinguishable from zero. Results from the linear regression model are consistent: outside China, industries with higher REE sensitivity patent more relative to less sensitive ones (column (7)), whereas in China the effect is insignificant and slightly negative (column (12)). Finally, the lower panel reports estimates based on percentage differences in patenting relative to China (triple-differences), which control for unobserved industry-specific shocks. In line with previous results, industries with higher REE intensity outside China patent relatively more than less REE-intensive industries, compared to their counterparts in China during the treatment period.

4.2 Trade Effects

Next, we study how manufacturing exports in downstream industries that use REEs respond to Chinese REE export restrictions. We estimate the following difference-in-differences specification, using export growth as the outcome variable:

$$y_{ist} = \beta REE\ Sensitivity_s \times post_t + \gamma \Delta_{ist} + \eta_{is} + \eta_{it} + \epsilon_{ist}. \tag{3}$$

The outcome variable y_{ist} is the annualized growth rate of exports for the 4-digit SIC manufacturing industry s by country i during year t, again considering the sample window from 2002 to 2018.[17]

[16] We normalize the dependent variable by the number of Chinese patents to allow for an easier interpretation of the coefficient of interest. Including observations with zero patent counts and estimating a standard triple-differences specification does not qualitatively affect our results.

[17] Note that while we grouped the 50 sample countries into 8 regions in the patent analysis due to more aggregated patent jurisdictions, we now consider variation at the more disaggregated country level.

The annualized export growth rate for period t is calculated using the midpoint of t and $t-1$ as the denominator. The coefficient of interest β is again the coefficient on an interaction term of our $REE\ Sensitivity_s$ measure with the treatment dummy $post_t$. All estimations include a full set of country-industry and country-year fixed effects η_{is} and η_{it}. We also include the time-varying industry controls described above (demand, subsidies, industry characteristics), weight regressions using export weights,[18] and cluster standard errors at the country-industry level. We again estimate (3) on various sub-samples and alternatively include all countries except China, the U.S., European economies, Japan, all countries, and China.

The upper panel of Table 2 presents the results from specification (3) using export growth as the outcome variable. The coefficient β on the interaction term $REE\ Sensitivity_s \times post_t$ is positive and statistically significant at the 1% level in column (1) for the sample of countries excluding China. This indicates that, outside China, exports of industries more reliant on REEs grew significantly faster relative to less sensitive industries within the same country during the treatment period compared to before. Quantitatively, a one-standard-deviation higher value in REE sensitivity is associated with a 0.35 percentage point larger midpoint growth rate of exports. The coefficient remains positive across all samples except for the case of China, where it is negative but not statistically significant. The effects are particularly pronounced for European countries and for Japan, while they are more moderate in the U.S.[19]

The bottom panel of Table 2 presents results from specifications where the outcome variable is defined as the difference between the midpoint export growth rate of a given country-industry outside China and the one of the corresponding industry in China, thereby differencing out any industry-specific shocks. We find that, relative to Chinese manufacturing industries, exports of more exposed industries outside of China grew significantly more in response to the REE supply shock.[20]

4.3 Robustness and Additional Results

In this section, we briefly report a number of additional results and robustness checks that are presented in more detail in Appendix B.

[18] We use the share of export values $w_{is} = exports_{is} / \sum_{i,s} exports_{is}$ in the period 2002-2004 as weights.

[19] In Appendix B.3, we use UN Comtrade trade data disaggregated at the finer 6-digit HS product code level. At this level, we can separate the effect on the growth of export values into price growth and the growth of physical quantities. We find that the positive effect on exports outside China was not driven by price increases but mostly by increases in quantity.

[20] Note that, due to weighting by exports, the coefficient for the specification in differences relative to China (lower panel) is not numerically equivalent to the coefficient difference between the coefficients for the non-China and the China sample from the upper panel.

Table 2: Downstream Export Growth – Rare-Earth Intense Manufacturing Industries

	Annualized Growth: Exports Value					
	NONCHN	USA	EUR	JPN	ALL	CHN
	(1)	(2)	(3)	(4)	(5)	(6)
RE Sens. × Post	0.880***	0.155	0.639*	1.685**	0.812***	-0.804
	(0.254)	(0.770)	(0.340)	(0.803)	(0.245)	(0.800)
Observations	271,740	6,048	107,895	5,979	277,723	5,983
Clusters	17,249	378	6,754	375	17,623	374
	Differences in Annualized Export Growth to China					
	NONCHN	USA	EUR	JPN		
	(7)	(8)	(9)	(10)		
RE Sens. × Post	3.548***	3.133***	3.540***	2.920**		
	(0.502)	(0.945)	(0.709)	(1.398)		
Observations	270,342	5,987	107,321	5,951		
Clusters	17,159	375	6,722	374		
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country x Ind F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Country x Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table presents coefficient estimates of β from the regression: $y_{ist} = \beta\, REE\ Sens._s \times post_t + \gamma\Delta_{ist} + \eta_{is} + \eta_{it} + \epsilon_{ist}$, where y_{ist} represents the annualized growth rate of export values for country-industry is in year t (upper panel) and the difference between the annualized growth rate of export values for country-industry is and the corresponding growth rate of the same industry s in China (lower panel). The annualized growth is calculated using the midpoint between t and $t-1$ as the denominator. The sample includes 4-digit SIC manufacturing industries from 2002-2018 across the 50 largest economies. The treatment intensity $REE\ Sens._s$ is a weighted sum of an REE element-specific complementarity index (ranging from 0 to 100), with weights based on total requirement shares for industry s: $REE\ Sens._s = \sum_e tr_{es} \times compl_e$. $post_t$ is a dummy variable set to 1 for 2010 and later years (post-China's REE export restrictions). Country subsamples include non-China, the U.S., European economies, Japan, all countries and China. All regressions include country-industry and country-year fixed effects. The control vector Δ_{ist} includes time-invariant measures of industry s's capital and labor intensity from the NBER CES manufacturing database, and country-industry-specific industrial subsidy fractions from the GTA database, all interacted with $post_t$. It also includes a lagged demand control at the region-industry-year level, constructed as the lagged weighted average growth rate of GDP of the ten largest importers from is. Regressions are weighted by the share of export values $w_{is} = exports_{is} / \sum_{i,s} exports_{is}$ from 2002-2004. Standard errors (in parentheses) are clustered at the country-industry level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Productivity: First, we examine how productivity growth in REE-intensive downstream industries responded to Chinese export restrictions. We again employ specification (3), using either TFP growth or labor productivity growth as the outcome variable. Results are reported in Appendix Table B.1.

We find that, outside China, productivity in more exposed downstream industries grew faster than in less exposed industries during the treatment period relative to the control period. By contrast, in China, productivity in more exposed industries grew more slowly in the treatment period compared to less exposed industries. These results suggest that the surge in REE-related patenting among industries most affected by China's export restrictions also translated into relatively accelerated productivity growth.

Alternative Treatment Measures: While the complementarity index in (1) is appealing because it is directly grounded in the production functions of REE-using industries and the chemical properties of individual elements, we also construct alternative measures of exposure to the Chinese REE supply shock using UN Comtrade data. Unlike the complementarity index, these measures vary at the country-industry level rather than only across industries. Our first measure of country-industry REE sensitivity combines the country-specific spike in unit values of REE imports with the total REE requirements of each industry (aggregated across elements).[21]

$$\textit{REE Sensitivity}_{is} = \left(\sum_e tr_{es}\right) \times \left(\ln(\textit{max REE import price}_i) - \ln(\textit{REE import price 2016}_i)\right). \tag{4}$$

Alternatively, we construct a second country-industry treatment indicator based on pre-shock import shares of REEs between 1995 and 2009. Specifically, for country c, we calculate the share of REE imports sourced from China relative to imports from a broader set of suppliers (China, the U.S., Australia, Russia, and India), and interact this with the total REE requirements of industry s:

$$\textit{REE Sensitivity}_{is} = \left(\sum_e tr_{es}\right) \times \frac{\textit{REE imports from CHN}_i}{\textit{REE imports from CHN, USA, AUS, RUS, IND}_i}. \tag{5}$$

For both shock measures, we treat HS codes 284690, 284610, and 280530 as REE-related and weight them by initial import shares.

[21] We calculate the price spike in unit import values using 2016 as the base year since we observe more cases of imports in REE-related HS codes in 2016 than in years before the introduction of China's REE policies in 2010. We have tested alternative benchmarks for the base year and obtained similar results.

Appendix Tables B.2, B.3, and B.4 report the corresponding estimates for patents, export growth and productivity growth. Outside China, we again find stronger REE related patenting activity, faster export and productivity growth in country-industries more exposed to the REE supply shock.

Exports at the Product Level: Appendix Table B.5 replicates the export growth results from Table 2 using more disaggregated trade data at the 6-digit HS product level. At this level of detail, we again find that more REE-intensive products exported from producers outside China experienced a relatively larger increase in export growth after the supply shock compared to less REE-intensive products. We further decompose export growth into changes in quantities and unit values. Separate regressions indicate that the effects are driven primarily by increases in export quantities rather than by a mechanical pass-through of higher factor prices.

5 A Quantitative Model of Trade and Directed Technological Change

Having presented the empirical evidence, in this section, we develop a model that can generate REE-biased innovation and technological change in response to a negative REE supply shock. The model embeds static directed technological change (Acemoglu, 2002) into a quantitative general-equilibrium gravity model of international trade (Caliendo and Parro, 2015; Fadinger et al., 2024).

Production features two factors: tradable REEs and a non-tradable factor, called equipped labor. The model flexibly combines standard Heckscher-Ohlin forces of comparative advantage and directed technological change. In response to a Chinese REE export tax, the REE factor becomes scarcer outside of China. Absent directed technological change, this leads to a cost increase that is more pronounced in REE-intensive industries and shifts comparative advantage and production towards labor-intensive industries. By contrast, in the presence of endogenous technology and complementarity between REEs and labor inputs, the increase in REE factor costs triggers innovation that is biased towards REEs, leading to productivity gains in REE-intensive industries relative to labor-intensive ones outside China. This technology effect counteracts Heckscher-Ohlin forces, and, depending on the magnitude of the productivity response, may weaken or dominate the former. In addition, the model features intermediates and inter-industry linkages, which generate amplification of policy changes, as price changes of the REE factor are passed on to downstream customers and other industries. Such amplification is necessary to obtain quantitatively accurate trade and welfare predictions (Caliendo and Parro, 2015).

The production side of the model is structured in four layers: final goods, Armington industry bundles, tradable industry goods, and factor-biased innovation activities. Figure 4 illustrates the model structure. At the most upstream level, monopolistically competitive innovation firms invent and produce differentiated varieties of labor- and REE-specific inputs. These varieties are then used, together with material inputs, to produce country- and industry-specific tradable goods. The tradable goods are aggregated into non-tradable, industry-specific Armington bundles within each country. At the most downstream level, these Armington bundles are further aggregated into non-tradable final goods, which serve either consumption or investment in innovation.

5.1 Setup

There are many countries, indexed by $i = 1, .., I$ and $j = 1, ...J$ and industries, indexed by $s = 1, ..., S$. For bilateral variables, the first country subindex denotes the location of consumption and the second subindex the location of production.

5.1.1 Tradable Industries

Industry goods are country-specific and tradable. The value-added production function of the country-specific industry goods combines quantities of REEs and equipped-labor input bundles Y_{Ris} and Y_{Lis}:

$$VA_{is} = \left[\gamma_s Y_{Ris}^{\frac{\varepsilon_s - 1}{\varepsilon_s}} + (1 - \gamma_s) Y_{Lis}^{\frac{\varepsilon_s - 1}{\varepsilon_s}} \right]^{\frac{\varepsilon_s}{\varepsilon_s - 1}} \tag{6}$$

A key parameter in (6) is the industry-specific elasticity of substitution between REEs and equipped-labor input bundles, denoted by ε_s. The value of ε_s determines if REEs are gross substitutes ($\varepsilon_s > 1$) or complements ($\varepsilon_s < 1$) with equipped labor in the production of industry value added. This elasticity will later govern the direction of technological change in response to changes in relative factor prices. In addition, $\gamma_s \in [0, 1]$ determines the dependence of industry s on REE inputs. The higher the value of γ_s, the more dependent a given industry is on the REE bundle.

In a further stage, value added is combined with a Cobb-Douglas aggregate of material bundles $M_{iss'}$ used by industry s and produced by industries s'. Here, $\phi_{iss'}$ denotes the IO coefficients (expenditure shares of country i industry s on goods produced by industry s'). The production function for gross output and the resource constraint of the industry goods are given by

$$Y_{is} = \Psi_{is} VA_{is}^{\phi_{is}} \prod_{s'}^{S} M_{iss'}^{\phi_{iss'}} = \sum_j d_{jis} Y_{jis}, \tag{7}$$

where $\Psi_{is} \equiv \phi_{is}^{-\phi_{is}} \prod_{s'} \phi_{iss'}^{-\phi_{iss'}}$ is a constant normalizing the production function. Output Y_{is} is used in all countries, where Y_{jis} denotes the quantity of the industry-s good that is produced in country i and used by country j and $d_{jis} \geq 1$ denotes iceberg-type trade costs with $d_{iis} = 1$.

Note that when ϕ_{is} tends to unity, so that material inputs are absent, the model converges to the production structure of Acemoglu (2002). Instead, when γ_s tends to zero, such that equipped labor is the only production factor, we are back to the workhorse quantitative trade model (Caliendo and Parro, 2015).[22]

5.1.2 Innovation and Directed Technological Change

In each country-industry, firms in the R_{is} and L_{is} layers are perfectly competitive and use a CES bundle of differentiated inputs ($y_{Ris}(a)$ or $y_{Lis}(a)$) to produce the REE input bundle Y_{Ris} or the equipped-labor input bundle Y_{Lis}. These input bundles cannot be traded across countries, and the technology to produce them does not diffuse. The production functions of the layers R_{is} and L_{is} are given by:

$$Y_{Ris} = E_{Ris} \left[\int_0^{A_{Ris}} y_{Ris}(a)^{\frac{\mu-1}{\mu}} da \right]^{\frac{\mu}{\mu-1}}, \quad Y_{Lis} = E_{Lis} \left[\int_0^{A_{Lis}} y_{Lis}(a)^{\frac{\mu-1}{\mu}} da \right]^{\frac{\mu}{\mu-1}} \tag{8}$$

Here, the terms $E_{Ris} = A_{Ris}^{\delta}$ and $E_{Lis} = A_{Lis}^{\delta}$ are externalities from the measures A_{Ris}, A_{Lis} of input varieties on downstream productivity. If $\delta > 0$, spillovers are positive, while if $\delta < 0$, there are negative spillovers. If $\delta = 0$, spillover effects are absent. The formulation of these spillover effects follows Benassy (1996) and allows disentangling love for variety from markups. Spillover effects are absent in Acemoglu (2002) and not required to generate directed technological change in response to changes in factor prices. However, they determine the strength of the technology response and the response of revenue in downstream industries to changes in relative factor prices. In particular, negative spillovers increase the technology response to changes in factor prices by increasing prices of input bundles and thus profits of innovators if inputs are complements (see equation (40) below). For example, they could result from (unmodeled) competition for a scarce R&D factor.

[22] We model REE inputs as part of value added rather than as separate material inputs for two reasons: first, it allows for a formulation that nests Acemoglu (2002) and Caliendo and Parro (2015); second, a highly disaggregated IO table that identifies REEs as distinct inputs is available only for the U.S., but not for other countries, as would otherwise be required. For the quantitative analysis, we rely on the World-Input-Output Database, which features more aggregated industry classifications and does not report REE-specific IO linkages.

The corresponding price indices for the REE- and labor-input bundles are:

$$P_{Ris} = E_{Ris}^{-1}\left[\int_0^{A_{Ris}} p_{Ris}(a)^{1-\mu}da\right]^{\frac{1}{1-\mu}}, \quad P_{Lis} = E_{Lis}^{-1}\left[\int_0^{A_{Lis}} p_{Lis}(a)^{1-\mu}da\right]^{\frac{1}{1-\mu}} \tag{9}$$

The inverse demand faced by an input firm that produces input variety a is:

$$p_{Ris}(a) = E_{Ris}^{\frac{\mu-1}{\mu}} P_{Ris} Y_{Ris}^{\frac{1}{\mu}} y_{Ris}(a)^{-\frac{1}{\mu}}, \quad p_{Lis}(a) = E_{Lis}^{\frac{\mu-1}{\mu}} P_{Lis} Y_{Lis}^{\frac{1}{\mu}} y_{Lis}(a)^{-\frac{1}{\mu}} \tag{10}$$

The measures A_{Ris} of REE-input firms and A_{Lis} of equipped-labor-input firms denote the state of technology. They are endogenous and determined by free entry into innovation. Input firms only sell domestically, operate under monopolistic competition, and hold a patent for their variety. For simplicity, we assume that input firms and their patent die after one period and are replaced by new entrants. Varieties of inputs are imperfect substitutes with elasticity of substitution $\mu > 1$. Each REE (labor) input variety is produced with a linear technology with the factor REE (labor) r_{is} (l_{is}) as input:

$$y_{Ris}(a) = r_{is}(a), \quad y_{Lis}(a) = l_{is}(a) \tag{11}$$

Input firms maximize profits, taking their inverse demand (10) and production technology (11) as given. Solving their profit-maximization problem yields the optimal prices of inputs

$$p_{Ris}(a) = p_{Ris} = \frac{\mu}{\mu-1} w_{Ri}, \quad p_{Lis}(a) = p_{Lis} = \frac{\mu}{\mu-1} w_{Li}, \tag{12}$$

which correspond to a markup over factor prices w_{Ri} (w_{Li}), and the variable profits of input monopolists

$$\begin{aligned} \pi_{Ris} &= \frac{p_{Ris} r_{is}}{\mu} = \frac{1}{\mu}\left(\frac{\mu}{\mu-1}\right)^{1-\mu} P_{Ris}^{\mu} E_{Ris}^{\mu-1} Y_{Ris} w_{Ri}^{1-\mu}, \\ \pi_{Lis} &= \frac{p_{Lis} l_{is}}{\mu} = \frac{1}{\mu}\left(\frac{\mu}{\mu-1}\right)^{1-\mu} P_{Lis}^{\mu} E_{Lis}^{\mu-1} Y_{Lis} w_{Li}^{1-\mu}. \end{aligned} \tag{13}$$

Inventing an input patent is associated with fixed costs f_{Ris} (or f_{Lis}) which are paid in units of the final good in country i with price P_i. Note that since $P_{Ris} = E_{Ris}^{-1} A_{Ris}^{\frac{1}{1-\mu}} p_{is}$ and $Y_{Ris} = E_{Ris} A_{Ris}^{\frac{\mu}{\mu-1}} r_{is}$, we have that $p_{Ris} r_{is} = P_{Ris} Y_{Ris}/A_{Ris}$ and similarly, $p_{Lis} l_{is} = P_{Lis} Y_{Lis}/A_{Lis}$. Free entry implies that inventing a new patent allows input firms to exactly recoup the innovation fixed cost:

$$\Pi_{Ris} = \frac{p_{Ris} r_{is}}{\mu} = \frac{P_{Ris} Y_{Ris}}{A_{Ris}\mu} = f_{Ris} P_i, \quad \Pi_{Lis} = \frac{p_{Lis} l_{is}}{\mu} = \frac{P_{Lis} Y_{Lis}}{A_{Lis}\mu} = f_{Lis} P_i \tag{14}$$

Taking ratios of the free-entry conditions yields the relative technology bias:

$$\frac{A_{Ris}}{A_{Lis}} = \frac{P_{Ris}Y_{Ris}}{P_{Lis}Y_{Lis}}\frac{f_{Lis}}{f_{Ris}} \tag{15}$$

Thus, the relative technology bias depends on the relative revenues of firms in the R_{is} compared to the L_{is} sector and any change in relative revenues will shift the relative technology bias.

