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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, sectoral TFP data, 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.

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1 Introduction

Governments traditionally use industrial policies to selectively promote economic activity in specific sectors. While industrial policy can aim at correcting market imperfections that misalign private and social benefits, its final effects are complex when economic sectors are interconnected through global value chains. Understanding the impact of industrial policy in this environment is particularly relevant for sectors that provide essential inputs for other sectors. In the context of geopolitical tensions and the green transition, rare earth elements (REEs) have gained increased attention. Their distinct role as critical inputs for many manufacturing goods, with few possibilities of substitution, inelastic supply, and concentration of their supply in China has sparked a broader debate about the fragility of global supply chains.

In this paper, we provide an empirical and quantitative analysis of the effects of China's policy that restricted the global supply of REEs. 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 innovation, long-term productivity growth, and reallocation of economic activity towards downstream sectors that are intensively using these essential inputs. Intuitively, when inputs are gross complements, 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 sectors that intensively use the input at the expense of other sectors. We show that REEs, because of their particular characteristics, are susceptible to these conditions.

REEs, crucial inputs in many manufacturing products due to their chemical properties, capture our interest 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. Finally, 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 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 generally 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 REE 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 amidst sourcing uncertainties. Global REE unit prices spiked by factors of 10 to 45 and remained high for about five years. 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-difference 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 individual patent to industries cross-checked with alternative methods.

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 are using REEs and improving the efficiency of those technologies, including by substituting REEs as inputs. This surge in REE-related patents exceeds the overall growth in industry patenting. 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.

Having shown that the REE supply shock triggered an increase in innovation and productivity in downstream industries, we assess the impact on the competitiveness of downstream industries by studying the evolution of exports. We find that manufacturing industries outside of China that are relatively REE-intensive expanded their exports relatively more 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 0.3 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 sectors 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-using industries outside of China expanded their 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 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) 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 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. Under this scenario, a Chinese export tax on REEs raises input costs for downstream industries — especially when the elasticity of substitution between REE inputs and labor is low and for industries that are more dependent on REEs. This leads to a contraction of REE-intensive industries in the rest of the world, while China's relative production 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 is the elasticity of substitution between REEs and labor. If REEs and labor are gross complements, a negative supply shock to REEs shifts the direction of innovation toward REE-saving technologies. In this case, rising global REE prices increase the profitability of innovations that improve REE efficiency. When innovation externalities are sufficiently strong, this technological response can more than offset the direct cost increase from higher REE prices, leading to a decline in downstream production costs. As a result, REE-intensive industries lower their prices and expand, while labor-intensive industries contract.

We calibrate our model using detailed trade and production data from the World Input-Output Database (WIOD) for the pre-shock year 2009. 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 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 REE and labor is well below unity in most industries. Given these estimates, we calibrate industry-specific REE input intensities using U.S. data. We find that industries with higher REE intensity exhibit lower substitution elasticities, providing empirical support for our proposed theoretical mechanism.

In our analysis of the general-equilibrium effects of a Chinese export tax on REE inputs, we show that the model qualitatively and quantitatively replicates the patterns observed in our reduced-form evidence. When technology adjusts 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 China and to contract within China. While the export tax yields a modest welfare gain for China, much of the negative impact on GDP and welfare in other countries is mitigated by the endogenous technological adjustment, which significantly reduces global demand for REE. 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 due to positive terms-of-trade effects, whereas other countries suffer considerable declines in real GDP and welfare. Overall, our analysis links the quantitative effects of export restrictions on REE to their distinctive technological features — namely low substitutability and inelastic supply—in a highly policy-relevant context.

Related Literature: The academic literature on trade and 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. Lashkaripour and Lugovskyy (2023) document the ineffective effects of trade policy and unilateral industrial policy for correcting misallocation. 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, 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.

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. Liu (2019) finds that targeted industrial policies can enhance efficiency by correcting distortions in upstream sectors. 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).

In the field of innovation, our work relates to studies such as Acemoglu (1998), Acemoglu (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 were 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 effect of a conscious industrial policy intervention regarding an essential inputs (with specific characteristics, such as low substitutability, wide variety of applications, concentrated and inelastic supply) on downstream innovation and productivity in third countries in a modern context. Moreover, our quantitative GE analysis of the downstream innovation effects of REE restrictions allows for a detailed welfare assessment.

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. 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 present the model and its quantification in Section 5 and 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.[3] We note four characteristics of REEs that distinguish them from other minerals.

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.[4]

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). Lanthanum, La ('lanthanein,' lying hidden), for example, occurs with Cerium, Ce. The deposits were found later to contain also Praseodymium ('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

[3] 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).

[4] 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 and 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.

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.[5]

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 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. 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 450%, 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. As a result, global production grew by just over 150% (from 60,000t to 91,000t). 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 during this period. In 2009, China's market share in global REE mine production reached 98% (see Figure A.1 in the Data Appendix).

[5]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 mild to moderate toxic (Harbison and Johnson 2015).

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).[6] The price jump was triggered by new Chinese export restrictions that tightened supply and heightened uncertainty in the context of geopolitical tensions. Beyond the extreme price spike, the main impact of China's export restrictions was supply uncertainty. The episode demonstrated China's 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).[7] 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 REE 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.

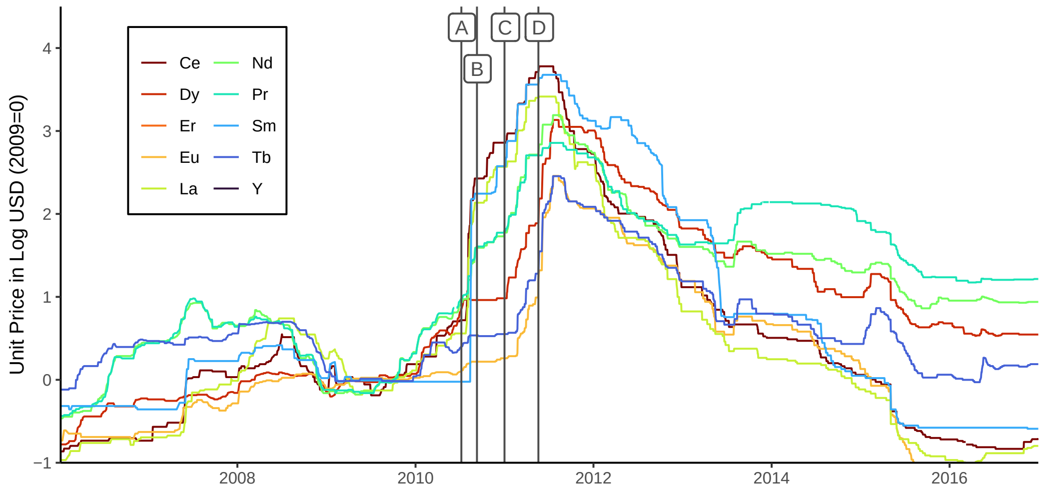
On March 13, 2012, the U.S., joined by Japan, the E.U. and Canada, requested WTO dispute settlement consultations. A WTO panel dismissed China's exemption argument based on conservation of an exhaustible natural resource and determined that the quotas were intended for industrial policy objectives (WTO 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).

Supply Chain and Innovation Responses: 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. Mining expanded in Australia, while

[6] 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%.

[7] 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).

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.

firms in the U.S. continued previously ongoing efforts to reopen Mountain Pass, though it took at least two years for new supply to reach markets, and both mines operated below planned capacity.[8] Production and processing remain reliant on China. Uncertainty constrained inventory use. Many Japanese firms, for example, stockpiled rather than released REEs, fearing depletion without fresh imports from China (Gholz and Hughes, 2021).[9] Firms sought to find substitutes for REEs, alternative manufacturing processes, improve efficiency and recycling efforts. Given the small quantities of REEs used in many applications, large-scale recycling was economically nonviable (Hurst, 2011). In addition, firms, from auto companies in Japan, such as Toyota and Honda, and abroad, such as Tesla, Renault, GM, and electronic companies, such as 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).[10]

[8]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).

[9]As noted by Bachmann et al. (2024), the actual response by firms and governments is consistent with the embargo's effectiveness in creating uncertainty on the reliability of the supply chain.

[10]In January 2011, GM filed a patent for a powder coating process that reduced Dy and Tb 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 Dy in the Prius and, in 2018, reduced Nd in electric

3 Data Sources and Descriptive Statistics

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 alloys, batteries, automobile catalysts, fluid catalyst cracking, phosphors and diodes, and solutions.[11] 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.4 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.

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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.

[11] 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.

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: As a first step, we identify patents as broadly related to REEs and link them to individual elements 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.5 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.1 in the Data Appendix lists the 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 a large language model (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.[12]

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 a 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.8.

[12] 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 equipment.

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 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 countries, we rely on data from the UNIDO Indstat database. Appendix A.4 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.

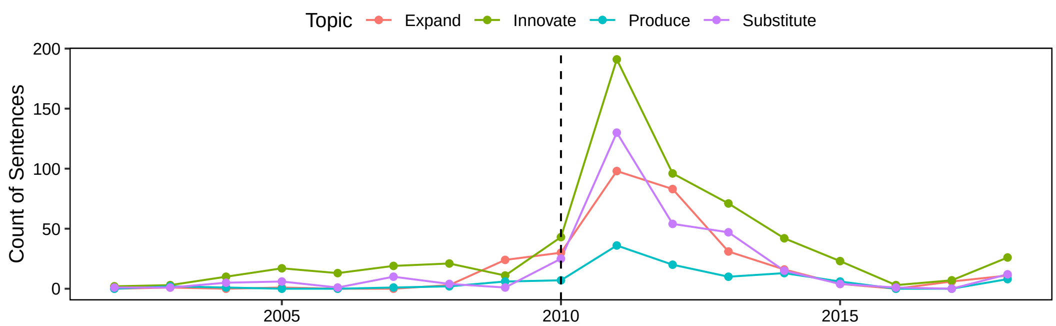
We construct a country-industry proxy of how strongly an industry is targeted by industrial policy using the subsidy database from the Global Trade Alert (GTA). This proxy is the share of subsidies – counted as the number of policy measures – going to a given country-industry relative to the total number of subsidy policies worldwide.