5.1.3 Final Goods and Armington Industry Bundles

At the most downstream level, there is a non-tradable final good Y_i, which is produced and used in each country. This final good can be used for two purposes. A part of its production serves final consumer demand (denoted by C_i), while the remainder is used to pay the fixed costs of innovation (denoted by $\sum_s A_{Ris}f_{Ris}$ and $\sum_s A_{Lis}f_{Lis}$). The final good is produced with a CES production function that combines Armington bundles of industry goods. The production function and resource constraint of the final good are given by

$$Y_i = \left[\sum_s \alpha_{is}^{\frac{1}{\rho}} Q_{is}^{\frac{\rho-1}{\rho}}\right]^{\frac{\rho}{\rho-1}} = C_i + \sum_s A_{Ris}f_{Ris} + \sum_s A_{Lis}f_{Lis}, \tag{16}$$

where Q_{is} corresponds to the quantity of the industry-s Armington bundle used in the production of the final good.

The Armington bundles M_{is} are produced with a CES technology that aggregates the tradable industry-s inputs Y_{ijs} from all countries j with an elasticity of substitution $\sigma_s > 1$. These Armington bundles serve two purposes. Either they are used as an input in the production of final goods (as Q_{is}), or they are used as intermediates in the production of tradable goods (as $M_{iss'}$). The production function and resource constraint of the Armington goods are given by

$$M_{is} = \left[\sum_j Y_{ijs}^{\frac{\sigma_s-1}{\sigma_s}}\right]^{\frac{\sigma_s}{\sigma_s-1}} = Q_{is} + \sum_{s'} M_{iss'}, \tag{17}$$

where $M_{iss'}$ is the quantity of industry-s Armington bundles used in industry s' within country i. The associated CES price index of the industry-s Armington bundle in country i is

$$P_{is} = \left[\sum_j P_{ijs}^{1-\sigma_s}\right]^{\frac{1}{1-\sigma_s}}, \tag{18}$$

with P_{ijs} being the price of the industry-s goods used in country i and produced in country j. The aggregate price index of the final good in country i is

$$P_i = \left[\sum_s \alpha_{is} P_{is}^{1-\rho}\right]^{\frac{1}{1-\rho}}. \tag{19}$$

Assuming perfect competition in Armington bundles, the bilateral trade value shares, measuring the import values of i from j relative to the total expenditure in country i, are given by:

$$\lambda_{ijs} = \frac{P_{ijs}Y_{ijs}}{P_{is}M_{is}} = \left(\frac{P_{ijs}}{P_{is}}\right)^{1-\sigma_s}. \tag{20}$$

5.1.4 Trade and Industrial Policy

We assume that China is the only country that has endowments of a homogeneous REE factor R_C that can be traded. In addition, it disposes of a non-discriminatory gross ad-valorem export tax $\tau_{XC} \geq 1$ on REE exports. Therefore, the price of REE inputs in country j is equal to $w_{Rj} = \tau_{XC} w_{RC}$. We assume that China's export tax revenue from factor exports of REEs is fully rebated to Chinese consumers with lump-sum transfers.

5.1.5 Goods and Factor Markets

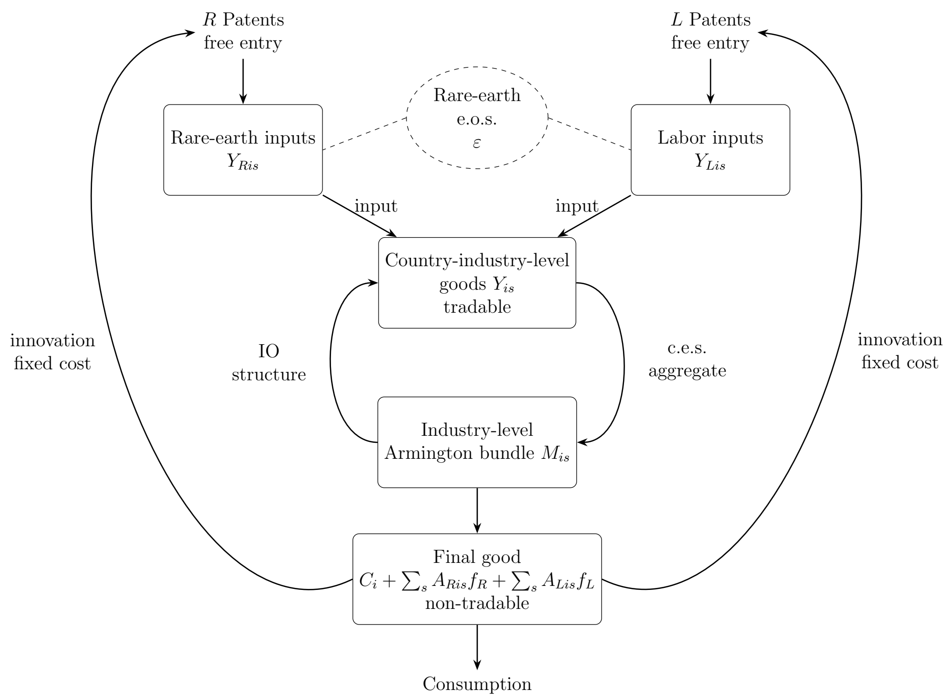
Denote the revenues of industry s in country i by $Rev_{is} = P_{iis}Y_{is}$. Product markets for industry-level Armington bundles clear if the industry's revenue equals expenditure on the industry's goods:

$$Rev_{is} = \sum_j \lambda_{jis} \left[\alpha_{js}\left(\frac{P_{js}}{P_j}\right)^{1-\rho}\left(w_{Lj}\sum_s \int_0^{A_{Ljs}} l_{js}(a)da + w_{Rj}\sum_s \int_0^{A_{Rjs}} r_{js}(a)da - D_j\right) + \sum_{s'} \phi_{ss'j} Rev_{js'}\right]. \tag{21}$$

The first term in the bracket corresponds to final expenditure of each country and the second term is intermediate expenditure by other industries. D_j is an (exogenous) aggregate imbalance. We assume that the factor income of REEs is attributed to expenditure and GDP of the country where the factor is used to produce value added.[23]

[23] GDP of each country equals gross national income, including revenue from export taxes, minus net factor income from abroad, minus aggregate imbalances. For China, net factor income from abroad corresponds to factor exports of the REE factor, while for the other countries it corresponds to imports of this factor (see Appendix C.1 for details). In Appendix C.1, we also consider a model variant which alternatively assumes that value added generated by REEs is fully attributed to expenditure in China. While this assumption leads to a different distribution of welfare levels, this makes no substantial difference for the relative welfare effects of China's REE industrial policy because REE income accounts for a small fraction of GDP.

Figure 4: Model Structure



Notes: The figure depicts the general-equilibrium structure of the model.

Labor is immobile across countries, and labor markets clear for each country:

$$\sum_s \int_0^{A_{Lis}} l_{is}(a)da = L_i \tag{22}$$

By contrast, the REE factor is tradable and the REE market clears at the world level:

$$\sum_i \sum_s \int_0^{A_{Ris}} r_{is}(a)da = R_C \tag{23}$$

5.2 Equilibrium

An equilibrium in this model determines a solution for *(i)* factor prices w_{RC} for China and w_{Li} $\forall i$; *(ii)* revenues, prices and trade shares for tradable country-industry pairs Rev_{is} $\forall i, s$, P_{is} $\forall i, s$, P_i $\forall i$, λ_{ijs} $\forall i, j, s$, P_{ijs} $\forall i, j, s$ and *(iii)* the size of input layers $P_{Lis} Y_{Lis}$ $\forall i, s$, $P_{Ris} Y_{Ris}$ $\forall i, s$.

This solution is determined by *(i)* $I \times S$ equations (24), determining Rev_{is}; *(ii)* $I \times J \times S$ equations (25) determining λ_{ijs}; *(iii)* $I \times J \times S$ equations (26) determining P_{ijs}; *(iv)* $I \times S$ equations

(27) determining P_{is}; *(v)* I equations (28) determining P_i; *(vi)* $2 \times I \times S$ equations of type (29) determining $P_{Ris}Y_{Ris}$ and $P_{Lis}Y_{Lis}$; *(vii)* I equations (32) determining w_{Li} and *(viii)* 1 equation (33), determining w_{RC}. Further, note that $w_{Ri} = w_{RC}\tau_{XC}$.

Market clearing for Armington goods is given by:

$$\begin{aligned} Rev_{is} =& \sum_j \lambda_{jis} \times \\ & \left[\alpha_{js}\left(\frac{P_{js}}{P_j}\right)^{1-\rho}\left(\sum_s \frac{\mu-1}{\mu} P_{Ljs}Y_{Ljs} + \sum_s \frac{\mu-1}{\mu} P_{Rjs}Y_{Rjs} - D_j\right) + \sum_{s'} \phi_{ss'j} Rev_{js'}\right] \quad \forall i, s, \end{aligned} \tag{24}$$

Bilateral trade shares are:

$$\lambda_{ijs} = \left(\frac{P_{ijs}}{P_{is}}\right)^{1-\sigma_s} \qquad \forall i, j, s \tag{25}$$

Bilateral prices are given by:

$$\begin{aligned} P_{ijs} =& d_{ijs}\left[\gamma_s^{\varepsilon_s}\left(\frac{P_{Rjs}Y_{Rjs}}{\mu f_{Rjs} P_j}\right)^{\delta(\varepsilon_s - 1) + \frac{\varepsilon_s - 1}{\mu - 1}} \left(\frac{\mu}{\mu - 1}\right)^{1-\varepsilon_s} w_{Rj}^{1-\varepsilon_s} + \right. \\ & \left. (1-\gamma_s)^{\varepsilon_s}\left(\frac{P_{Ljs}Y_{Ljs}}{\mu f_{Ljs} P_j}\right)^{\delta(\varepsilon_s - 1) + \frac{\varepsilon_s - 1}{\mu - 1}} \left(\frac{\mu}{\mu - 1}\right)^{1-\varepsilon_s} w_{Lj}^{1-\varepsilon_s}\right]^{\frac{\phi_{is}}{1-\varepsilon_s}} \prod_{s'} P_{js'}^{\phi_{jss'}} \quad \forall i, j, s \end{aligned} \tag{26}$$

Industry-level price indices are defined as:

$$P_{is} = \left[\sum_j P_{ijs}^{1-\sigma_s}\right]^{\frac{1}{1-\sigma_s}} \qquad \forall i, s \tag{27}$$

Aggregate price levels are given by:

$$P_i = \left[\sum_s \alpha_{is} P_{is}^{1-\rho}\right]^{\frac{1}{1-\rho}} \qquad \forall i \tag{28}$$

Revenues of the R_{is} and L_{is} layers are given by:

$$P_{Ris}Y_{Ris} = \gamma_s \phi_{is} Rev_{is} \times \tag{29}$$
$$\left[\gamma_s + (1-\gamma_s) \left(\frac{(1-\gamma_s) f_{Ris}}{\gamma_s f_{Lis}} \right)^{\frac{(\varepsilon_s - 1)\{\mu\kappa_s + (\mu-1)^2 \varepsilon_s \delta\}}{(\mu-\varepsilon_s)[\mu - \varepsilon_s - \delta(\mu-1)(\varepsilon_s - 1)]}} \left(\frac{r_{is}}{l_{is}} \right)^{\frac{(1-\varepsilon_s)\{\delta(\mu-1)^2(\varepsilon_s-1) + (\mu-1)\kappa_s\}}{(\mu-\varepsilon_s)\kappa_s}} \right]^{-1} \quad \forall i, s,$$

$$P_{Lis}Y_{Lis} = (1-\gamma_s) \phi_{is} Rev_{is} \times \tag{30}$$
$$\left[(1-\gamma_s) + \gamma_s \left(\frac{(1-\gamma_s) f_{Ris}}{\gamma_s f_{Lis}} \right)^{\frac{(1-\varepsilon_s)\{\mu\kappa_s + (\mu-1)^2 \varepsilon_s \delta\}}{(\mu-\varepsilon_s)\kappa_s}} \left(\frac{r_{is}}{l_{is}} \right)^{\frac{(\varepsilon_s - 1)\{\delta(\mu-1)^2(\varepsilon_s-1) + (\mu-1)\kappa_s\}}{(\mu-\varepsilon_s)\kappa_s}} \right]^{-1} \quad \forall i, s,$$

where $\kappa_s \equiv \mu - \varepsilon_s + \delta(\mu - 1)(1 - \varepsilon_s)$ and

$$\frac{r_{is}}{l_{is}} = \frac{f_{Ris}}{f_{Lis}} \frac{w_{Li}}{w_{Ri}} \quad \forall i, s. \tag{31}$$

Labor markets clear in each country:

$$\sum_s \frac{\mu - 1}{\mu} P_{Lis} Y_{Lis} = w_{Li} L_i \quad \forall i \tag{32}$$

The REE market clears at the world level:

$$\sum_{i \neq C} \sum_s \frac{\mu - 1}{\mu} P_{Ris} Y_{Ris} \tau_{XC}^{-1} + \sum_s \frac{\mu - 1}{\mu} P_{RCs} Y_{RCs} = w_{RC} R_C \tag{33}$$

The Model with Exogenous Technology: For comparison, we also consider a version of the model where A_{Ris} and A_{Lis} are exogenously given and do not respond to policy. In this case, the free entry conditions do not hold. With exogenous technology, equilibrium equations (29) need to be replaced by:

$$P_{Ris}Y_{Ris} = \gamma_s \phi_{is} Rev_{is} \times \tag{34}$$
$$\left[\gamma_s + (1-\gamma_s) \left(\frac{\gamma_s}{1-\gamma_s} \right)^{1-\varepsilon_s} \left(\frac{A_{Ris}}{A_{Lis}} \right)^{(1-\varepsilon_s)\left(\delta + \frac{\mu}{\mu-1} - 1\right)} \left(\frac{w_{Li}}{w_{Ri}} \right)^{1-\varepsilon_s} \right]^{-1}$$

$$P_{Lis}Y_{Lis} = (1-\gamma_s) \phi_{is} Rev_{is} \times \tag{35}$$
$$\left[(1-\gamma_s) + \gamma_s \left(\frac{\gamma_s}{1-\gamma_s} \right)^{\varepsilon_s - 1} \left(\frac{A_{Ris}}{A_{Lis}} \right)^{(\varepsilon_s - 1)\left(\delta + \frac{\mu}{\mu-1} - 1\right)} \left(\frac{w_{Li}}{w_{Ri}} \right)^{\varepsilon_s - 1} \right]^{-1}$$

Moreover, (26) becomes:

$$
\begin{aligned}
P_{ijs} = & d_{ijs}\Big[\gamma_s^{\varepsilon_s} A_{Ris}^{\delta(\varepsilon_s-1)+\frac{\varepsilon_s-1}{\mu-1}} \left(\frac{\mu}{\mu-1}\right)^{1-\varepsilon_s} w_{Rj}^{1-\varepsilon_s} + \\
& (1-\gamma_s)^{\varepsilon_s} A_{Lis}^{\delta(\varepsilon_s-1)+\frac{\varepsilon_s-1}{\mu-1}} \left(\frac{\mu}{\mu-1}\right)^{1-\varepsilon_s} w_{Lj}^{1-\varepsilon_s}\Big]^{\frac{\phi_{is}}{1-\varepsilon_s}} \prod_{s'} P_{js'}^{\phi_{jss'}}
\end{aligned} \tag{36}
$$

The remaining equilibrium conditions are unaffected.

Welfare: Welfare is measured by consumption of the non-tradable final good C_i. By dividing the expression for aggregate expenditure in (24) by the consumer price index and subtracting innovation investment, we obtain the following welfare expression:

$$
C_i = \frac{1}{P_i}\left[\underbrace{\sum_s \frac{\mu-1}{\mu} P_{Lis} Y_{Lis}}_{\substack{\text{Value Added} \\ \text{from Labor}}} + \underbrace{\sum_s \frac{\mu-1}{\mu} P_{Ris} Y_{Ris}}_{\substack{\text{Value Added} \\ \text{from REEs}}} - D_i\right] - \underbrace{\sum_s A_{Ris} f_{Ris} - \sum_s A_{Lis} f_{Lis}}_{\text{Innovation Investment}}. \tag{37}
$$

Consumption corresponds to real expenditure minus investment where expenditure is given by aggregate value added (GDP) minus the aggregate imbalance.

5.3 Discussion

Direction of Innovation Bias: Using the model, we can analytically determine the direction in which the innovation bias, measured by the ratio $\frac{A_{Ris}}{A_{Lis}}$, shifts in response to changes in the factor-input ratio $\frac{r_{is}}{l_{is}}$ for each country-industry pair is.