3.4 Descriptive Patterns

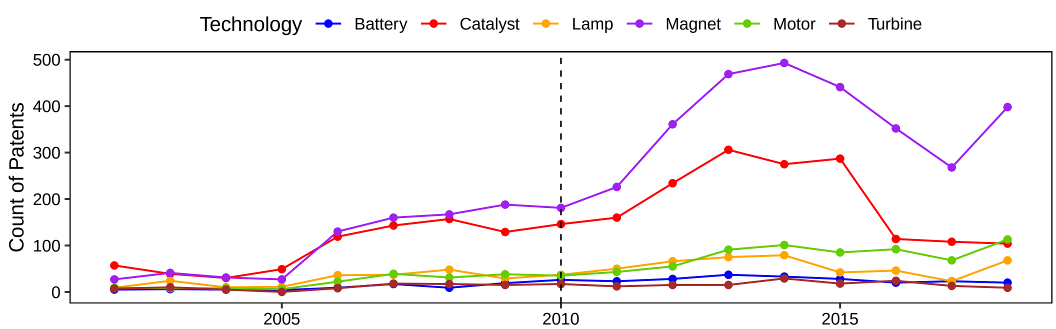
Figure 1 shows composite REE price indices (log USD) over the sample period. Prices surged around 2010, peaked shortly after, then declined sharply and stabilized at a lower level. At the individual REE level, prices rose by a factor of 10 to 45. This spike reflects the global supply shock triggered 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 anticipated that China's export restrictions might be permanent or might recur in the future.

Figure 2: The Rare-Earth 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.

Figure 2 depicts additional descriptive patterns present in the data. 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 counts of newly granted patents that relate to REE. These patents generally increase over time, particularly in magnet and catalyst technologies, indicating a growing emphasis on innovation in these areas. Moreover, the trend strongly accelerates 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 in REE prices around 2010 significantly influenced producer behavior and innovation activities.

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 differences-in differences specification with variable treatment intensity. We estimate the following count model for patents:

$$y_{rst} = \beta \mathit{REE\ Sensitivity}_s \times \mathit{post}_t + \gamma \Delta_{rst} + \eta_{rs} + \eta_{rt} + \epsilon_{rst}. \tag{1}$$

The outcome variable y_{rst} is the stock of granted REE patents for the 4-digit SIC manufacturing industry s from region r in year t, considering the sample window from 2002 until 2018. Our coefficient of interest β is the coefficient on an interaction term of the industry's REE sensitivity measure $\mathit{REE\ Sensitivity}_s$ described below with a step dummy post_t which is one from the year 2010 onward. This corresponds to the period after China first implemented export restrictions and proxies for regime change in the supply-chain environment related to REEs. We always include a full set region-sector and region-time fixed effects that control for the average level of patenting at the region-sector level and region-specific shocks, respectively, as well as a set of industry-region-time-specific control variables that we describe below.

As a measure for the exposure of an industry s to the REE supply shock, we make use of the element-level total requirements from our constructed IO table and an index of element-level REE complementarity from Graedel et al. (2015). This complementarity stems from the physical and chemical properties of elements, not economic factors, and is based on expert assessment. Dysprosium, for example, ranks as the least substitutable, while Samarium is the most. Between two sectors using equal REE amounts, the one relying on harder-to-substitute elements faces greater exposure to REE supply shocks. For instance, sectors needing Dysprosium for permanent magnet motors –with inadequate substitutes– are more exposed than those using REEs in nickel-metal hydride batteries, which can be replaced by lithium-ion alternatives.

To construct the exposure variable $REE\ Sensitivity_s$, we multiply total requirements tr_{es} of each REE e for industry s with the index of complementarity $compl_e$ (ranging between 0 if perfect substitutes are available to 100 if an element cannot be substituted at all) and aggregate over the REE inputs:

$$REE\ Sensitivity_s = \sum_e tr_{es} \times compl_e. \tag{2}$$

This variable measures the exposure of industry s to the REE supply shock. $REE\ Sensitivity_s$ is high if the total requirements of REE inputs are large and these REE inputs are very complementary.

We estimate (1) using Poisson pseudo-maximum likelihood estimation. An important control variable that we include throughout all specifications, is the total patent stock in industry s from region r during year t (in logs) to proxy for overall movements in the industry's innovation activity that might be unrelated to innovation in REE-related activities. One potential concern is that the surge in economic activity of REE-intensive industries may be driven by local subsidies or an increase in demand for their output (e.g., because some of REE-intensive industries are important for the green transformation). We thus additionally control for the capital and labor intensity of each industry (time-invariant) as well as for the (time-invariant) industry-region-specific subsidy intensity (from the Global Trade Alert database), and a time-varying country-industry-specific demand proxy, all interacted with $post_t$. The demand proxy is the weighted GDP growth of the top 10 importing countries in year t (measured in midpoint growth rates) by industry-region. We cluster standard errors at the country-industry level, following Abadie et al. (2023).