To illustrate this, we first take the ratio of the production functions for the R_{is} and L_{is} input layers, as given in equation (8):

$$
\frac{Y_{Ris}}{Y_{Lis}} = \frac{E_{Ris}}{E_{Lis}} \left(\frac{A_{Ris}}{A_{Lis}}\right)^{\frac{\mu}{\mu-1}} \frac{r_{is}}{l_{is}}. \tag{38}
$$

Next, combining this expression with the relative demand equation $\frac{Y_{Ris}}{Y_{Lis}} = \left(\frac{\gamma_s}{1-\gamma_s}\right)^{\varepsilon_s} \left(\frac{P_{Ris}}{P_{Lis}}\right)^{-\varepsilon_s}$, we derive an expression for the relative revenues of firms in the R_{is} and L_{is} sectors:

$$
\frac{P_{Ris}Y_{Ris}}{P_{Lis}Y_{Lis}} = \frac{\gamma_s}{1-\gamma_s} \left(\frac{E_{Ris}}{E_{Lis}}\right)^{\frac{\varepsilon_s-1}{\varepsilon_s}} \left(\frac{A_{Ris}}{A_{Lis}}\right)^{\frac{\mu}{\mu-1}\frac{\varepsilon_s-1}{\varepsilon_s}} \left(\frac{r_{is}}{l_{is}}\right)^{\frac{\varepsilon_s-1}{\varepsilon_s}} \tag{39}
$$

Combining (39) with (15), we can solve for the relative technology bias as a function of the input ratio:

$$\frac{A_{Ris}}{A_{Lis}} = \left(\frac{f_{Lis}}{f_{Ris}}\frac{\gamma_s}{1-\gamma_s}\right)^{\frac{(\mu-1)\varepsilon_s}{\kappa_s}} \left(\frac{r_{is}}{l_{is}}\right)^{\frac{(\mu-1)(\varepsilon_s-1)}{\kappa_s}} \tag{40}$$

When $\mu > 1$ (a necessary condition to ensure well-defined profit maximization by monopolistic producers) and $\varepsilon_s < 1$ (indicating that REEs and equipped labor are gross complements), the expression in (40) is decreasing in $\frac{r_{is}}{l_{is}}$ ($\kappa_s > 0$) if $\delta \geq 0$, or if $|\delta| < \frac{\mu-\varepsilon_s}{(\mu-1)(\varepsilon_s-1)}$ and $\delta < 0$. Under these conditions, a negative REE supply shock — i.e., a decline in $\frac{r_{is}}{l_{is}}$ — biases innovation toward increasing the efficiency of REE inputs. This effect is stronger in industries with larger REE intensity γ_s. In industries with $\varepsilon_s > 1$, the REE supply shock instead triggers innovation that is biased towards equipped labor.

The underlying intuition is as follows: with complementary inputs, the price effect (arising from an increase in P_{Ris}/P_{Lis}) dominates the negative market-size effect (due to reduced r_{is}/l_{is}). Consequently, developing technologies that enhance the productivity of the REE-intensive sector R_{is} becomes relatively more profitable than innovations in the labor-intensive sector L_{is}.

Moreover, provided that $\kappa_s > 0$, the sensitivity of the technology bias to changes in $\frac{r_{is}}{l_{is}}$ increases with the magnitude of negative δ. This reflects the role of negative spillovers: when inputs are complementary, such spillovers reduce the productivity of competitors, raising the price of the input bundle (P_{Ris}/P_{Lis}) and thereby increasing the profitability of innovation despite falling output levels. This effect is captured in the expression for relative revenue (41), which results from substituting (40) into (39):

$$\begin{aligned}\frac{P_{Ris}Y_{Ris}}{P_{Lis}Y_{Lis}} = & \left(\frac{f_{Lis}}{f_{Ris}}\right)^{\frac{\mu(\varepsilon_s-1)\kappa_s+(\mu-1)^2\varepsilon_s\delta(\varepsilon_s-1)}{(\mu-\varepsilon_s)\kappa_s}} \left(\frac{\gamma_s}{1-\gamma_s}\right)^{\frac{\varepsilon_s(\mu-1)\kappa_s+(\mu-1)^2\varepsilon_s\delta(\varepsilon_s-1)}{(\mu-\varepsilon_s)\kappa_s}} \\ & \left(\frac{r_{is}}{l_{is}}\right)^{\frac{(\mu-1)(\varepsilon_s-1)\kappa_s+(\mu-1)^2(\varepsilon_s-1)^2\delta}{(\mu-\varepsilon_s)\kappa_s}}\end{aligned} \tag{41}$$

Similarly to the case of technology bias, the expression for relative revenue is decreasing in $\frac{r_{is}}{l_{is}}$ under analogous conditions, implying that a negative REE supply shock increases the relative profitability of the R_{is} sector.

By contrast, the relative output of the REE sector, Y_{Ris}/Y_{Lis}, increases with the input ratio $\frac{r_{is}}{l_{is}}$:

$$\frac{Y_{Ris}}{Y_{Lis}} = \left(\frac{f_{Lis}}{f_{Ris}}\frac{\gamma_s}{1-\gamma_s}\right)^{\frac{\varepsilon_s}{\mu-\varepsilon_s}\left(\mu+\frac{\delta(\mu-1)^2\varepsilon_s}{\kappa_s}\right)} \left(\frac{r_{is}}{l_{is}}\right)^{\frac{\varepsilon_s(\mu-1)}{\mu-\varepsilon_s}\left(1+\frac{\delta(\mu-1)(\varepsilon_s-1)}{\kappa_s}\right)}. \tag{42}$$

Finally, equation (31) shows that the optimal input ratio is inversely related to the relative price of REEs.

Impact on Comparative Advantage: By comparing the expressions for unit costs under endogenous (26) and exogenous technologies (36), we gain insight into how the competitiveness of downstream industries and comparative advantage responds to an increase in the price of the REE factor.

Under exogenous technology, an increase in w_{Rj} raises production costs — an effect that is more pronounced in industries with higher REE intensity γ_s and and lower substitutability ε_s. (*factor-cost effect*). According to the trade-share equation (20), this reduces bilateral exports of downstream REE-intensive industries relative to labor-intensive ones. This effect captures standard Heckscher-Ohlin forces of comparative advantage.

By contrast, under endogenous technology, an increase in w_{Rj} also induces a technological response via an associated increase in $P_{Ris}Y_{Ris}$ (*technology effect*). This effect is also more powerful in industries with larger γ_s and smaller ε_s. If the technology effect is sufficiently strong, it can outweigh the factor-cost effect, thereby enhancing the relative competitiveness of downstream REE-intensive industries. As a result, exports of these industries may increase relative to those of labor-intensive industries despite the rise in input costs.

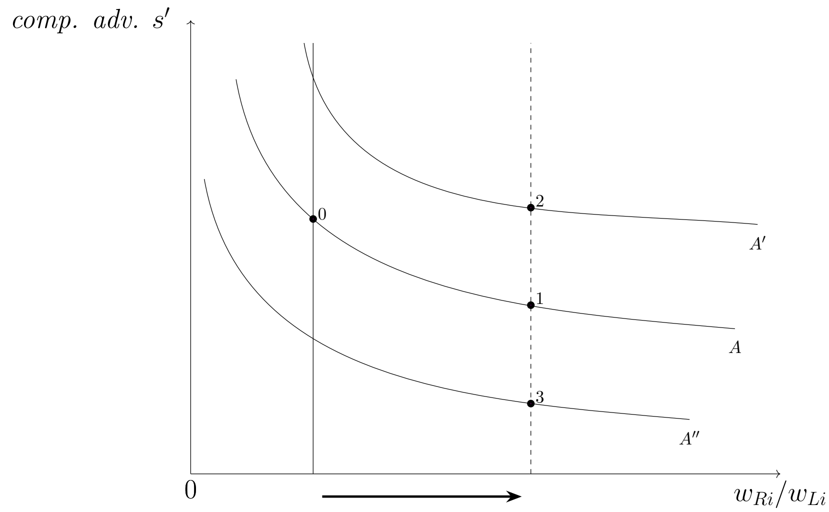
This can be illustrated with the help of Figure 5. The figure shows relative unit costs $P_{iis}/P_{iis'}$ for two industries s and s' (i.e., comparative advantage of industry s' relative to s) and highlights potential equilibrium adjustments in response to an increase in the relative price of REEs. Industry s' is relatively more REE-intensive than industry s, so that relative unit-cost curves A, A' and A'' are downward sloping in the relative price of REE w_{Ri}/w_{Li}.

Starting from an initial equilibrium at point 0, an increase in the price of REE leads to a new equilibrium with new relative unit costs. When technologies are held fixed, the adjustment occurs along the A curve to the new equilibrium point 1: the REE-intensive industry loses some of its competitiveness compared to the labor-intensive one due to the relatively intensive use of the REE factor, whose relative price has risen (the standard Heckscher-Ohlin force).

However, if the endogenous response of the technology bias towards REEs is sufficiently strong, the new relative unit-cost curve shifts upwards (denoted as A') such that at this alternative equilibrium point 2, the competitiveness of the REE-intensive industry increases relative to that of the labor-intensive one.

Alternatively, if the innovation bias were to shift in the opposite direction (e.g., if REEs and labor were gross substitutes), relative unit costs would become A''. In this alternative equilibrium

Figure 5: Comparative Advantage, Factor Prices and Directed Technological Change



Notes: The figure plots possible responses of comparative advantage of industry s' relative to s $(P_{iis}/P_{iis'})$ to an increase in the relative REE factor price. Industry s' is relatively more intensive in REEs. Holding constant technologies, adjustment occurs along a given curve A from point 0 to 1 (Heckscher-Ohlin effect). Curves A' and A'' depict relative unit cost curves $P_{iis}/P_{iis'}$ for different possible responses of technological change (technology effect). Adjustment may occur from point 0 to 2 or from 0 to 3.

(point 3), the technology response would amplify standard Heckscher-Ohlin forces and the REE-intensive industry would further lose in terms of competitiveness compared to the case of exogenous technology.

Finally, IO linkages between industries introduce noise into the above mechanisms and can either amplify or weaken the response of comparative advantage: e.g., an REE-intensive industry may face a cost increase in the bundle of intermediate inputs relative to a labor-intensive one, counteracting the technology effect.

As our model flexibly nests all these effects of the response of comparative advantage to an export tax on REEs, we need to calibrate the model in order to obtain the qualitative and quantitative general-equilibrium response of trade, production and welfare.

6 Quantification

In this section, we first calibrate the model to a baseline economy that matches moments before REE export restrictions were imposed by China. We then provide a quantitative assessment of China's REE export restrictions and study the impact that they would have had in a counterfactual economy without endogenous technological change.

6.1 Taking the Model to the Data

We calibrate the model to a baseline economy in 2009, the year before the REE restrictions. We aggregate the world into 5 regions relevant for our analysis: China, Europe, Japan, the U.S., and the rest of the world (RoW), including all remaining countries. We consider 14 industries: 12 manufacturing industries, agriculture and services. Such aggregation compared to our reduced-form analysis is necessary since we use the World Input-Output Tables (WIOD, 2012 release) to match international trade and production data and IO linkages.

Externally Calibrated Parameters: We set the trade elasticity σ_s equal to 6 for all industries, a standard value in the literature (Costinot and Rodríguez-Clare, 2014). We choose a substitution elasticity in the innovation layer μ of 6.5, implying a markup of 18%, consistent with estimates from De Loecker and Eeckhout (2018). The elasticity of substitution of final demand is set to 1.36, following Redding and Weinstein (2024).

Estimating the Substitution Elasticity for REEs: A key object in our calibration is the industry-specific substitution elasticity between REEs and equipped labor (ε_s) since this elasticity governs the response of input costs and innovation to a REE supply shock. To shift the direction of innovation towards REEs in response to a positive REE price shock, as in the empirical findings, REEs must be gross complementary inputs ($\varepsilon_s < 1$). Although input substitution elasticities are typically estimated from variation in input expenditure shares, this information is not available at the country-industry level for REEs. Instead, we exploit the structure of the model to identify this elasticity of substitution from the relation between relative factor prices and the direction of innovation in each industry.

Our model implies the following structural relationship between relative patents A_{Ris}/A_{Lis} and relative factor prices w_{Ri}/w_{Li}:

$$\log\left(\frac{A_{Ris}}{A_{Lis}}\right) = \beta_s \log\left(\frac{w_{Ri}}{w_{Li}}\right) + \delta_s + u_{is}, \tag{43}$$

where the coefficient of interest is $\beta_s \equiv \frac{(1-\varepsilon_s)(\mu-1)}{\kappa_s}$, $\delta_s \equiv \frac{\varepsilon_s(\mu-1)}{\kappa_s}\log\left(\frac{\gamma_s}{1-\gamma_s}\right)$ is an industry fixed effect, and the structural error term, which we assume to be orthogonal to relative factor prices, is $u_{is} \equiv \frac{\mu-1}{\kappa_s}\log\left(\frac{f_{Lis}}{f_{Ris}}\right)$.[24] This equation can be estimated from data on the relative number of REE

[24] We refer to Appendix C.2 for a derivation.

patents, REE unit import values, and wages. We use our patent data, classified with the LLM algorithm described in Section 3.2 for regions other than China. The unit value of REEs for each country is obtained by dividing the value of REE imports by that country by the physical quantity. Finally, labor costs for each country are calculated from the Penn World Tables. We estimate (43) separately for each 2-digit manufacturing SIC code, using a panel of 4 regions (Europe, Japan, U.S., ROW) over the sample period from 2002 to 2018 and back out ε_s for given values of the other parameters. Finally, we aggregate the resulting estimates to the level of WIOD industries by taking averages weighted by value added. Intuitively, we assume that changes in local REE prices outside of China are driven mostly by global supply and are therefore uncorrelated with local innovation fixed costs, which affects local demand.

Calibrating the REE Intensity: Another important parameter is the REE intensity of each industry γ_s. From cost minimization, we obtain the following expression for the REE expenditure share in value added:

$$\frac{P_{Ris}Y_{Ris}}{P_{VAis}VA_{is}} = \frac{1}{1+\left(\frac{1-\gamma_s}{\gamma_s}\right)^{\varepsilon_s}\left(\frac{P_{Lis}}{P_{Ris}}\right)^{1-\varepsilon_s}} \tag{44}$$

To compute γ_s, we rely on data for the U.S. Using total requirements of REE for each industry – which we obtain from the IO table presented in Subsection 3.1 – combined with data on value added, ideal price indices P_{Ris} and P_{Lis} for the U.S., and estimates for ε_s, we can back out γ_s for all industries s.[25]

Table 3 presents the estimates of ε_s and γ_s by industry, sorted by the decreasing values of ε_s. We estimate $\varepsilon_s \in [0.774, 1.389]$, with point estimates below unity in most industries.[26] It should be noted that those industries with the lowest substitution elasticities also tend to be the the most REE-intensive ones. We thus expect a strong REE-biased technology response in REE-intensive industries when the relative price of REE increases. By contrast, labor-intensive industries have values of ε_s above unity, implying a labor-biased technology response.

[25] REE total requirements represent the value of REE required for each dollar of *final* demand. Therefore, we can obtain the ratio of REE expenditure to value added on the left-hand side by multiplying the REE total requirement for each industry with its ratio of final demand to value added, calculated from the supply-use table. Since this ratio is based on U.S. data, we also use U.S. data for labor cost, REE unit import prices and patent data to calculate the ideal price indices P_{Lis} and P_{Ris} from equation (9).

[26] These estimates are relatively high compared to estimates for oil (Hassler et al., 2021). However, note that our 12 manufacturing industries are highly aggregated. As a consequence, these estimates do not just reflect technical substitution options between inputs but also consumers' substitution possibilities across different goods within industries (e.g., for transport equipment, between electric vehicles and combustion engines). Furthermore, these industries may contain activities where REEs are less relevant or more substitutable (e.g., basic metals and fabricated metals include non-magnet metal products that do not use REEs). When we zoom in to certain product categories, such as vehicle motors and permanent magnets, we obtain lower estimates.

Internally Calibrated Parameters: For each country-industry pair, we take bilateral trade shares λ_{ijs}, consumption expenditure shares $\alpha_{is}\left(P_{is}/P_i\right)^{1-\rho}$, value-added shares in gross output ϕ_{is} and direct requirement shares in gross output $\phi_{iss'}$ directly from the data, using trade and production data from WIOD. We calibrate equipped-labor endowments according to country-level employment data adjusted for human-capital differences from the Penn World Tables (PWT release 10.01). Given estimates for γ_s and ε_s, we calibrate the innovation fixed costs in each country to exactly match relative patents $\frac{A_{Ris}}{A_{Lis}}$ for each industry, using values for the U.S.[27]

We calibrate the model to fit equation (24) and exactly match the initial real GDP differences between countries by iterating over the level of exogenous imbalances, taking into account differences in price levels P_i between economies, which we also obtain from the PWT.

Finally, we calibrate the parameter δ, which governs the strength of the innovation spillovers, by matching the model-implied response of directed technological change across industries outside of China to China's REE policy (described below) with the one in the data. Specifically, we regress the model-implied change in relative patents in response to China's REE policy on industry-specific REE sensitivity, defined as $\frac{\gamma_s}{\varepsilon_s}$. This measure of REE sensitivity is similar to the one used in the reduced-form estimation equation (1), as industries with high REE intensity and low substitutability are the most exposed (it rises with the REE cost share and falls with substitutability). We then choose the value of δ to match the standardized estimate resulting from this regression with its empirical counterpart from column (1) of Table 1. We match standardized coefficients because the units of REE sensitivity used in the empirical estimates are different from the ones in the model, so that any monotone rescaling of the regressor or the use of closely related alternatives leaves the targeted moment, and hence δ, virtually unchanged. This procedure implies a value of δ of -1.7, i.e. negative spillover effects.[28]

6.2 A Quantitative General-Equilibrium Assessment of the 2010 REE Supply Shock

Calibrating REE Export Taxes: Next, we provide a quantitative assessment of China's industrial policy on REEs. As discussed in Section 2.3, China introduced export restrictions on REEs in 2010. In our quantitative analysis, we thus focus on the effects of an REE export tax set by China on all countries, starting from a calibrated baseline economy.

Since the magnitude of the REE tax is not directly observable and the mix of Chinese REE trade-policy instruments does not map into a single statutory export tax rate, we discipline the tax rate

[27]Technical details on the calibration procedure are provided in Appendix C.

[28]Since estimating ε_s requires picking a value for δ and this in turn affects other parameters, we loop over this procedure.