Table 1 reports our estimates of (1). The sample only counts those patents that the LLM identifies as patents that either improve the efficiency of REEs or help to substitute the use of REEs. We find that industries that are more sensitive to the REE supply shock innovated more in the treatment

Table 1: Patents in Rare-Earth Intense Manufacturing Industries

	REE-Enhancing Patents					
	NONCHN (1)	ALL (2)	USA (3)	EUR (4)	JPN (5)	CHN (6)
REE Sens. × Post	15.46***	14.36***	17.91**	18.43***	25.65**	2.886
	(4.943)	(5.155)	(7.227)	(6.026)	(11.05)	(19.35)
Observations	5,561	7,606	1,200	1,140	972	2,045
Clusters	387	531	81	74	66	144
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: $y_{rst} = \beta\, \textit{REE Sens.}_s \times post_t + \gamma\Delta_{rst} + \eta_{rs} + \eta_{rt} + \epsilon_{rst}$ with Poisson pseudo-maximum likelihood estimation. The outcome y_{rst} represents granted REE-related patents that improve the efficiency of REE 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. 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: $\textit{REE Sens.}_s = \sum_e tr_{es} \times compl_e$. $post_t$ is a dummy variable set to 1 for 2010 and later years (post-China's REE export restrictions). Region subsamples include non-China, all regions, the U.S., European economies, Japan, 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 Global Trade Alert 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. In the cases of USA and CHN, this demand control is excluded due to high collinearity with the fixed effects. Standard errors (in parentheses) are clustered at the region-industry level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

period than before compared to less affected industries. For the non-China subsample, a one standard-deviation higher value of REE sensitivity is associated with 7.4% larger stock of REE-enhancing patents after the 2010 supply shock. This effect was particularly strong in European countries, the U.S. and Japan. Perhaps not surprisingly, industries more sensitive to REE inputs also patented slightly more REE technologies in China during the treatment period compared to industries. However, this difference in patenting behavior was much less pronounced than in other economies and is statistically indistinguishable from zero.

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

$$y_{ist} = \beta \mathit{REE\ Sensitivity}_s \times \mathit{post}_t + \gamma \Delta_{ist} + \eta_{is} + \eta_{it} + \epsilon_{ist}. \tag{3}$$

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 mid-point of t and $t-1$ as the denominator. The coefficient of interest β is again the coefficient on an interaction term of our $\mathit{REE\ Sensitivity}_s$ 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[13] and cluster standard errors at the country-industry level.

The regression results presented in Table 2 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 total factor productivity (TFP) growth, while the bottom panel examines labor productivity growth. In the full sample (column 2), there is a positive and significant impact of REE shock exposure on both TFP and labor productivity growth. A one standard-deviation higher value in REE sensitivity is associated with 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 4 and 5).[14] Japanese industries with a one standard-deviation higher REE sensitivity boast around 0.5 percentage-point higher growth rate in productivity, both using the TFP and labor productivity measures. In contrast, Chinese industries (columns 6 and 12) show a negative response, with a

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

[14]European economies in our sample of 50 countries include Austria, Belgium, Switzerland, Czech Republic, Germany, Denmark, Spain, Finland, France, United Kingdom, Ireland, Italy, Netherlands, Norway, Poland, Portugal, Romania, and Sweden.

Table 2: Productivity Growth of Rare-Earth Intense Manufacturing Industries

	Annualized Growth: Total Factor Productivity					
	NONCHN	ALL	USA	EUR	JPN	CHN
	(1)	(2)	(3)	(4)	(5)	(6)
REE Sens. × Post	0.498*	0.466*	0.479*	0.555**	1.029***	-2.142***
	(0.260)	(0.259)	(0.281)	(0.242)	(0.370)	(0.742)
Observations	183,818	186,770	6,323	88,055	5,679	2,952
Clusters	14,981	15,350	452	6,306	414	369
	Annualized Growth: Labor Productivity					
	NONCHN	ALL	USA	EUR	JPN	CHN
	(7)	(8)	(9)	(10)	(11)	(12)
REE Sens. × Post	0.391**	0.377**	0.0825	0.202	1.039**	-0.633
	(0.176)	(0.175)	(0.565)	(0.159)	(0.417)	(0.764)
Observations	183,818	186,770	6,323	88,055	6,482	2,952
Clusters	14,981	15,350	452	6,306	436	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 (bottom 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, all countries, the U.S., European economies, Japan, 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.4 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 Global Trade Alert 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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.

4.2 Trade Effects

Effects on Downstream Manufacturing Exports: Next, we study how manufacturing exports from third countries and from China itself respond to the Chinese REE export restrictions, using 4-digit SIC trade data from UN Comtrade for our set of sample countries over the period from 2002 until 2018.

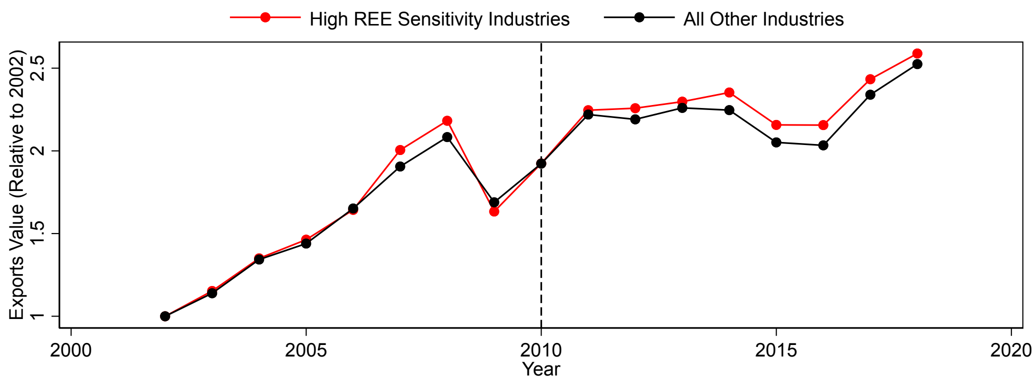
We again estimate (3) on various sub-samples and alternatively include all countries except China, all countries, the U.S., European economies, Japan and China, using export growth as outcome variable. All estimations include a full set of country-industry and country-year fixed effects η_{is} and η_{it} and the set of time-varying industry controls (demand, subsidies, industry characteristics). Estimated standard errors are again corrected for clustering at the country-industry level and we weight by the start-of-sample export shares.

The upper panel of Table 3 presents the results from specification (3) using export growth as the outcome variable. The coefficient β on the interaction term $\textit{REE Sensitivity}_s \times \textit{post}_t$ 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 REE inputs grew significantly faster relative to less sensitive sectors 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 0.3 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.[15]

The bottom panel of Table 3 presents results from similar 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 (triple differences). We find that, relative to the same Chinese manufacturing industries, exports of more exposed industries outside of China grew significantly more in response to the REE supply shock.

[15] In Appendix A.7, 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.

Figure 3: High and Low Rare-Earth Sensitivity Industries: Exports Values (2002=100)



Notes: The figure provides evidence of parallel trends in exports values of high REE sensitivity industries and all other industries before 2010. It plots the exports value by manufacturing industries that are classified in the top 25 percentile of REE sensitivity and the exports value by all other manufacturing industries. The plotted values are normalized to the exports value in the base year 2002. REE sensitivity is constructed following equation (2). The sample consists of the top 50 countries by GDP excluding China. The plotted values have been normalized to 1 for the year 2002.

To make sure that our results are not driven by pre-trends in REE-intensive industries compared to other industries, Figure 3 visualizes the total exports of high REE-sensitivity industries versus all other industries. The two trends were parallel before the event in 2010 aside from the slight shift around the trade collapse of the Global Financial Crisis. Moreover, in line with the results in Table 3, we do observe an increase in REE intensive manufacturing exports relative to other exports starting after the Chinese REE exports restrictions. Note that, consistent with the innovation channel, the relative increase in exports takes some time build up and starts to decline again after sanctions are lifted in 2015.

Alternative Treatment Measures: While using the index of complementarity in (2) has the appeal that it is directly related to the production functions of REE using industries and the chemical properties of elements, we can use UN Comtrade to construct alternative measures of exposure to the Chinese REE supply shock that vary at the country-industry level instead of varying only across industries. Our first measure of country-industry REE sensitivity uses the country-level price spike in unit values of REE imports interacted with the total requirements of REE of each industry (aggregated across elements):[16]

$$REE\ Sensitivity_{is} = \left(\sum_e tr_{es}\right) \times \left(\ln(max\ REE\ import\ price_i) - \ln(REE\ import\ price\ 2009_i)\right). \tag{4}$$

[16] We have used different benchmarks for the price level, obtaining similar results.

Table 3: Downstream Export Growth – Rare-Earth Intense Manufacturing Industries

	Annualized Growth: Exports Value					
	NONCHN	ALL	USA	EUR	JPN	CHN
	(1)	(2)	(3)	(4)	(5)	(6)
REE Sens. × Post	0.856***	0.793***	0.350	0.661**	1.526**	-0.729
	(0.249)	(0.240)	(0.758)	(0.332)	(0.766)	(0.821)
Observations	271,740	277,723	6,048	107,895	5,979	5,983
Clusters	17,249	17,623	378	6,754	375	374
	Differences in Annualized Export Growth to China					
	NONCHN	ALL	USA	EUR	JPN	
	(7)	(8)	(9)	(10)	(11)	
REE Sens. × Post	3.516***	3.351***	3.251***	3.562***	2.832*	
	(0.495)	(0.476)	(0.936)	(0.698)	(1.471)	
Observations	270,342	276,325	5,987	107,321	5,951	
Clusters	17,159	17,533	375	6,722	374	
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: $y_{ist} = \beta\, \mathit{REE\ Sens.}_s \times post_t + \gamma\Delta_{ist} + \eta_{is} + \eta_{it} + \epsilon_{ist}$, 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 (bottom 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 $\mathit{REE\ Sens.}_s$ 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: $\mathit{REE\ Sens.}_s = \sum_e tr_{es} \times compl_e$. $post_t$ is a dummy variable set to 1 for 2010 and later years (post-China's REE export restrictions). Country subsamples include non-China, all countries, the U.S., European economies, Japan, 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 Global Trade Alert 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Alternatively, we build a second country-industry treatment indicator that uses pre-shock import shares of REE elements in country c sourced from China relative to REEs sourced from a larger set of countries (China, the U.S., Australia, Russia or India) again interacted with the total requirement of REEs of industry s:

$$REE\ Sensitivity_{is} = \left(\sum_{e} tr_{es}\right) \times \frac{REE\ imports\ from\ CHN_i}{REE\ imports\ from\ CHN,\ USA,\ AUS,\ RUS,\ IND_i}. \qquad (5)$$

For both shock measures, we consider HS codes 284690, 284610, and 280530 as REE relevant and weigh them by initial import shares. Appendix Table A.6 reports the estimates based on both alternative shock measures using the different regional samples. In line with our previous results, we find that export growth of downstream industries increased relatively more in those country-industries where the REE supply shock was relatively more important.

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 technical change (Acemoglu, 2002) into a quantitative general-equilibrium gravity model of international trade (Caliendo and Parro, 2015; Fadinger et al., 2024). The production side of the model consists of the following four layers: final goods, Armington industry bundles, tradable industry goods and a layer for factor-biased innovation activities.

5.1 Setup

There are many countries, indexed by $i = 1,..,I$ and $j = 1,...J$ and industries, indexed by $s = 1,...,S$. 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 rare-earth and 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 sector-specific elasticity of substitution between REE and labor input bundles, denoted by ε_s. The value of ε_s determines if REE are gross substitutes ($\varepsilon_s > 1$) or complements ($\varepsilon_s < 1$) with 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. Moreover, $\gamma_s \in [0, 1]$ determines the dependence of industry s on REE inputs. The higher the value of γ_s, the more dependent a given sector 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 sector s and produced by sectors s'. Here, $\phi_{iss'}$ denotes the IO coefficients (expenditure shares of country i industry s on goods produced by sector 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 $d_{iis} = 1$.

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 labor input bundle Y_{Lis}. These inputs 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:

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

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 firms on downstream productivity. If $\delta > 0$, spillovers are positive, while if $\delta < 0$, there are negative spillovers. If $\delta = 0$, spillover effects are absent.[17]

[17] 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

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

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

and the inverse demand of an input firm producing variety a of inputs is given by

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

The measures A_{Ris} of REE input firms and A_{Lis} of 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 $\mu_s > 1$. Each REE (labor) input variety is produced with a linear technology with the factor REE 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

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

and the variable profits of input monopolists:

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

Inventing an input patent is associated with fixed costs f_{Ri} (or f_{Li}) which are paid in units of the final good in country i with price P_i. Note that since $P_{Ris} = E_{Ris}^{-1} A_{Ris}^{\frac{1}{1-\mu_s}} p_{is}$ and $Y_{Ris} = E_{Ris} A_{Ris}^{\frac{\mu_s}{\mu_s-1}} r_{is}$, 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:

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

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 (43) below). For example, they could result from (unmodeled) competition for a scarce factor.

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

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

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

5.2 Consumption and Final Goods

We now specify the remainder of the model. Figure 4 provides a graphical representation of the model structure. At the most downstream level, there is a non-tradable final good Y_i, that 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 $\sum_s A_{Ris}f_{Ri}$ and $\sum_s A_{Lis}f_{Li}$). 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

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

where Q_{is} corresponds to the quantity of 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 $j = 1, ..., J$ 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 country-specific 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:

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

5.2.1 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. It additionally disposes of a non-discriminatory gross ad-valorem export tax $\tau_{XC} \geq 1$ on the exports of REEs. Therefore, the price of REE inputs in country j is equal to $w_{Rj} = \tau_{XC} w_{RC}$.

5.2.2 Goods and Factor Markets

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

$$Rev_{is} = \sum_j \lambda_{jis} \left[\alpha_{js} \left(\frac{P_{js}}{P_j}\right)^{1-\rho} (w_{Lj} L_j + I_C \times w_{RC} R_C + T_j - TB_j - NFIA_j) + \sum_{s\prime} \phi_{ss'j} Rev_{s'j}\right]. \tag{21}$$