Table 3: Estimates of ε_s and γ_s

Manufacturing Industry	ε_s	γ_s
Transport equipment	0.774	0.00097
Basic metals and fabricated metal	0.828	0.00125
Rubber and plastics	0.841	0.00010
Mining, petroleum, and coal products	0.884	0.00047
Computer and electronic products	0.931	0.00031
Chemicals and chemical products	0.936	0.00001
Other non-metallic mineral products	0.945	0.00005
Machinery	0.991	0.00047
Food, beverages, and tobacco	1.177	0.00005
Wood and paper products	1.186	0.00003
Furniture and misc. manufacturing	1.306	0.00002
Textiles and textile products	1.389	0.00004

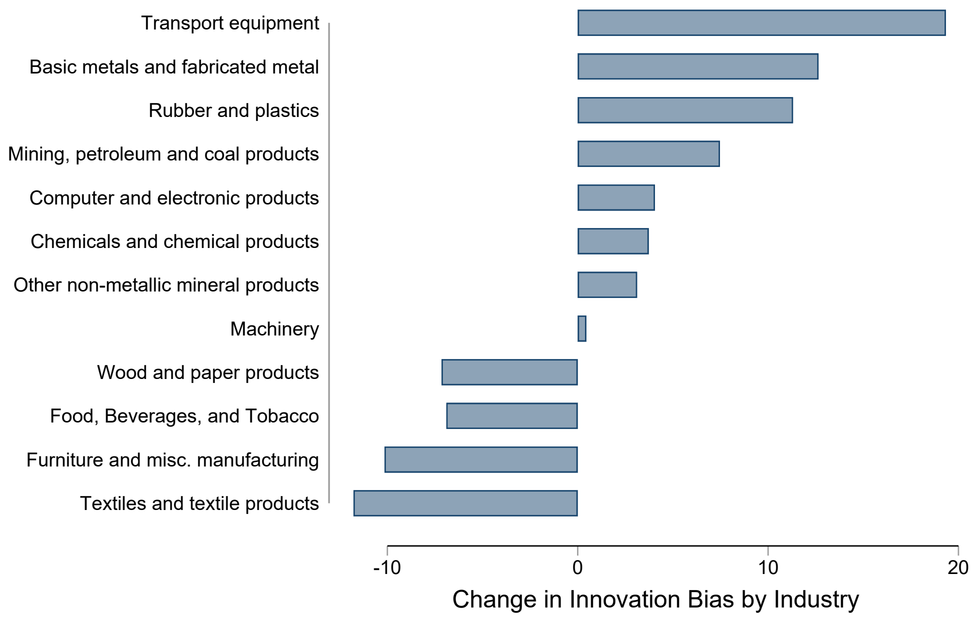
Notes: The table shows estimates of the REE elasticity of substitution ε_s and REE intensity γ_s used in the quantification.

using statistics on prices. We infer an export-tax equivalent of $\tau_{XC} = 3$ from the average wedge between the Free on Board and the Ex Works REE prices (measured in RMB) between 2010 and 2012. Below, we report the results of this policy experiment.

Directed Technological Change: Figure 6 visualizes the impact of China's REE export tax on the industry-level innovation response in other countries. Specifically, the figure shows the relative change in industry-level innovation bias $\Delta(A_{Ris}/A_{Lis})$, averaged over countries excluding China. There is substantial heterogeneity in the level and direction of the innovation response across industries. As discussed in Subsection 5.3, the shift in the innovation bias towards REEs is stronger, the lower the elasticity of substitution ε_s in a given industry. Consistent with the model predictions, the innovation bias shifts towards REEs in those industries where REEs and equipped labor are complements. By contrast, it shifts towards equipped labor in all other industries. Quantitatively, the shift in the innovation bias ranges between 19 p.p. for Transport Equipment (the industry with the lowest value of ε_s) and -12 p.p. for Textiles (the industry with the largest value of ε_s).

Exports and Revenues: Next, we assess how industry-level exports and revenues of other countries respond to China's REE export tax. As explained in Section 5.3, the link between the technology response and shifts in comparative advantage is not straightforward in our model, due to both counteracting Heckscher-Ohlin effects and IO linkages between industries. Panel (a) of

Figure 6: Effect on Directed Technological Change



Notes: The figure plots relative changes in A_{Ris}/A_{Lis} outside of China (measured in % change from the baseline economy) in response to the introduction of an REE export tax by China. Regions are weighted according to real GDP in the baseline economy.

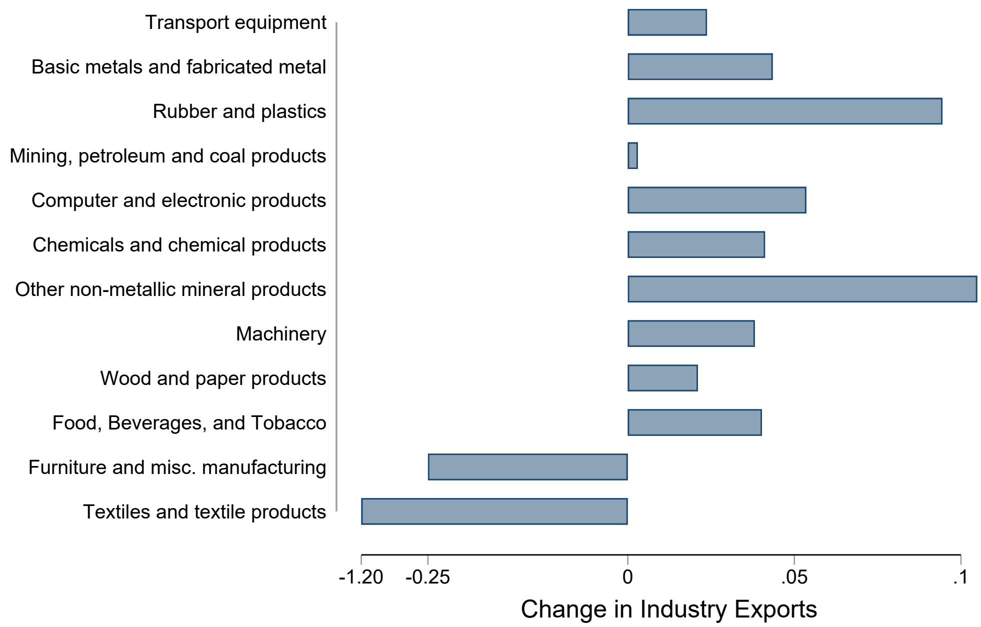
Figure 7 depicts changes in exports by industry for countries other than China. We normalize exports by total global exports of the respective industry. Consistent with our empirical estimates (see Table 2), more REE-intensive industries also expand their exports relatively more compared to less REE-intensive ones. Quantitatively, changes in exports are fairly small in most industries. Exceptions are the two industries with the largest substitution elasticities ε_s (Furniture and Misc. Manufacturing as well as Textiles), which contract by -0.23% and -1.16%, respectively. Panel (b) depicts changes in industry revenues (normalized by global industry revenue). Again, we find that industries which shift their innovation bias toward REEs contract relatively less, compared to those which shift their innovation bias towards equipped labor.[29] Once more, the magnitudes of revenue responses are fairly small.

GDP and Welfare: We now turn to a discussion of the effects of China's REE export tax on countries' GDP and welfare. To highlight the role of directed technological change in cushioning the general-equilibrium impact of China's policies, we contrast our results with a counterfactual scenario under fixed technologies. In that counterfactual, we examine the impact that China's

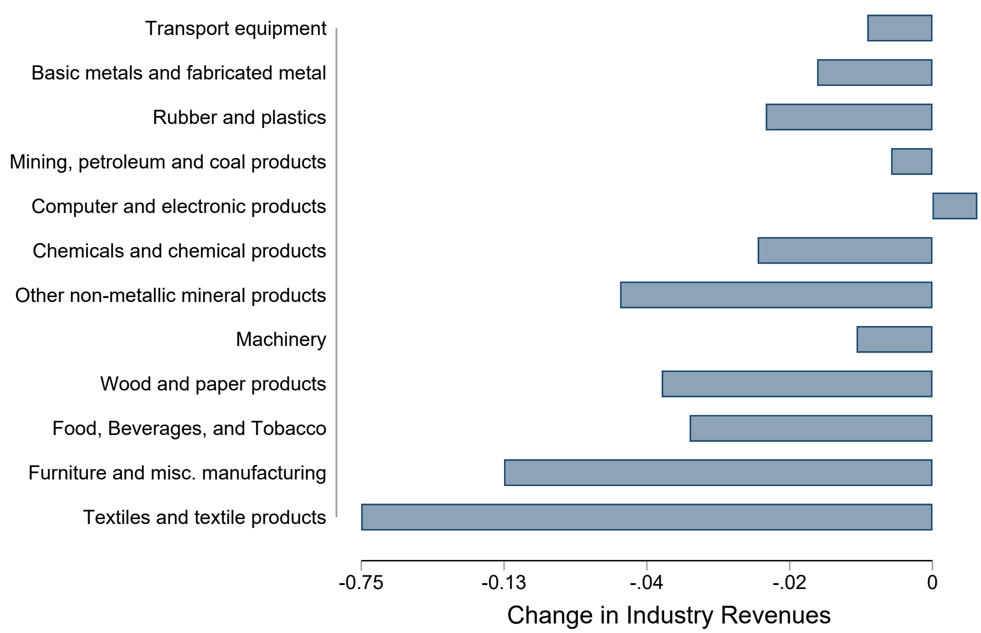
[29]Note that since the reduced-form estimates in Section 4 are relative statements across industries and do not allow identifying absolute effects, a positive coefficient on the treatment variable is consistent with a negative average general-equilibrium effect of China's policy.

Figure 7: Effects on Exports and Revenues

(a) Exports

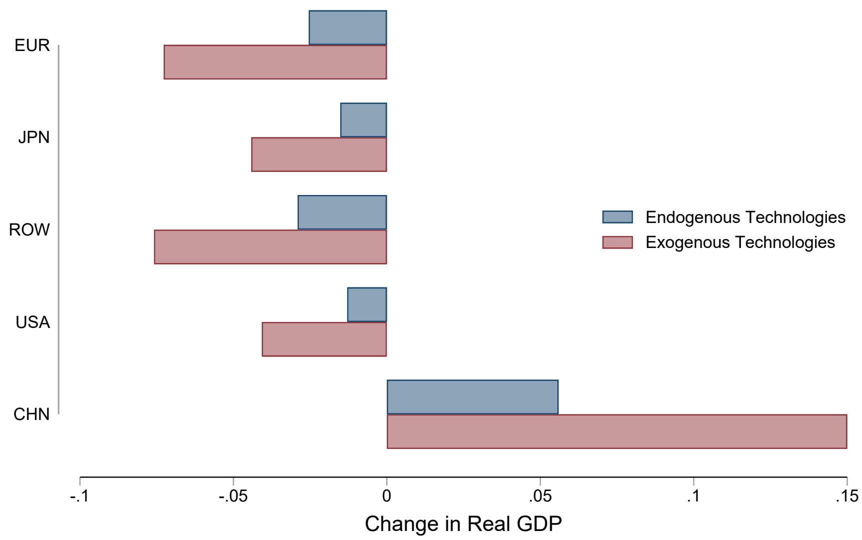


(b) Revenues



Notes: The figure plots average relative changes in exports and revenues outside of China (measured in % change from the baseline economy) in response to the introduction of an REE export tax by China. Exports and revenues are expressed as the share in total global exports or revenues within each industry.

Figure 8: Effect on Real GDP



Notes: The figure plots relative changes in real GDP (measured in % change from the baseline economy) in response to the introduction of an REE export tax by China.

REE export tax would have had if technologies had remained fixed at their initial levels.

Figure 8 depicts the impact of China's export tax on real GDP. While real GDP outside China declines somewhat, output losses are very small throughout (between 0.013% and 0.029%). The gain in China's real GDP is a bit larger and corresponds to 0.056%.

In the counterfactual scenario where technologies are held fixed, the negative impact of China's policy on other countries' real GDP is substantially larger. In the absence of directed technological change, GDP losses in other countries are around three times larger (between 0.041% and 0.076%) than those under endogenous technologies. Similarly, China's real GDP gain is also substantially larger (around 0.15%).

Intuitively, under fixed technologies China's policies would cause a large increase in production costs in other countries – in particular in REE-intensive industries with low elasticities of substitution – implying a loss in competitiveness and a reduction in value added. At the same time, China's REE-intensive industries would face lower input costs and gain in terms of competitiveness and value added. Directed technological change thus cushions the impact of China's policies abroad by reducing foreign industries' dependence on REEs.

Welfare is measured in terms of real consumption, as given by (37). To obtain real expenditure, nominal GDP needs to be adjusted for aggregate imbalances and deflated by the consumer price index. To obtain real consumption, we also deduct innovation investment. Consequently, while more innovation raises real GDP, it also has a dampening effect on consumption due to the presence of innovation fixed costs. Figure 9 shows the effects of China's REE export tax on welfare. Again, we contrast the results with the counterfactual case of fixed technologies. Under endogenous technologies, the impact of China's REE export tax on consumption is negligible. In Europe, consumption declines by 0.021%, while the reduction is even smaller in the U.S. and in Japan (0.009% and 0.012%, respectively). In China, consumption increases by about 0.030%. The small welfare losses outside of China result from a combination of small GDP effects and a shift in innovation from labor-intensive to REE-intensive industries, which leads to a slight reduction in aggregate investment. Overall, the small welfare effects resulting from China's export tax on REEs reflect declining global demand for REEs due to the strong technological response.

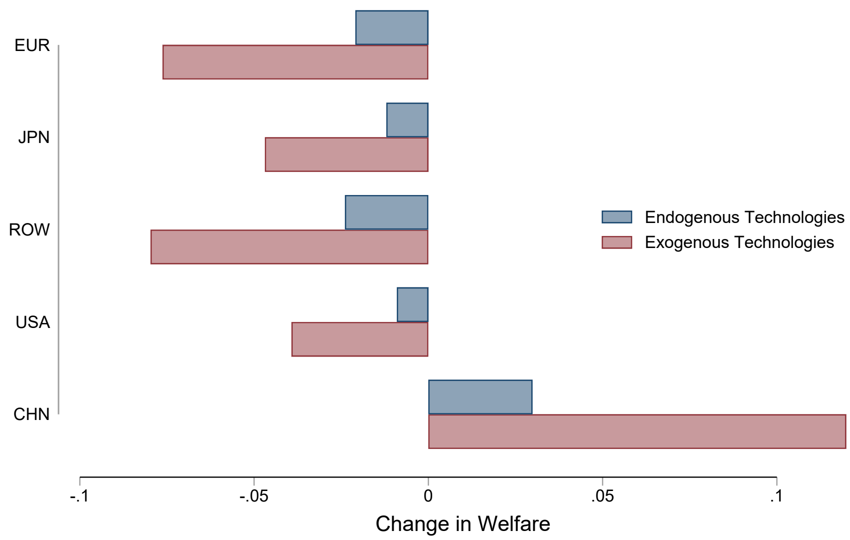
By contrast, the welfare effects are much larger in the presence of exogenously fixed technologies. To make consumption changes under both scenarios comparable, we deduct the costs of innovation investment in the model with fixed technologies but keep investment constant throughout.[30] In this counterfactual scenario, the REE export tax generates a large transfer of value added to China, a consequence of the fairly inelastic factor demand, reflecting the low substitutability of REEs. Notably, China's welfare increases by around 0.120% – a magnitude comparable to the estimated U.S. welfare gains from NAFTA (see Caliendo and Parro, 2015). The welfare losses for the other countries are also significantly larger than in the case of endogenous technologies, amounting to 0.076% in Europe, around 0.039% in the U.S. and 0.047% Japan.

Table C.1 in Appendix C decomposes welfare changes into changes in the individual components of consumption (real value added of labor, real value added of REEs, investment). The upper two panels depict the growth rates of individual components under endogenous and exogenous technologies, while the bottom panel presents initial shares of each component. The aggregate growth rate of consumption can then be obtained by multiplying the growth rates of the components by their respective shares and summing them. In both cases, the largest negative effect of China's REE export tax on countries outside of China is on the value added that is generated by the REE factor. Welfare changes under endogenous technologies are cushioned by a small decrease in investment. In the case of exogenous technologies, the reduction in the value added from labor is substantially larger, reflecting the complementarities between REEs and labor, while investment is unchanged. Overall, this leads to a much larger drop in consumption.

Instead, China's welfare gains are mostly driven by an increase in local value added from REEs within China, as Chinese producers benefit from the lower factor price of REEs. This effect is particularly salient under exogenous technologies: in this case, China's comparative advantage strongly shifts towards REE-intensive industries, which, due to the complementarity, also increases value added from labor.

[30] Figure C.1 in Appendix C plots changes in gross national expenditures, i.e., before deducting investment costs. This leads to qualitatively similar results.

Figure 9: Effect on Welfare



Notes: The figure plots relative changes in welfare (measured in % consumption change from the baseline economy) in response to the introduction of an REE export tax by China.

6.3 Other Counterfactual Analyses

We briefly discuss a number of additional quantitative results. First, we assess the impact of the policy in an alternative version of the model. This alternative assumes that all value added that is created from the factor REE leads to expenditure in China, the country of factor ownership, instead of creating local expenditure in the country of production. Second, we discuss implications of a reduction in REE supply, $\Delta R_C < 0$. Third, we quantify the impact that the 2010 REE policy would have had in a situation with a larger global supply and use of REEs that is comparable with current levels.

Alternative Gross National Expenditures: In our baseline model, all value added that is produced with the REE factor creates local expenditure. Here, we alternatively assume that China receives factor incomes from abroad equal to the foreign value added from REEs and dispenses it. Subsection C.1 in Appendix C outlines how the equilibrium definition changes under that assumption. While this alternative assumption has implications for the distribution of income and expenditure levels across countries, we find the effects on relative changes to be quantitatively rather small. Figure C.2 in Appendix C plots welfare changes for this scenario. In fact, the welfare losses outside of China remain similar to the baseline scenario. Welfare gains for China are somewhat smaller under that model alternative. This is because part of China's terms-of-trade improvement is offset by a reduction in the value added generated by REEs outside of China.

Reduction in REE Supply: Beyond China's trade-policy interventions on REEs, the level of REE mining and processing also decreased after 2010 (see Figure A.2 in Appendix A). Here, we evaluate the effect of a pure supply restriction. We assume that the global supply of REEs R_C falls by 20% without the introduction of an export tax on REEs. This counterfactual allows us to differentiate between the impact of an export tax and a supply restriction. While the supply restriction also biases innovation towards REEs in industries where the elasticity ε_s is below unity, there are several differences compared to the impact of the export tax: the supply cut increases the relative REE factor price globally. Consequently, the decline in supply shifts the innovation bias in the same way in all countries. This implies that there is no expansion of REE-intensive industries relative to other ones outside of China. Since China's factor income of REEs decreases due to the lower supply of REEs, the pure supply restriction implies a welfare loss both for China and for the rest of the world. At first glance, it may seem puzzling that China's rent from the REE factor declines when the physical endowment is reduced, given that the unit price rises. Aggregate demand for the factor, however, is shaped by cross-industry reallocation and by REE-saving technological change that accelerates worldwide after the supply cut. These margins make aggregate REE demand elastic, so the price increase is insufficient to offset the 20% supply drop and China's factor rent falls. Figure C.3 in Appendix C plots welfare changes for this scenario.

Increased REE Use and Supply: Finally, we study the impact that the Chinese REE export tax would have on a world that is more dependent on REEs. By 2025, the production and usage of REEs has approximately doubled compared to 2010 levels. We therefore consider the effect of the export tax in a world where China has an REE endowment that is twice as large as in the baseline economy. We find that the REE export tax has qualitatively similar effects, but that the magnitudes are a bit larger. For example, under endogenous technologies, the export tax causes a welfare gain in China of 0.034% compared to 0.030% in the baseline calibration. Similarly, also under exogenous technologies, the welfare effects are slightly larger: China's welfare increases by 0.145% instead of 0.120%. Figure C.4 in Appendix C plots welfare changes for this counterfactual. Consequently, even in a world that is more dependent on REEs, the effects of China's export restrictions remain modest.

7 Conclusion

How did China's export restrictions on REEs in 2010 affect downstream manufacturing industries, both globally and domestically? In this paper, we provide an empirical and quantitative assessment of the effects of China's policy that unexpectedly restricted the global supply of REEs.

Our key finding is that this policy – that created an adverse supply shock of essential inputs – triggered innovation and reallocation of economic activity towards foreign downstream industries that intensively use these essential inputs.

We provide reduced-form causal evidence based on a constructed IO table that accounts for individual REE inputs and an LLM-classified patent corpus on innovation in REE-using industries across the world. We find that REE-using industries outside China innovated in a way that reduced their dependence on REEs and exported more relative to industries that are less REE intensive.

To quantify the general-equilibrium effects of China's export restrictions, we then develop a novel quantitative trade model that incorporates directed technological change. We calibrate the model using trade, production and patent data. Leveraging the model structure, we estimate the elasticity of substitution between REEs and equipped labor, finding that these inputs are complementary in most industries. Consistent with our reduced-form evidence, our model predicts that an increase in the international REE price – caused by a Chinese export tax – induces technological change aimed at reducing REE usage, that is sufficiently strong to offset the impact of rising input costs. In contrast to a counterfactual economy with exogenously fixed technologies, we show that the endogenous innovation response outside of China has prevented large real GDP and welfare losses while the positive GDP and welfare impact on China was largely dampened compared to a counterfactual world with fixed technologies.

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A Data Appendix

A.1 Imputing REEs into the Supply-Use Table

We first convert REE use numbers from the USGS report (Bleiwas and Gambogi, 2013), which are in metric tons, to USD million using a combination of prices from BCC (2015) and Asian Metal, both at the element level. BCC reports global consumption of REEs by element, both in metric tons and USD million units, giving us the prices per unit. For elements not reported by BCC, we impute their prices by extrapolating from Asian Metal, which reports prices in Chinese markets. We also extrapolate the numbers to 2012 using the compounded annual growth rate of overall rare earth consumption from 2010 to 2012, which is based on data from USGS Mineral Commodity Summaries.

For imputation into the supply-use table, we match each "general category" of REE content from the USGS report into its corresponding NAICS code, which the BEA's SUT uses. Table A.2 presents this matching, which determines which using sectors (columns) we assign the REE use numbers to. For instance, we match the "Fluid Cracking Catalysts" category with "Petroleum Refineries" column. Unfortunately, not all categories of REEs applications can be neatly matched to NAICS. This is an issue especially for the category of permanent magnets, which is the largest in metric tons and USD value. The closest match is the NAICS code for "Other fabricated metal manufacturing." While this NAICS code includes permanent magnets, it also includes industrial pattern manufacturing, steel wool manufacturing, and various others.

To alleviate this lack of granularity in the input sector "Other fabricated metal manufacturing", we split it into magnet and non-magnet production. We then draw from the list of the final use of permanent magnets from Alonso et al. (2023) and BCC (2015) to assign NAICS codes, which would use inputs from the newly split magnet sector, while the rest would take inputs from the artificial non-magnet sector. Table A.3 presents the list of magnet-using sectors along with the split weights. For example, the NAICS sector "Turbine and turbine generator set units manufacturing" takes USD 55 million of inputs from "Other fabricated metal manufacturing". Since we assigned this sector as magnet-using with full weight in our IO table, it would take all USD 55 million of inputs from "Other fabricated metal manufacturing – Magnets" and none from "Other fabricated metal manufacturing – Non-magnets".

Meanwhile, we assign REEs as an input to the NAICS code for "Other Basic Inorganic Chemical Manufacturing" for the supplying sectors (rows). This is the closest match for rare earth oxides, which are the form of REE inputs reported in the USGS report. We split this NAICS code into six rows: five for the individual REEs specified in our raw data source and one for non-REEs. We then impute the numbers into the corresponding supply-use pairs, e.g. the USD value of Nd for magnets is assigned to the cell with the supplying NAICS of “Other Basic Inorganic Chemical Manufacturing – Nd” and the using NAICS of “Other fabricated metal manufacturing – Magnets”. We leave the diagonal cells for the split REE compound sectors empty, e.g., “Other Basic Inorganic Chemical Manufacturing – Nd” does not use inputs supplied by itself or from the other REE compounds. As for the column and row totals, we split them using proportions from the values of each REE oxides approximated from USGS.

Using the imputed supply-use table, we compute total requirement of the supplying REE sector, carved out from ”Other Basic Inorganic Chemical Manufacturing”, by each using NAICS industry. As a last step, we convert these numbers to the SIC-level by using concordance mapping from Pierce and Schott (2012) as the outcomes we study vary at the SIC (and country) level.

Table A.1: Rare Earth Total Requirements (10^{-3} USD of REE per 1 USD of SIC Final Demand)

No	SIC	Description	All	Ce	La	Nd	Pr	Dy
1	3691	Storage Batteries	6.93	0.00	6.93	0.00	0.00	0.00
2	3499	Fabricated Metal Products, NEC	5.91	0.00	0.00	4.06	0.18	1.66
3	3625	Relays and Industrial Controls	0.58	0.00	0.00	0.40	0.02	0.16
4	3511	Turbines and Turbine Generator Sets	0.53	0.00	0.00	0.36	0.02	0.15
5	3292	Asbestos Products	0.47	0.01	0.00	0.32	0.01	0.13
6	3714	Motor Vehicle Parts and Accessories	0.41	0.09	0.00	0.22	0.01	0.09
7	3519	Internal Combustion Engines, NEC	0.39	0.19	0.00	0.14	0.01	0.06
8	3585	Refrigeration and Heating Equipment	0.37	0.18	0.00	0.13	0.01	0.05

Table A.2: Categories of Rare-Earth Applications from the U.S. Geological Survey

General Category (USGS)	NAICS Code	NAICS Description
Alloys	331110	Iron and steel mills and ferroalloy manufacturing
Batteries	335911	Storage battery manufacturing
Automobile catalyst	336390	Other motor vehicle parts manufacturing
Fluid catalytic cracking	324110	Petroleum refineries
Magnets	332999	Other fabricated metal manufacturing (split into magnet and non-magnet)

Table A.3: NAICS Codes Designated as Magnet-Using

NAICS Code	NAICS Description	Weight
333415	Air conditioning, refrigeration, and warm air heating equipment manufacturing	1.0000
333611	Turbine and turbine generator set units manufacturing	1.0000
333613	Mechanical power transmission equipment manufacturing	1.0000
334112	Computer storage device manufacturing	1.0000
334118	Computer terminals and other computer peripheral equipment manufacturing	1.0000
334510	Electromedical and electrotherapeutic apparatus manufacturing	1.0000
334610	Manufacturing and reproducing magnetic and optical media	1.0000
335222	Household refrigerator and home freezer manufacturing	1.0000
335312	Motor and generator manufacturing	1.0000
335314	Relay and industrial control manufacturing	1.0000
336111	Automobile manufacturing	1.0000
336310	Motor vehicle gasoline engine and engine parts manufacturing	1.0000
336320	Motor vehicle electrical and electronic equipment manufacturing	1.0000
336350	Motor vehicle transmission and power train parts manufacturing	1.0000
336390	Other Motor Vehicle Parts Manufacturing	1.0000
336411	Aircraft manufacturing	1.0000
336414	Guided missile and space vehicle manufacturing	1.0000
339112	Surgical and medical instrument manufacturing	1.0000
339114	Dental equipment and supplies manufacturing	1.0000
339910	Jewelry and silverware manufacturing	1.0000
33391A	Pump and pumping equipment manufacturing	1.0000
33441A	Other electronic component manufacturing	1.0000
3363A0	Motor vehicle steering, suspension component (except spring), and brake systems manufacturing	1.0000
33641A	Propulsion units and parts for space vehicles and guided missiles	1.0000
332913	Plumbing fixture fitting and trim manufacturing	0.2500
333111	Farm machinery and equipment manufacturing	0.2500
333120	Construction machinery manufacturing	0.2500
333517	Machine tool manufacturing	0.2500
333618	Other engine equipment manufacturing	0.2500
334513	Industrial process variable instruments manufacturing	0.2500
336413	Other aircraft parts and auxiliary equipment manufacturing	0.2500
33299A	Ammunition, arms, ordnance, and accessories manufacturing	0.2500
33329A	Other industrial machinery manufacturing	0.2500
33399A	Other general purpose machinery manufacturing	0.2500
334111	Electronic computer manufacturing	0.0625
334300	Audio and video equipment manufacturing	0.0625
336412	Aircraft engine and engine parts manufacturing	0.0625

Notes: The table lists the weights we use for splitting the NAICS code for "Other fabricated metal manufacturing" into "magnets" and "non-magnets". For each NAICS code that uses USD x million input from "Other fabricated metal manufacturing" and has weight w, in the imputed input-output table it would take USD xw million from "magnets" and USD $x(1-w)$ million from "non-magnets".

Table A.4: Keywords for the Rare-Earth Patent Search

Element	Keywords
Cerium	cerium ceo2
Dysprosium	dysprosium dy2o3
Erbium	erbium er2o3
Gadolinium	gadolinium gd2o3
Holmium	holmium ho2o3
Lanthanum	lanthanum la2o3
Lutetium	lutetium lu2o3
Neodymium	neodymium nd2o3 ndfeb rare earth magnet rare-earth magnet rare earth element magnet rare-earth element magnet nib magnet neo magnet nd2fe14b prnd
Praseodymium	praseodymium pr2o3
Praseodymium	prnd ndfeb rare earth magnet rare-earth magnet rare earth element magnet rare-earth element magnet nib magnet neo magnet nd2fe14b
Scandium	scandium sc2o3
Samarium	samarium sm2o3 smco rare earth magnet rare-earth magnet rare earth element magnet rare-earth element magnet
Terbium	terbium tb4o7
Yttrium	yttrium y2o3
Ytterbium	ytterbium yb2o3
Europium	europium eu2o3

Notes: The table lists keywords used to search for REE patents from Google Patent Research database. Eu, Pm, and Tm were excluded due to being too rare for most industrial applications.

A.2 Index of Complementarity

We use the substitute performance index developed by Graedel et al. (2015) to account for whether REE inputs used by the sector are highly complementary in the production function. The concept of complementarity here arises from exogenous physical and chemical properties of the elements. The index is constructed by listing potential substitutes for each element's primary uses and then assessing their performance as informed by the assimilation of research and expert opinion.

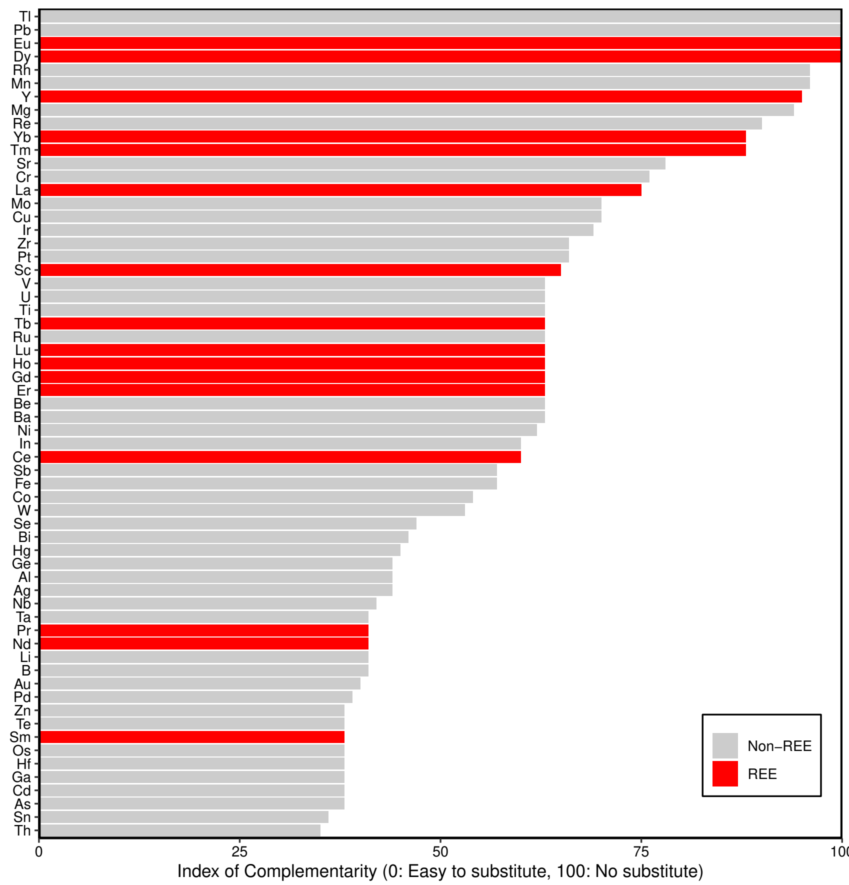
For example, for Cerium (CE), the authors analyze different applications (e.g., "Glass polishing"), application details (e.g., "Used to polish precision optics"), percentage of application (e.g., 25% global use), primary substitute (e.g., iron oxide), and substitute performance (e.g., "adequate"). For instance, in the application of glass polishing—which accounts for 25% of global cerium use—the primary substitute is iron oxide, with an "adequate" performance rating. However, in battery alloys (10%), cerium is replaced by lithium-ion batteries, rated as a "good" substitute, reflecting greater ease of replacement. For "other" uses like arc welding and carbon arc lighting (16%), no substitute is identified, and the performance is marked as "not applicable." By assigning numerical scores to performance ratings—such as "adequate" or "good"—and weighting them by the percentage of cerium use in each application, the author quantifies overall substitutability. This results in a composite index that reflects the difficulty of replacing cerium across its various industrial roles.

There is considerable variation among REE elements, with Dysprosium being the least substitutable and samarium being the most (Figure A.1).

A.3 Constructing a Country-Industry Productivity Panel

The primary data sources to construct a comprehensive panel dataset for TFP and labor productivity across countries and industries are the United Nations Industrial Development Organization (UNIDO) INDSTAT and OECD STAN databases. UNIDO INDSTAT provides detailed industry-level data on economic indicators such as value added, employment, and capital formation, available at both the 3-digit and 4-digit ISIC levels for Revisions 3 and 4. ISIC Rev. 3 offers extensive historical coverage up to 2008, while Rev. 4 provides improved coverage from 2008 onwards. All monetary values are expressed in current US dollars. Due to the unbalanced nature of the 4-digit INDSTAT data, substantial imputation is necessary to construct a balanced panel. The process involves nearest-neighbor interpolation to fill missing observations within the 4-digit data wherever possible. Annual growth rate series at the more consistently available 2-digit ISIC level are computed and used to adjust the imputed data at the 4-digit level Remaining gaps are filled using 2-digit level data that are split into 4-digit industries based on time-invariant employment shares.

Figure A.1: Index of Complementarity by Element



This imputation process is performed separately for both versions of INDSTAT (ISIC Rev. 3 and Rev. 4) to maintain consistency with their respective coverage periods.

We derive initial capital stock estimates at the country-industry level from OECD STAN. When initial capital stock data are missing, estimates are obtained through nearest-neighbor interpolation or – if still missing – a regression approach using gross capital formation as a predictor. For the following sample years, we use the perpetual inventory method and data on gross capital formation to obtain a measure of the capital stock, assuming a depreciation rate of 8%. We deflate capital stocks and other variables in nominal U.S. dollars using the price deflators for capital and consumer prices from the Penn World Tables vers. 9.1.

TFP is calculated as the residual from an OLS regression estimated at the 2-digit ISIC level, where the log of value added is regressed against the logs of capital stocks and the log of employment. Labor productivity is derived as the log difference of value added and employment.

Finally, we map the ISIC productivity data to SIC manufacturing industries using 2 concordances mapping 4-digit ISIC Rev. 3 or ISIC Rev. 4 to SIC codes. The mapping from ISIC Rev. 4 is done via ISIC Rev. 3.1 as an intermediate step. In cases where mappings are not unique, ISIC industries are weighted based on time-invariant employment weights. Only productivity data at the U.S. SIC level where less than one-third of the data is imputed is used to ensure data integrity and reliability.

For U.S. and Japan, we use data from their respective manufacturing survey or census in place of the UNIDO INDSTAT database. For the former, we use the NBER CES manufacturing database, which have shipment, inputs and productivity variables as well as price deflators readily available at the 4-digit SIC level. We construct a similar dataset for Japan by assembling the country's annual Manufacturing Census data from the Ministry of Economy, Trade and Industry (METI) from the years 2002 to 2018. METI's data comprises of output (shipment and production) and input (number of employees, salaries expense, raw materials usage, and tangible fixed assets) variables, as in the NBER CES manufacturing database, at the 4-digit JSIC level for all establishments with 30 or more employees. This covers 521 manufacturing industries after combining the eleventh, twelfth and thirteenth JSIC revisions.

To obtain real values for Japan's productivity measures, we make use of price indices from the Bank of Japan's Input-Output Price Index (IOPI) dataset. For raw material prices, we use input weights from Japan's 2005 input-output table to calculate the weighted average of input price indices for each input-output sector classification. Since some inputs from the input-output table have no matching price indices from IOPI, we impute with Japan's producer price index for total intermediate goods. Meanwhile for service inputs, we use price indices from BoJ's Japan Services Producer Price Index dataset. We build a concordance between Japan's input-output sector classification with JSIC to merge the price indices into the manufacturing census data.

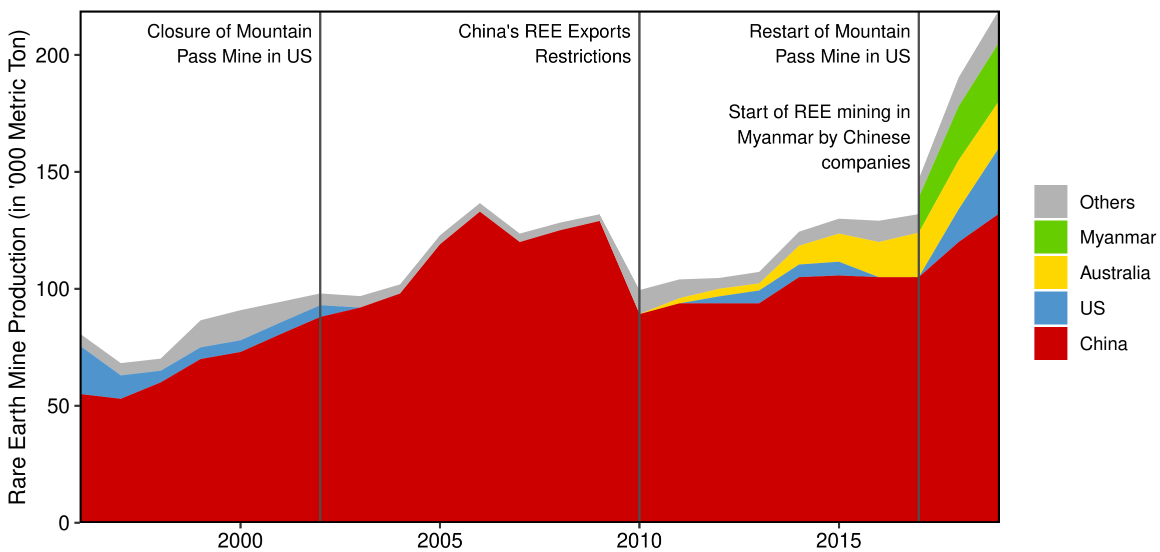
We then calculate TFP measures as residual of the factor inputs employees, capital, and raw materials, imitating the approach employed by the NBER CES manufacturing database for comparability. Specifically, we subtract from output growth the growth in the number of employees, raw materials excluding energy, energy, and fixed assets, each weighted by their share in output in Yen value. Finally, we map the JSIC-level data to SIC manufacturing industries using our manually-constructed concordance.