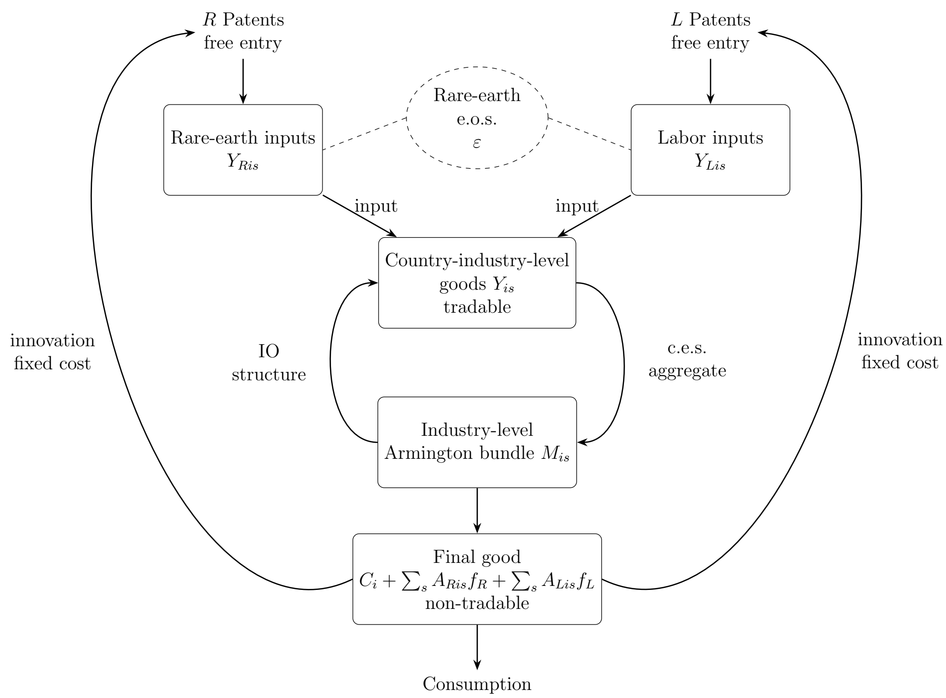
Here, I_C is an indicator variable that equals unity when j is China and zero for all other countries j. TB_j is the (exogenous) trade imbalance and

$$NFIA_j = \begin{cases} -w_{Rj} \sum_{s=1}^{S} \int_0^{A_{Rjs}} r_{js}(a) da, & \text{if } j \neq C \\ \sum_{j \neq C} w_{Rj} \sum_{s=1}^{S} \int_0^{A_{Rjs}} r_{js}(a) da, & \text{if } j = C \end{cases} \tag{22}$$

are net factor incomes from abroad, $NFIA_j$, arising from the use of the REE factor for countries other than China and for China, respectively. Total export tax revenue on net exports of REEs are fully rebated to consumers with lump-sum transfers T_j:

$$T_j = I_C \times (\tau_{XC} - 1) w_{RC} (R_C - \sum_s A_{RjC} r_{Cs}).$$

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:

$$\sum_s \int_0^{A_{Lsi}} l_s(a)da = L_i. \tag{23}$$

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

$$\sum_j \sum_s \int_0^{A_{Rjs}} r_{js}(a)da = R_C. \tag{24}$$

5.3 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 (25), determining Rev_{is}; *(ii)* $I \times J \times S$ equations (28) determining λ_{ijs}; *(iii)* $I \times J \times S$ equations (29) determining P_{ijs}; *(iv)* $I \times S$ equations

(30) determining P_{is}; *(v)* I equations (31) determining P_i; *(vi)* $2 \times I \times S$ equations of type (32) determining $P_{Ris}Y_{Ris}$ and $P_{Lis}Y_{Lis}$; *(vii)* I equations (35) determining w_{Li} and *(viii)* 1 equation (36), determining w_{RC}. Further, note that $w_{Ri} = w_{RC}\tau_{XC}$.

Market clearing for Armington goods is given by:

$$\begin{aligned} Rev_{is} =& \sum_j \lambda_{jis} \times \\ & \left[\alpha_{js}\left(\frac{P_{js}}{P_j}\right)^{1-\rho}(w_{Lj}L_j + I_C \times w_{RC}R_C + T_j - TB_j - NFIA_j) + \sum_s \phi_{ss'j}Rev_{js}\right] \quad \forall i, s, \end{aligned} \tag{25}$$

with net factor incomes from abroad being:

$$NFIA_j = \begin{cases} -\sum_{s=1}^{S}\left(\frac{\mu_s-1}{\mu_s}\right)(P_{Rjs}Y_{Rjs}), & \forall j \neq C \\ \sum_{j\neq C}\sum_{s=1}^{S}\left(\frac{\mu_s-1}{\mu_s}\right)(P_{Rjs}Y_{Rjs}), & \forall j = C. \end{cases} \tag{26}$$

Transfers T_j are given by:

$$T_j = I_C \times (\tau_{XC} - 1)[w_{RC}R_C - \sum_s \left(\frac{\mu_s - 1}{\mu_s}\right)\tau_{RCs}^{-1}(P_{RCs}Y_{RCs})], \tag{27}$$

where I_C is an indicator that equals unity for $j = China$.