Table A.5: List of Sample Countries in Empirical Analysis

ISO Code	Country Name	ISO Code	Country Name
ARE	United Arab Emirates	ISR	Israel
ARG	Argentina	ITA	Italy
AUS	Australia	JPN	Japan
AUT	Austria	KOR	South Korea
BEL	Belgium	MEX	Mexico
BGD	Bangladesh	MYS	Malaysia
BRA	Brazil	NGA	Nigeria
CAN	Canada	NLD	Netherlands
CHE	Switzerland	NOR	Norway
CHL	Chile	NZL	New Zealand
CHN	China	PAK	Pakistan
COL	Colombia	PER	Peru
CZE	Czech Republic	PHL	Philippines
DEU	Germany	POL	Poland
DNK	Denmark	PRT	Portugal
EGY	Egypt	ROM	Romania
ESP	Spain	RUS	Russia
FIN	Finland	SAU	Saudi Arabia
FRA	France	SGP	Singapore
GBR	United Kingdom	SWE	Sweden
HKG	Hong Kong	THA	Thailand
IDN	Indonesia	TUR	Turkey
IND	India	USA	United States of America
IRL	Ireland	VNM	Vietnam
IRN	Iran	ZAF	South Africa

Notes: The table lists the sample countries in our empirical analysis, which are the 50 largest economies based on their GDP.

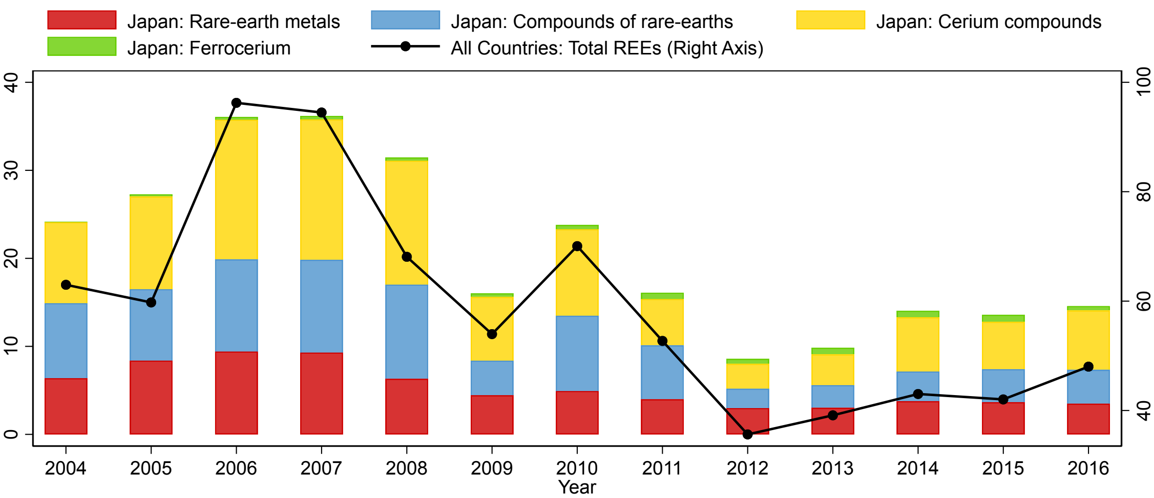
Figure A.2: Rare-Earth Mine Production Across Countries



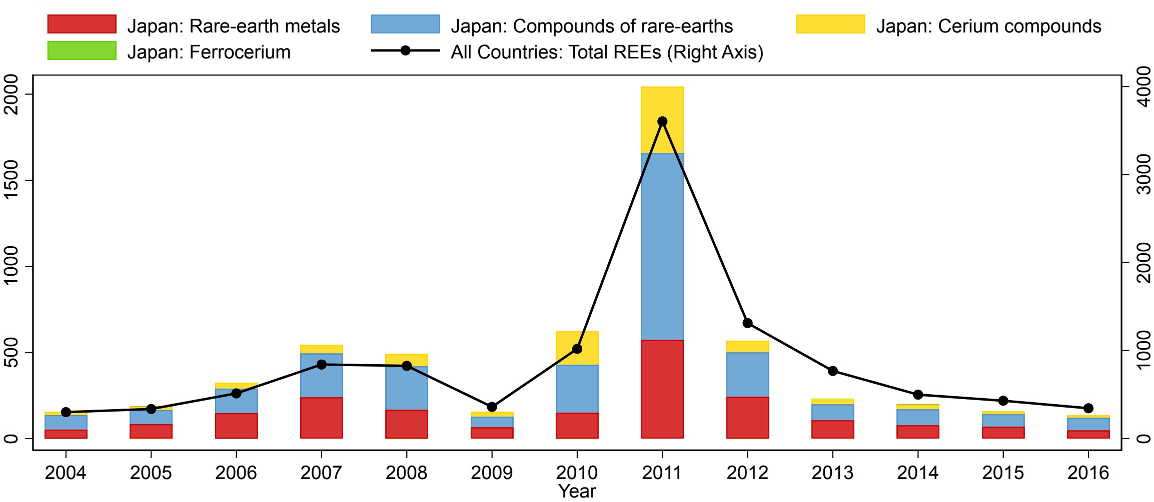
Notes: The figure plots production of REEs for major producing economics using data from the *Mineral Yearbooks* of the U.S. Geological Survey.

Figure A.3: Annual REE Imports from China

(a) Quantity (in metric ton)



(b) Value (in USD million)



Notes: The figure presents import values of REEs from China by Japan and all countries, broken down by sub-categories of REE commodities for the former. Data is sourced from UN Comtrade.

A.4 Examples of Patents

Figures A.4 to A.6 present selected REE-related patents from our dataset to exemplify the innovation response to the REE supply-shock episode. These are patents filed after 2010 whose content could have the effect of reducing or substituting the use of REEs as inputs. They have also been handpicked to represent the variety of REE downstream uses.

Figure A.4: US8480815B2: Magnet Powder Coating Process

(12) **United States Patent**
Wang

(10) **Patent No.: US 8,480,815 B2**
(45) **Date of Patent: Jul. 9, 2013**

(54) **METHOD OF MAKING ND-FE-B SINTERED MAGNETS WITH DY OR TB**

(75) Inventor: **Yucong Wang**, West Bloomfield, MI (US)

(73) Assignee: **GM Global Technology Operations LLC**, Detroit, MI (US)

(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 58 days.

(21) Appl. No.: **13/007,203**

(22) Filed: **Jan. 14, 2011**

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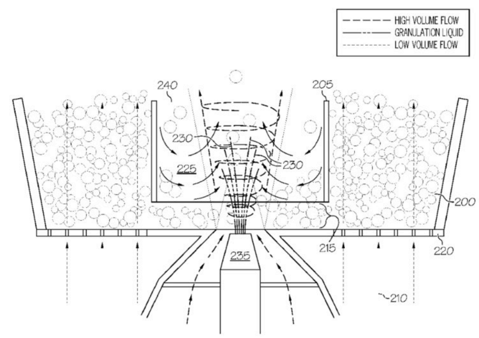
Plusa, et al., Domain Structure and Domain-Wall Energy in Polycrystalline R2Fe14B Compounds (R=Pr, Nd, Gd, Dy), Journal of the Less-Common Metals, 1987, pp. 231-243, vol. 133, The Netherlands.
Rodewald, Magnetization and Aging of Sintered Nd-Fe-B Magnets, Journal of the Less-Common Metals, 1985, pp. 77-81, vol. 111, The Netherlands.
Machida, et al., Improved Magnetic Properties of Small-Sized Nd-Fe-B Magnets and Their Application for DC brush-less Micro-Motors, Center for Advanced Science and Innovation, Osaka University, May 2, 2005, pp. 25-30, Japan.
Herget, et al., Metallurgical Methods for the Production of Rare Earth-Transition Metal Permanent Magnet Materials, MPR Jun. 1987, pp. 438-444.
Japanese Office Action with a due date of Apr. 21, 2013 pertaining to JP Application No. 2011-245644.

3

DETAILED DESCRIPTION OF THE INVENTION

Magnets made using the present process use much less Dy or Tb than those made using the conventional methods while obtaining similar magnetic properties. In the present process, the Dy or Tb coated Nd—Fe—B powders are used to make the magnet, which results in a non-uniform distribution of Dy or Tb in the magnet, which can be seen and measured using a scanning electron microscope with a microprobe. This enables the present process to use much less Dy or Tb for the similar magnetic properties. For example, the amount of Dy and/or Tb can be reduced by about 20% or more compared to conventional processes, or about 30% or more, or about 40% or more, or about 50% or more, or about 60% or more, or about 70% or more, or about 80% or more, or about 90% or more. By non-uniform distribution, we mean that Dy and/or Tb are distributed or concentrated at the interface of the

Assuming the weight of permanent magnet pieces is about 1-1.5 kg per electric motor, and a yield of the machined permanent magnet (PM) pieces of typically about 55-60%, 2-3 kg of PM per motor would be required, or 4-6 kg per vehicle (some hybrid vehicles may use one induction motor and one PM motor). Moreover, Dy is also widely used by other industries. The only RE mine in the United States does not have any significant amounts of Dy. Therefore, reducing the Dy or Tb usage in permanent magnets would have a very significant cost impact.



Notes: The figure shows excerpts of patent US8480815B2. In January 2011, the US firm GM Global Technology Operations filed a patent for a powder coating process that uses much less Dy and Tb as coating for REE magnets. The patent claims to reduce the amount of Dy and Tb used by at least 20% while maintaining similar magnetic properties. The patent cites supply constraints as motivation as "the only RE mine in the United States does not have any significant amounts of Dy", which could be an implicit reference to the difficulties of importing these elements from China.

Figure A.5: KR101281549B1: Position Sensors Without REE

(19) Korean Intellectual Property Office (KR)

(12) Patent Registration Publication (B1)

(45) Announcement date: July 3, 2013

(11) Registration number 10-1281549

(24) Registration date: June 27, 2013

(51) International Patent Classification (Int. Cl.)

G01D 5/12 (2006.01) G01B 7/30 (2006.01)

(21) Application No. 10-2012-0064020

(22) Application date: June 15, 2012

Examination request date June 15, 2012

(56) Prior art search documents

KR1020070043000 A

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US6912923 B2

Total number of claims: 6 claims (54)

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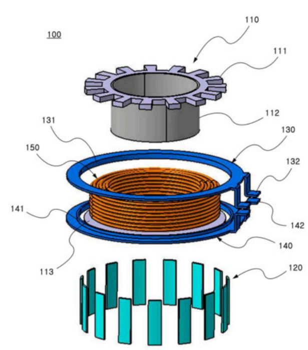
Examiner: Kim Hye-won



The collected magnetic flux may be transmitted to the magnetic sensor (not shown) through the house terminals 33 and 34 to detect the twist between the axes by the manipulation of the handle.

However, in the conventional position sensor structure, although the sensor output can be sufficiently generated by the detection of the desired magnetic flux amount, there is a cost problem due to the recent increase of the rare earth price because the permanent magnet of rare earth material is used.

Accordingly, it is an object of the present invention to provide a position sensor having an improved structure so that a permanent magnet of rare earth material is not used.

Notes: The figure shows excerpts of patent KR101281549B1. Around one year after REE prices peaked, the Korean firm Daesung Electric Co filed a patent in South Korea for position sensors with a modified structure that removes the need for permanent REE magnets. The patent cites the positive price shock as its motivation, stating that "there is a cost problem due to the recent increase of the rare earth price". Position sensors have many downstream applications, from manufacturing processes to transport equipments including automobiles.

Figure A.6: US9387464B2: Catalyst for Exhaust Gas Purification

(12) **United States Patent**
Miura et al.

(10) **Patent No.:** **US 9,387,464 B2**
(45) **Date of Patent:** **Jul. 12, 2016**

(54) **IRON OXIDE-ZIRCONIA COMPOSITE OXIDE AND METHOD FOR PRODUCING SAME, AND EXHAUST GAS PURIFICATION CATALYST**

(71) Applicants: **Masahide Miura**, Toyota (JP); **Atsushi Tanaka**, Toyota (JP); **Takahiro Suzuki**, Toyota (JP); **Tadashi Suzuki**, Seto (JP); **Toshitaka Tanabe**, Nagakute (JP); **Naoki Takahashi**, Nagoya (JP)

(72) Inventors: **Masahide Miura**, Toyota (JP); **Atsushi Tanaka**, Toyota (JP); **Takahiro Suzuki**, Toyota (JP); **Tadashi Suzuki**, Seto (JP); **Toshitaka Tanabe**, Nagakute (JP); **Naoki Takahashi**, Nagoya (JP)

(73) Assignee: **TOYOTA JIDOSHA KABUSHIKI KAISHA**, Toyota-shi, Aichi (JP)

(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 0 days.

(21) Appl. No.: **14/384,283**

(22) PCT Filed: **Apr. 26, 2013**

(2013.01); ***B01J 23/83*** (2013.01); ***B01J 35/002*** (2013.01);

(Continued)

(58) **Field of Classification Search**
CPC B01J 21/04; B01J 21/066; B01J 23/10; B01J 23/56; B01J 23/63; B01J 23/745; B01J 23/76; B01J 23/83; B01J 23/8906; B01J 23/894
USPC 502/302–304, 326, 327, 332–334, 336, 502/338, 339, 349, 355
See application file for complete search history.

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(Continued)

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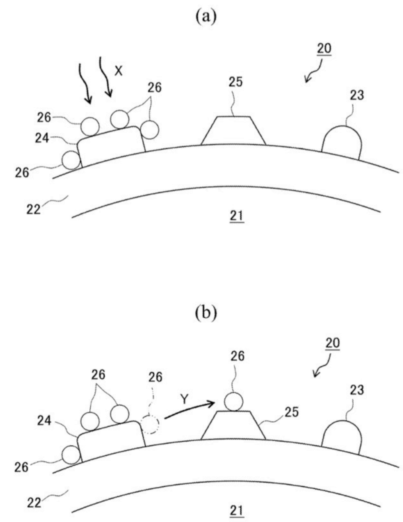
JP	10-216509 A	8/1998

FIG. 38



(57) **ABSTRACT**

A composite oxide with a high oxygen storage capacity is provided without using cerium. The composite oxide is an iron oxide-zirconia composite oxide containing iron, zirconium, and a rare-earth element. The total content of Fe_2O_3, ZrO_2, and an oxide of the rare-earth element is not less than 90 mass %, the content of an iron oxide in terms of Fe_2O_3 is 10 to 90 mass %, and the absolute value of the covariance COV (Fe, Zr+X) of the composite oxide, which has been baked in the atmosphere at a temperature of greater than or equal to 900° C. for 5 hours or more, is not greater than 20.

ite oxide obtained by causing an iron oxide to be supported on a support containing ceria.

Cerium contained in such composite oxides is expensive, and a problem has emerged that cerium is now difficult to obtain stably due to the deterioration of the procurement environment in recent years. Thus, suppressing the amount of cerium used is considered.

However, it is recognized by one of ordinary skill in the art that when the content of cerium is reduced in a composite

Notes: The figure shows excerpts of patent US9387464B2. In April 2016, Toyota Motor from Japan filed a patent for a composite oxide used in catalysts for exhaust gas purification. This type of catalysts uses mainly cerium, the REE with the greatest price jump in 2010-2011. The patented composite oxide still needs to use REEs but it does not have to be cerium. In the example, it preferably uses lanthanum and yttrium. Similar to the other patent examples, the patent mentions recent supply issues in its background: "cerium contained in such composite oxides is expensive, and a problem has emerged that cerium is now difficult to obtain stably due to the deterioration of the procurement environment in recent years." This patent comes only a few years after the REE supply shock but builds on recent patents from before the supply shock: "Meanwhile, JP 2008-93496 A (Patent Literature 5) discloses a promoter clathrate containing an iron oxide, which is a promoter of an exhaust gas purification catalyst, and a zirconia solid solution (e.g., Example 2). In such a promoter clathrate, the iron oxide is covered with the zirconia solid solution. Thus, sintering of the iron oxide is suppressed, and consequently, an exhaust gas purification catalyst containing such a promoter clathrate exhibits excellent catalyst activity."

B Empirical Appendix

B.1 Productivity Effects:

Here, we study the impact of the policy change on measures of productivity of REE-using industries. We estimate the following differences-in-differences specification, using productivity growth as the outcome variable:

$$y_{ist} = \beta \textit{REE Sensitivity}_s \times \textit{post}_t + \gamma\Delta_{ist} + \eta_{is} + \eta_{it} + \epsilon_{ist}. \tag{B.1}$$

The outcome variable y_{ist} is the annualized growth rate of productivity for the 4-digit SIC manufacturing industry s by country i during year t, again considering the sample window from 2002 until 2018. The annualized productivity growth rate for the period t is computed using the midpoint of t and $t-1$ as the denominator. The coefficient of interest β is again the coefficient on an interaction term of our $\textit{REE Sensitivity}_s$ measure with the treatment dummy $\textit{post}_t$. All estimations include a full set of country-industry and country-year fixed effects η_{is} and η_{it}. We also include the time-varying industry controls described in the main text (demand, subsidies, industry characteristics), weight regressions using export weights and cluster standard errors at the country-industry level.

The regression results presented in Table B.1 highlight the impact of the REE supply shock on productivity growth of REE-using manufacturing industries across different country groups. The top panel focuses on TFP growth, while the bottom panel examines labor productivity growth. A one standard-deviation higher value in REE sensitivity is associated with a 0.19 and 0.16 percentage-point higher growth rate of TFP and labor productivity, respectively, after the REE supply shock. More exposed European and Japanese industries in particular experience a significant increase in TFP (columns 3 and 4). In the full sample (column 5), there is a positive and significant impact of REE shock exposure on both TFP and labor productivity growth. In contrast, Chinese industries (columns 6 and 12) show a negative response, with a significant decline in TFP growth and an insignificant but negative coefficient for labor productivity growth. These results suggest that while REE-using industries in some economies, particularly in Europe and Japan, adapted to the Chinese REE policy with productivity gains, Chinese industries themselves faced relative productivity losses.

B.2 Results with Alternative REE Sensitivity Measures

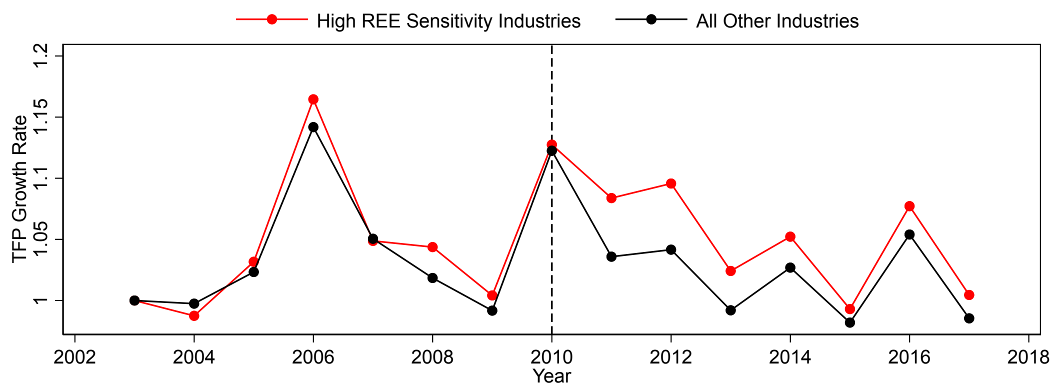
We consider an alternative construction of REE sensitivity where industry-level total requirements of REE, now aggregated across elements, are multiplied with country-level initial share of REE

Table B.1: Productivity Growth of Rare-Earth Intense Manufacturing Industries

	Annualized Growth: Total Factor Productivity					
	NONCHN	USA	EUR	JPN	ALL	CHN
	(1)	(2)	(3)	(4)	(5)	(6)
REE Sens. × Post	0.498*	0.479*	0.555**	1.029***	0.466*	-2.142***
	(0.260)	(0.281)	(0.242)	(0.370)	(0.259)	(0.742)
Observations	183,818	6,323	88,055	5,679	186,770	2,952
Clusters	14,981	452	6,306	414	15,350	369
	Annualized Growth: Labor Productivity					
	NONCHN	USA	EUR	JPN	ALL	CHN
	(7)	(8)	(9)	(10)	(11)	(12)
REE Sens. × Post	0.391**	0.0825	0.202	1.039**	0.377**	-0.633
	(0.176)	(0.565)	(0.159)	(0.417)	(0.175)	(0.764)
Observations	183,818	6,323	88,055	6,482	186,770	2,952
Clusters	14,981	452	6,306	436	15,350	369
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country × Ind F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Country × Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table presents coefficient estimates of β from the regression: $y_{ist} = \beta\, \textit{REE Sens.}_s \times post_t + \gamma\Delta_{ist} + \eta_{is} + \eta_{it} + \epsilon_{ist}$, where y_{ist} represents the annualized growth rate of productivity for country-industry is in year t, TFP (upper panel) or labor productivity measured as value added per worker (lower panel). The annualized growth is calculated using the midpoint between t and $t-1$ as the denominator. The sample includes 4-digit SIC manufacturing industries from 2002-2018 across the 50 largest economies. The treatment intensity $\textit{REE Sens.}_s$ is a weighted sum of an REE element-specific complementarity index (ranging from 0 to 100), with weights based on total requirement shares for industry s: $\textit{REE Sens.}_s = \sum_e tr_{es} \times compl_e$. $post_t$ is a dummy variable set to 1 for 2010 and later years (post-China's REE export restrictions). Country subsamples include non-China, the U.S., European economies, Japan, all countries and China. For the country subsamples of the U.S. and Japan, we use the data from NBER CES manufacturing database and Japan's Annual Manufacturing Census, respectively (see Appendix A.3 for notes). All regressions include country-industry and country-year fixed effects. The control vector Δ_{ist} includes time-invariant measures of industry s's capital and labor intensity from the NBER CES manufacturing database, and subsidy fractions from the GTA database, all interacted with $post_t$, and the lagged weighted average growth rate of GDP of the ten largest importers from is. Regressions are weighted by the share of export values $w_{is} = exports_{is}/\sum_{i,s} exports_{is}$ from 2002-2004. Standard errors (in parentheses) are clustered at the country-industry level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure B.1: High and Low REE Sensitivity Industries: Total Factor Productivity



Notes: The figure plots the average of TFP growth of manufacturing industries (weighted by initial values in 2002-2004) that are classified above the 75th percentile of REE sensitivity (red) and for all other manufacturing industries (black). Growth rates are annualized growth calculated using the midpoint between t and $t-1$ as the denominator. The sample includes 4-digit SIC manufacturing industries from 2002-2018 across the 50 largest economies excluding China. REE sensitivity is constructed following equation (1). The plotted values are normalized to the value in the base year 2003.

imports from China instead of with element-level complementarity index. We use UN Comtrade to construct alternative measures of exposure to the Chinese REE supply shock that vary at the country-industry level–considering HS codes 284690, 284610, and 280530– and weighing them by initial import shares, using:

1. Country-level price spike in unit values of REE imports interacted with the total requirements of REE of each industry (aggregated across elements):

$$REE\ Sensitivity_{is} = \left(\sum_e tr_{es}\right) \times (\ln(max\ REE\ import\ price_i) - \ln(REE\ import\ price\ 2016_i))\,.$$

2. Pre-shock import shares of REEs in country c sourced from China relative to REEs sourced from a larger set of countries (China, the U.S., Australia, Russia or India) interacted with the total requirement of REEs in industry s:

$$REE\ Sensitivity_{is} = \left(\sum_e tr_{es}\right) \times \frac{REE\ imports\ from\ CHN_i}{REE\ imports\ from\ CHN,\ USA,\ AUS,\ RUS,\ IND_i}$$

Table B.2 shows that REE-related patenting of downstream industries increased relatively more in those country-industries where the REE supply shock was relatively more important. Table B.3

shows similar results for export growth.

B.3 Results at HS-Product-Code Level

We also run our downstream export-growth regressions at the HS-product-code level instead of SIC as in the baseline. The purpose of this is to assess the robustness of our findings as well as to decompose the effect on exports into its quantity and unit price components. The latter is possible since the raw UN Comtrade data, before converting to SIC-level, also include the physical quantity of exports. We calculate unit prices by simply dividing exports value with exports quantity. We exclude HS codes for which there was a change in the unit of physical quantity, but this applies to less than 5% of observations for our sample period. For the REE-sensitivity variable, we reconstruct it at the HS-level by converting NAICS-level total requirements to HS using the Pierce-Schott concordance instead of the SIC concordance. We make use of the same concordance to convert our control variables.

For export values, we find that the results are qualitatively similar to our baseline regressions at the SIC level. Specifically, for all our sub-samples except for the U.S. and China, exports of product codes that are more sensitive to REE inputs exhibit significantly larger growth during the treatment period compared to before than exports of less sensitive products by the same country. The same regressions for export quantities and unit values confirm that the effects for non-China countries are mostly driven by adjustments in the quantity of exports rather than just by passing through higher input prices. This is demonstrated by the coefficients for non-China and all countries except for the U.S. in the exports unit value regressions being not significant or less so than in the exports quantity regressions. For European countries and Japan, where the positive exports effect is most pronounced, the coefficient magnitudes are similarly larger for physical quantity.[31]

[31] By contrast, in the U.S. quantity responses are not significant and price increases play a role.

Table B.2: Patents in Rare-Earth Intense Manufacturing Industries, Robustness using Country-Level Rare-Earth Import Intensity

	REE-Enhancing Patents				
	NONCHN	USA	EUR	JPN	ALL
	(1)	(2)	(3)	(4)	(5)
	REE Sens.$_{is}$ based on REE import price surge				
REE Sens. × Post	426.1***	363.9***	624.8***	921.5**	425.4***
	(100.6)	(124.0)	(185.2)	(373.8)	(102.4)
Observations	5,561	1,200	1,140	972	7,606
Clusters	387	81	74	66	531
	REE-Enhancing Patents				
	NONCHN	USA	EUR	JPN	ALL
	(6)	(7)	(8)	(9)	(10)
	REE Sens.$_{is}$ based on the REE import share from CHN				
REE Sens. × Post	1143.0***	1201.6**	1222.8***	1849.2***	1075.3***
	(320.8)	(471.8)	(409.7)	(691.5)	(318.4)
Observations	5,561	1,200	1,140	972	7,606
Clusters	387	81	74	66	531
Controls	Yes	Yes	Yes	Yes	Yes
Region × Ind F.E.	Yes	Yes	Yes	Yes	Yes
Region × Year F.E.	Yes	Yes	Yes	Yes	Yes

Notes: The table presents coefficient estimates of β from the regression: $y_{rst} = \beta \, REE\ Sens._{rs} \times post_t + \gamma \Delta_{rst} + \eta_{rs} + \eta_{rt} + \epsilon_{rst}$ with Poisson pseudo-maximum likelihood estimation. The outcome y_{rst} represents granted REE-related patents that improve the efficiency of REEs or help find ways to substitute REE usage. The sample includes 4-digit SIC manufacturing industries (with at least one REE-related patent) from 2002-2018 across 8 regions. Regions capture the location of the patent assignee and include Australia, China, European Union, Korea, Russia, Japan, U.S. and the Rest of the World. In the upper panel, $REE\ Sens._{rs}$ measures the impact of the REE import price surge in region r and is calculated as the product of the total REE requirement share in industry s and the REE import price spike in region r. The price spike is defined as the logarithmic difference between the peak weighted REE import price across REE-related HS codes 280530, 284690 and 284610 (typically occurring between 2011 and 2013) and the average REE import price in 2016. $REE\ Sens._{rs} = (\sum_e tr_{es}) \times (\ln(max\ REE\ import\ price_r) - \ln(REE\ import\ price\ 2016_r))$. In the bottom panel, $REE\ Sens._{rs}$ is based on the average share of REE imports from China before the Chinese export restrictions and is calculated as the product of the total REE requirement share in industry s and the proportion of REE imports from China relative to total REE imports from China, the USA, Australia, Russia, and India in region r between 1995 and 2009. $REE\ Sens._{rs} = (\sum_e tr_{es}) \times (REE\ imports\ from\ CHN_r / REE\ imports\ from\ CHN,\ USA,\ AUS,\ RUS,\ IND_r)$. $post_t$ is a dummy variable set to 1 for 2010 and later years (post-China's REE export restrictions). All regressions include region-industry and region-year fixed effects. The control vector Δ_{ist} includes time-invariant measures of industry s's capital and labor intensity from the NBER CES manufacturing database, and region-industry-specific industrial subsidy fractions from the GTA database, all interacted with $post_t$. It also includes a lagged demand control at the region-industry-year level, constructed by taking the log of the weighted yearly real GDP of the top 10 importer countries for that region-industry. The top 10 importer countries are identified by ranking importer countries by trade value in the period 1996-2009. Standard errors (in parentheses) are clustered at the region-industry level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.3: Downstream Export Growth of Rare-Earth Intense Manufacturing Industries, Robustness using Country-Level Rare-Earth Import Intensity

	Annualized Growth: Exports Value				
	NONCHN	USA	EUR	JPN	ALL
	(1)	(2)	(3)	(4)	(5)
	REE Sens.$_{is}$ based on REE import price surge				
REE Sens. × Post	25.92***	7.516	29.88***	52.50*	26.38***
	(8.088)	(18.64)	(11.18)	(26.74)	(8.020)
Observations	166,701	6,048	78,044	5,979	172,684
Clusters	10,500	378	4,884	375	10,874
	Annualized Growth: Exports Value				
	NONCHN	USA	EUR	JPN	ALL
	(6)	(7)	(8)	(9)	(10)
	REE Sens.$_{is}$ based on the REE import share from CHN				
REE Sens. × Post	75.99***	20.35	78.18***	119.1**	77.50***
	(20.59)	(53.98)	(26.79)	(53.74)	(20.59)
Observations	178,330	6,048	78,044	5,979	184,313
Clusters	11,236	378	4,884	375	11,610
Controls	Yes	Yes	Yes	Yes	Yes
Country × Ind F.E.	Yes	Yes	Yes	Yes	Yes
Country × Year F.E.	Yes	Yes	Yes	Yes	Yes

Notes: The table presents coefficient estimates of β from the regression: $y_{ist} = \beta\ REE\ Sens._{is} \times post_t + \gamma\Delta_{ist} + \eta_{is} + \eta_{it} + \epsilon_{ist}$, where y_{ist} represents the annualized growth rate of export values for country-industry is in year t. The annualized growth is calculated using the midpoint between t and $t-1$ as the denominator. The sample includes 4-digit SIC manufacturing industries from 2002-2018 across the 50 largest economies, excluding China. In the upper panel, $REE\ Sens._{is}$ measures the impact of the REE import price surge in country i and is calculated as the product of the total REE requirement share in industry s and the REE import price spike in country i. The price spike is defined as the logarithmic difference between the peak weighted REE import price across REE-related HS codes 280530, 284690 and 284610 (typically occurring between 2011 and 2013) and the average REE import price in 2016. $REE\ Sens._{is} = (\sum_e tr_{es}) \times (\ln(max\ REE\ import\ price_i) - \ln(REE\ import\ price\ 2016_i))$. In the bottom panel, $REE\ Sens._{is}$ is based on the average share of REE imports from China before the Chinese export restrictions and is calculated as the product of the total REE requirement share in industry s and the proportion of REE imports from China relative to total REE imports from China, the USA, Australia, Russia, and India in i between 1995 and 2009. $REE\ Sens._{is} = (\sum_e tr_{es}) \times (REE\ imports\ from\ CHN_i / REE\ imports\ from\ CHN,\ USA,\ AUS,\ RUS,\ IND_i)$. $post_t$ is a dummy variable set to 1 for 2010 and later years (post-China's REE export restrictions). Country subsamples include non-China, the U.S., European economies, Japan and all countries. All regressions include country-industry and country-year fixed effects. The control vector Δ_{ist} includes time-invariant measures of industry s's capital and labor intensity from the NBER CES manufacturing database, and country-industry-specific industrial subsidy fractions from the GTA database, all interacted with $post_t$, as well as the lagged weighted average growth rate of GDP of the ten largest importers from is. Regressions are weighted by the share of export values $w_{is} = exports_{is} / \sum_{i,s} exports_{is}$ from 2002-2004. Standard errors (in parentheses) are clustered at the country-industry level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.4: Productivity Growth of Rare-Earth Intense Manufacturing Industries, Robustness using Country-Level Rare-Earth Import Intensity

	NONCHN	USA	EUR	JPN	ALL
	Annualized Growth: Total Factor Productivity				
	(1)	(2)	(3)	(4)	(5)
	REE Sens.$_{is}$ based on REE import price surge				
REE Sens. × Post	16.17*	12.92*	18.48**	37.76***	15.07*
	(8.672)	(7.127)	(8.230)	(12.63)	(9.030)
Observations	177,577	5,320	88,055	4,978	182,791
Clusters	14,272	380	6,306	363	14,646
	Annualized Growth: Total Factor Productivity				
	NONCHN	USA	EUR	JPN	ALL
	(6)	(7)	(8)	(9)	(10)
	REE Sens.$_{is}$ based on the REE import share from CHN				
REE Sens. × Post	40.05*	38.25*	46.36**	80.53***	41.46*
	(22.02)	(20.52)	(19.60)	(27.85)	(22.49)
Observations	183,818	5,320	88,055	4,978	189,032
Clusters	14,981	380	6,306	363	15,355
	Annualized Growth: Labor Productivity				
	NONCHN	USA	EUR	JPN	ALL
	(11)	(12)	(13)	(14)	(15)
	REE Sens.$_{is}$ based on REE import price surge				
REE Sens. × Post	9.945	3.391	2.489	38.67***	9.372
	(6.161)	(13.94)	(5.113)	(14.90)	(6.344)
Observations	177,577	5,320	88,055	5,685	182,791
Clusters	14,272	380	6,306	383	14,646
	Annualized Growth: Labor Productivity				
	NONCHN	USA	EUR	JPN	ALL
	(16)	(17)	(18)	(19)	(20)
	REE Sens.$_{is}$ based on the REE import share from CHN				
REE Sens. × Post	31.12**	10.40	17.11	86.25***	32.23**
	(13.96)	(39.64)	(12.74)	(32.32)	(14.16)
Observations	183,818	5,320	88,055	5,685	189,032
Clusters	14,981	380	6,306	383	15,355
Controls	Yes	Yes	Yes	Yes	Yes
Country × Ind F.E.	Yes	Yes	Yes	Yes	Yes
Country × Year F.E.	Yes	Yes	Yes	Yes	Yes

Notes: The table presents coefficient estimates of β from the regression: $y_{ist} = \beta\, \textit{REE Sens.}_{is} \times post_t + \gamma\Delta_{ist} + \eta_{is} + \eta_{it} + \epsilon_{ist}$, where y_{ist} represents the annualized growth rate of productivity for country-industry is in year t, TFP (upper two panels) or labor productivity measured as value added per worker (lower two panels). The annualized growth is calculated using the midpoint between t and $t-1$ as the denominator. The sample includes 4-digit SIC manufacturing industries from 2002-2018 across the 50 largest economies. In the first and third panels, *REE Sens.$_{is}$* measures the impact of the REE import price surge in country i and is calculated as the product of the total REE requirement share in industry s and the REE import price spike in country i. The price spike is defined as the logarithmic difference between the peak weighted REE import price across REE-related HS codes 280530, 284690 and 284610 (typically occurring between 2011 and 2013) and the average REE import price in 2016. $\textit{REE Sens.}_{is} = (\sum_e tr_{es}) \times (\ln(\textit{max REE import price}_i) - \ln(\textit{REE import price 2016}_i))$. In the second and fourth panels, *REE Sens.$_{is}$* is based on the average share of REE imports from China before the Chinese export restrictions and is calculated as the product of the total REE requirement share in industry s and the proportion of REE imports from China relative to total REE imports from China, the USA, Australia, Russia, and India in i between 1995 and 2009. $\textit{REE Sens.}_{is} = (\sum_e tr_{es}) \times (\textit{REE imports from CHN}_i / \textit{REE imports from CHN, USA, AUS, RUS, IND}_i)$. $post_t$ is a dummy variable set to 1 for 2010 and later years (post-China's REE export restrictions). Country subsamples include non-China, the U.S., European economies, Japan and all countries. For the country subsamples of the U.S. and Japan, we use the data from NBER-CES Manufacturing Database and Japan's Annual Manufacturing Census, respectively (see Appendix A.3 for notes). All regressions include country-industry and country-year fixed effects. The control vector Δ_{ist} includes time-invariant measures of industry s's capital and labor intensity from the NBER CES manufacturing database, and country-industry-specific industrial subsidy fractions from the GTA database, all interacted with $post_t$, as well as the lagged weighted average growth rate of GDP of the ten largest importers from is. Standard errors (in parentheses) are clustered at the country-industry level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.5: Downstream Export Growth of Rare-Earth Intense Manufacturing Industries, HS-Level Data

	Annualized Growth: Exports Value					
	NONCHN (1)	USA (2)	EUR (3)	JPN (4)	ALL (5)	CHN (6)
REE Sens. × Post	1.532***	0.543	1.682***	1.617*	1.533***	1.434
	(0.312)	(1.040)	(0.412)	(0.938)	(0.303)	(1.397)
	Annualized Growth: Exports Quantity					
	NONCHN (7)	USA (8)	EUR (9)	JPN (10)	ALL (11)	CHN (12)
REE Sens. × Post	1.164***	-0.753	1.129***	1.536	1.083***	-0.103
	(0.347)	(0.984)	(0.403)	(1.330)	(0.335)	(1.123)
	Annualized Growth: Exports Unit Value					
	NONCHN (13)	USA (14)	EUR (15)	JPN (16)	ALL (17)	CHN (18)
REE Sens. × Post	0.390	1.918***	0.481	0.0987	0.473*	1.584
	(0.246)	(0.520)	(0.302)	(0.770)	(0.242)	(1.194)
Observations	2,016,181	53,871	865,220	53,423	2,075,321	59,140
Clusters	157,752	4,003	64,376	4,028	161,850	4,098
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country × Ind F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Country × Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table presents coefficient estimates of β from the regression: $y_{ist} = \beta\, REE\ Sens._s \times post_t + \gamma\Delta_{st} + \eta_{is} + \eta_{it} + \epsilon_{ist}$, where y_{ist} represents the annualized growth rate of export values, quantity and unit price for country-industry is in year t. The annualized growth is calculated using the midpoint between t and $t-1$ as the denominator. The sample includes 6-digit HS product codes from 2002-2018 across the 50 largest economies. The treatment intensity $REE\ Sens._s$ is a weighted sum of an REE element-specific complementarity index (ranging from 0 to 100), with weights based on total requirement shares for industry s: $REE\ Sens._s = \sum_e tr_{es} \times compl_e$. $post_t$ is a dummy variable set to 1 for 2010 and later years (post-China's REE export restrictions). Country subsamples include non-China, the U.S., European economies, Japan, all countries and China. All regressions include country-industry and country-year fixed effects. The control vector Δ_{ist} includes time-invariant measures of industry s's capital and labor intensity from the NBER CES manufacturing database, all interacted with $post_t$. Standard errors (in parentheses) are clustered at the country-industry level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C Model and Quantitative Appendix

C.1 The Model with Rents from REEs Accruing to China

In the baseline model in the main text we assume that value added that is produced with REEs leads to local expenditure. Observe that equation (24) can alternatively be written as follows:

$$Rev_{is} = \sum_j \lambda_{jis} \left[\alpha_{js} \left(\frac{P_{js}}{P_j} \right)^{1-\rho} (w_{Lj} L_j + I_C \times w_{RC} R_C + I_C \times T_C - D_j - NFIA_j) + \sum_{s\prime} \phi_{ss'j} Rev_{js'} \right]. \tag{C.1}$$

Final expenditure of each country equals gross national income $w_{Lj} L_j + I_C \times w_{RC} R_C + I_C \times T_C$, minus net factor income from abroad ($NFIA_j$) minus imbalances D_j. I_C is an indicator variable that equals unity when j is China and zero for all other countries j. Here,

$$NFIA_j = \begin{cases} -w_{Rj} \sum_s \int_0^{A_{Rjs}} r_{js}(a) da, & \text{if } j \neq C \\ \sum_{j \neq C} w_{Rj} \sum_s \int_0^{A_{Rjs}} r_{js}(a) da, & \text{if } j = C \end{cases} \tag{C.2}$$

is measured gross of export taxes. For China, this term corresponds to factor exports of the REE factor, while for the other countries it corresponds to imports of this factor. Thus, we assume that value added and expenses generated by REEs are attributed to the location where the factor operates.

China's export tax revenue from factor exports of REEs is fully rebated to local consumers with lump-sum transfers T_C:

$$T_C = I_C \times (\tau_{XC} - 1) w_{RC} \sum_{j \neq C} \sum_s \int_0^{A_{Rjs}} r_{js}(a) da.$$

Alternatively, one may assume that global value added from REEs generates expenditure in China. Under this assumption,

$$\begin{aligned} Rev_{is} = & \sum_j \lambda_{jis} \times \\ & \left[\alpha_{js} \left(\frac{P_{js}}{P_j} \right)^{1-\rho} (w_{Lj} L_j + I_C \times w_{RC} R_C + I_C \times T_C - D_j) + \sum_{s'} \phi_{ss'j} Rev_{js'} \right] \quad \forall i, s, \end{aligned} \tag{C.3}$$

In this model variant, the expression for welfare (37) becomes

$$C_i = \frac{1}{P_i}\left[\underbrace{\sum_s \left(\frac{\mu-1}{\mu}\right) P_{Lis} Y_{Lis}}_{\substack{\text{Value Added}\\ \text{from Labor}}} + I_C \times \underbrace{\sum_j \sum_s \left(\frac{\mu-1}{\mu}\right) P_{Rjs} Y_{Rjs}}_{\substack{\text{Value Added}\\ \text{from REEs}}} - D_i\right] - \underbrace{\sum_s A_{Ris} f_{Ris} - \sum_s A_{Lis} f_{Lis}}_{\text{Innovation Investment}}. \tag{C.4}$$

C.2 Derivation of an Estimation Equation for ε_s

Combining (15) with relative demand $\frac{Y_{Ris}}{Y_{Lis}} = \left(\frac{\gamma_s}{1-\gamma_s}\right)^{\varepsilon_s}\left(\frac{P_{Ris}}{P_{Lis}}\right)^{-\varepsilon_s}$ yields

$$\frac{A_{Ris}}{A_{Lis}} = \left(\frac{\gamma_s}{1-\gamma_s}\right)^{\varepsilon_s}\left(\frac{P_{Ris}}{P_{Lis}}\right)^{1-\varepsilon_s}\frac{f_{Lis}}{f_{Ris}} = \left(\frac{\gamma_s}{1-\gamma_s}\right)^{\varepsilon_s}\left(\frac{A_{Ris}}{A_{Lis}}\right)^{(1-\varepsilon_s)(\frac{1}{1-\mu}-\delta)}\left(\frac{w_{Ri}}{w_{Li}}\right)^{1-\varepsilon_s}\frac{f_{Lis}}{f_{Ris}}, \tag{C.5}$$

where the last equality uses $P_{Ris} = A_{Ris}^{\frac{1}{1-\mu}-\delta}\frac{\mu}{\mu-1}w_{Ri}$ and the corresponding expression for P_{Lis}. Solving for A_{Ris}/A_{Lis}, we obtain an expression of relative patents as a function of relative factor prices w_{Ri}/w_{Li}:

$$\frac{A_{Ris}}{A_{Lis}} = \left(\frac{\gamma_s}{1-\gamma_s}\right)^{\frac{\varepsilon_s(\mu-1)}{\kappa_s}}\left(\frac{w_{Ri}}{w_{Li}}\right)^{\frac{(1-\varepsilon_s)(\mu-1)}{\kappa_s}}\left(\frac{f_{Lis}}{f_{Ris}}\right)^{\frac{\mu-1}{\kappa_s}}. \tag{C.6}$$

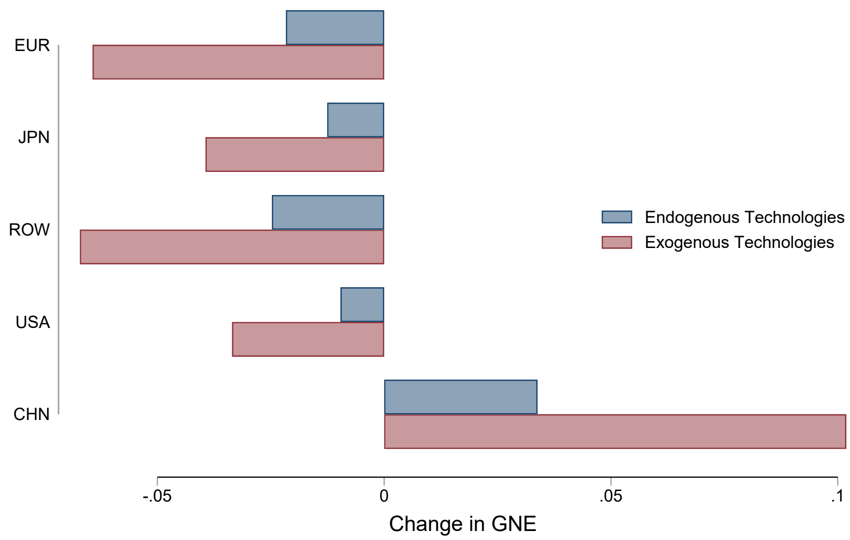
Taking logs, we obtain our regression specification:

$$\log\left(\frac{A_{Ris}}{A_{Lis}}\right) = \beta_s \log\left(\frac{w_{Ri}}{w_{Li}}\right) + \delta_s + u_{is}. \tag{C.7}$$

C.3 Algorithm to Calibrate the Model to a Baseline Economy

We calibrate the model to an initial baseline economy, using the following fixed-point iteration routine. An outer loop iterates over fixed costs f_{Ris} for given f_{Lis} until the model matches $\frac{A_{Ris}}{A_{Lis}}$ to relative U.S. patents in the data for 2009, according to equation (15). Within that outer loop, the algorithm iterates over an inner loop that adjusts Rev_{is} to be consistent with clearing product markets according to equation (24), iterates over imbalances to match country-level GDP for the given Rev_{is} and calculates the corresponding factor expenditures. Once relative patents and GDP are matched, the algorithm moves on to prices and trade costs. First, it solves for the set of bilateral prices P_{ijs} between each exporter and importer in each sector that exactly reproduces the observed trade shares λ_{ijs} and calculates the respective price indices P_{is} and P_i. With these prices and the model-implied unit costs of production, it then infers iceberg trade costs d_{ijs}. Lastly, it

Figure C.1: Effect on Gross National Expenditures



Notes: The figure plots relative changes in GNE (measured in % change from the baseline economy) in response to the introduction of an REE export tax by China.

calibrates the demand weights α_{is} so that, when combined with the sectoral prices, they replicate the observed spending patterns and the overall price level in each country. At this point, the baseline economy is fully specified.

C.4 Algorithm to Solve the Model

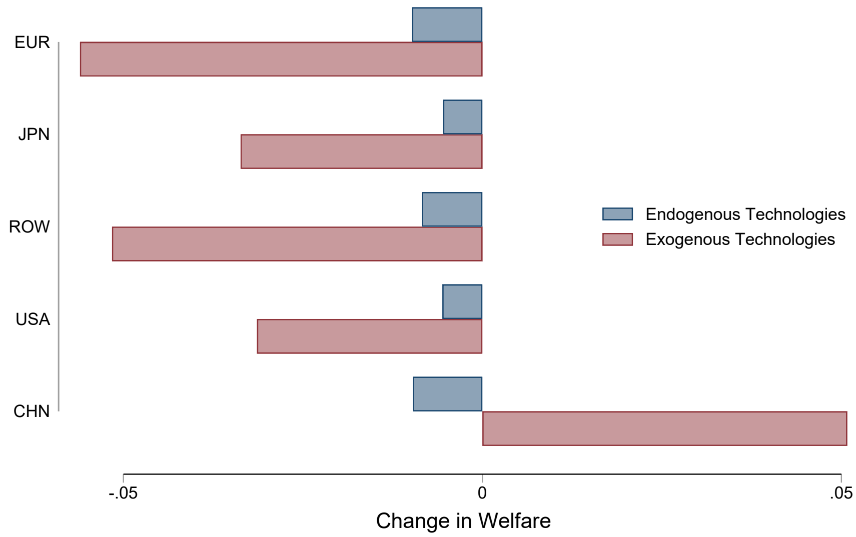
For given parameter values, the model can be solved by the following fixed-point iteration routine. An outer loop iterates over Rev_{is} to clear product markets, according to equation (24). Within that loop, first innovation responses and factor shares are calculated for given levels of Rev_{is}. Second, we can directly solve for factor prices to clear factor markets as described in equations (32) and (33). Third, we iterate over the system of bilateral prices P_{ijs} to make them consistent with (26), (27) and (28).

Table C.1: Decomposition of Consumption Changes

	Growth with Endogenous Technologies				
Country i	$\Delta(VA_{Li}/P_i)$ $\times 100\%$	$\Delta(VA_{Ri}/P_i)$ $\times 100\%$	$\Delta(D_i/P_i)$ $\times 100\%$	ΔI_i $\times 100\%$	ΔC_i $\times 100\%$
EUR	-0.014	-10.951	0.003	-0.025	-0.021
JPN	-0.009	-10.675	0.007	-0.015	-0.012
ROW	-0.013	-11.225	0.005	-0.029	-0.024
USA	-0.008	-10.417	0.004	-0.013	-0.009
CHN	0.028	15.000	-0.072	0.056	0.030
	Growth with Exogenous Technologies				
Country i	$\Delta(VA_{Li}/P_i)$ $\times 100\%$	$\Delta(VA_{Ri}/P_i)$ $\times 100\%$	$\Delta(D_i/P_i)$ $\times 100\%$	ΔI_i $\times 100\%$	ΔC_i $\times 100\%$
EUR	-0.054	-17.323	-0.010	0.000	-0.076
JPN	-0.033	-17.304	-0.003	0.000	-0.047
ROW	-0.051	-18.068	-0.008	0.000	-0.080
USA	-0.033	-16.386	-0.004	0.000	-0.039
CHN	0.105	24.351	-0.128	0.000	0.120
	Initial Contributions to Welfare				
Country i	(VA_{Li}/P_i)	(VA_{Ri}/P_i)	(D_i/P_i)	I_i	C_i
EUR	102.447	0.109	16.091	-18.646	100.000
JPN	105.148	0.066	13.916	-19.130	100.000
ROW	103.311	0.145	15.354	-18.810	100.000
USA	94.233	0.042	22.866	-17.141	100.000
CHN	97.141	0.180	20.373	-17.695	100.000

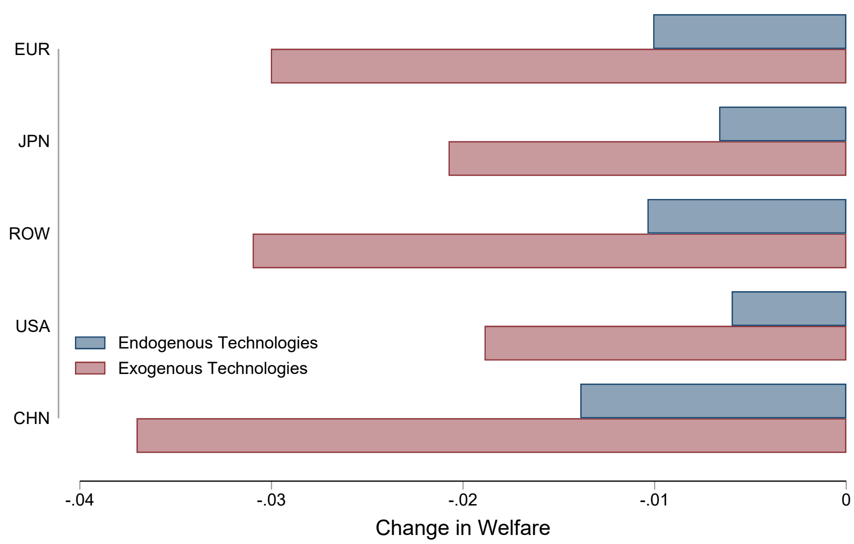
Notes: The table shows changes of the individual parts of welfare (measured in % change from the baseline economy) in response to the introduction of an REE export tax by China (first two panels) and the initial contributions of the individual parts to welfare (third panel). Note that the table reports percentage changes and signed level shares (investment contributes negatively to consumption). Overall consumption changes in % can be obtained by multiplying the growth rates of the individual parts with the signed shares and summing them.

Figure C.2: Effect on Welfare under Alternative Gross National Expenditures



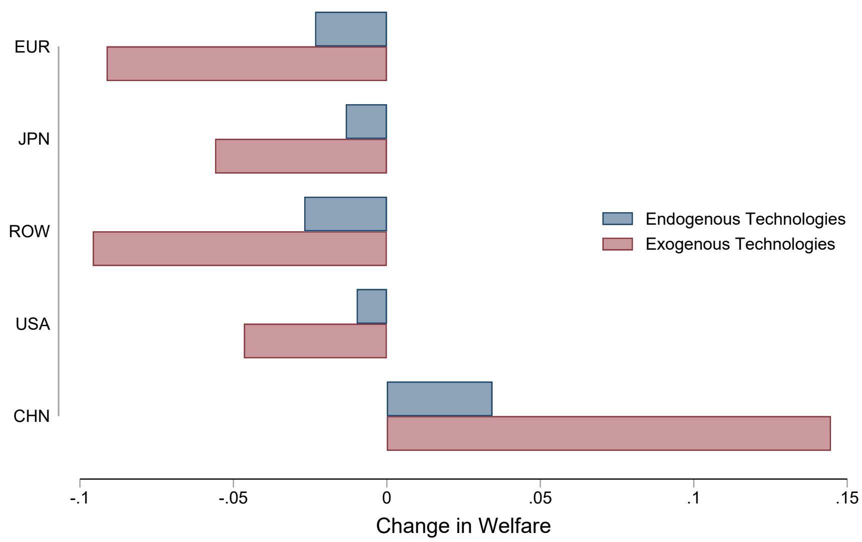
Notes: The figure plots relative changes in welfare (measured in % consumption change from the baseline economy) in response to the introduction of an REE export tax by China for an alternative specification of GNE where REE value added accrues to China (see Appendix C.1).

Figure C.3: Effect on Welfare of a Reduction in the Chinese REE Endowment



Notes: The figure plots relative changes in welfare (measured in % consumption change from the baseline economy) in response to a 20% reduction in the Chinese REE endowment R_C.

Figure C.4: Effect on Welfare under Alternative Levels of REE Use and Supply



Notes: The figure plots relative changes in welfare (measured in % consumption change from the baseline economy) in response to the introduction of an REE export tax by China for a twice as large level of REE supply.