Bilateral trade shares are:

$$\lambda_{ijs} = \left(\frac{P_{ijs}}{P_{is}}\right)^{1-\sigma_s} \quad \forall i, j, s. \tag{28}$$

Bilateral prices are given by:

$$\begin{aligned} P_{ijs} =& d_{ijs}[\gamma_s^{\varepsilon_s}\left(\frac{P_{Rjs}Y_{Rjs}}{\mu_s f_R P_j}\right)^{\delta(\varepsilon_s-1)+\frac{\varepsilon_s-1}{\mu_s-1}}\left(\frac{\mu_s}{\mu_s-1}\right)^{1-\varepsilon_s}(w_{Rj})^{1-\varepsilon_s} + \\ & (1-\gamma_s)^{\varepsilon_s}\left(\frac{P_{Ljs}Y_{Ljs}}{\mu_s f_L P_j}\right)^{\delta(\varepsilon_s-1)+\frac{\varepsilon_s-1}{\mu_s-1}}\left(\frac{\mu_s}{\mu_s-1}\right)^{1-\varepsilon_s}(w_{Lj})^{1-\varepsilon_s}]^{\frac{\phi_{is}}{1-\varepsilon_s}}\prod_{s'} P_{js}^{\phi_{jss'}} \quad \forall i, j, s. \end{aligned} \tag{29}$$

Industry-level price indices are defined as:

$$P_{is} = \left[\sum_j P_{ijs}^{1-\sigma_s}\right]^{\frac{1}{1-\sigma_s}} \quad \forall i, s. \tag{30}$$

Aggregate price levels are given by:

$$P_i = \left[\sum_s \alpha_{is} P_{is}^{1-\rho} \right]^{\frac{1}{1-\rho}} \quad \forall i. \tag{31}$$

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

$$\begin{aligned} P_{Ris}Y_{Ris} =& \gamma_s \phi_{is} Rev_{is} \times \\ & \left[\gamma_s + (1-\gamma_s) \left(\frac{(1-\gamma_s) f_{Ri}}{\gamma_s f_{Li}} \right)^{\frac{(\varepsilon_s - 1)\{\mu_s \kappa_s + (\mu_s - 1)^2 \varepsilon_s \delta\}}{(\mu_s - \varepsilon_s)[\mu_s - \varepsilon_s - \delta(\mu_s - 1)(\varepsilon_s - 1)]}} \left(\frac{r_{is}}{l_{is}} \right)^{\frac{(1-\varepsilon_s)\{\delta(\mu_s-1)^2(\varepsilon_s-1) + (\mu_s-1)\kappa_s\}}{(\mu_s - \varepsilon_s)\kappa_s}} \right]^{-1} \forall i, s, \end{aligned} \tag{32}$$

$$\begin{aligned} P_{Lis}Y_{Lis} =& (1-\gamma_s) \phi_{is} Rev_{is} \times \\ & \left[(1-\gamma_s) + \gamma_s \left(\frac{(1-\gamma_s) f_{Ri}}{\gamma_s f_{Li}} \right)^{\frac{(1-\varepsilon_s)\{\mu_s \kappa_s + (\mu_s - 1)^2 \varepsilon_s \delta\}}{(\mu_s - \varepsilon_s)\kappa_s}} \left(\frac{r_{is}}{l_{is}} \right)^{\frac{(\varepsilon_s-1)\{\delta(\mu_s-1)^2(\varepsilon_s-1) + (\mu_s-1)\kappa_s\}}{(\mu_s - \varepsilon_s)\kappa_s}} \right]^{-1} \forall i, s, \end{aligned} \tag{33}$$

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

$$\frac{r_{is}}{l_{is}} = \frac{f_{Ri}}{f_{Li}} \frac{w_{Li}}{w_{Ri}} \quad \forall i, s. \tag{34}$$

Labor markets clear in each country:

$$\sum_s \left(\frac{\mu_s - 1}{\mu_s} \right) (P_{Lis} Y_{Lis}) = w_{Li} L_i \quad \forall i. \tag{35}$$

The REE market clears at the world level:

$$\sum_j \sum_s \left(\frac{\mu_s - 1}{\mu_s} \right) (P_{Rjs} Y_{Rjs}) \tau_{XC}^{-1} = w_{RC} R_C. \tag{36}$$

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 (32) need to be replaced by:

$$
\begin{aligned}
P_{Ris}Y_{Ris} =& \gamma_s \phi_{is} Rev_{is} \times \\
& \left[\gamma_s + (1-\gamma_s)\left(\frac{\gamma_s}{1-\gamma_s}\right)^{1-\varepsilon_s}\left(\frac{A_{Ris}}{A_{Lis}}\right)^{(1-\varepsilon_s)\left(\delta+\frac{\mu_s}{\mu_s-1}-1\right)}\left(\frac{w_{Li}}{w_{Ri}}\right)^{1-\varepsilon_s}\right]^{-1} \qquad (37)\\
P_{Lis}Y_{Lis} =& (1-\gamma_s)\phi_{is} Rev_{is} \times \\
& \left[(1-\gamma_s) + \gamma_s\left(\frac{\gamma_s}{1-\gamma_s}\right)^{\varepsilon_s-1}\left(\frac{A_{Ris}}{A_{Lis}}\right)^{(\varepsilon_s-1)\left(\delta+\frac{\mu_s}{\mu_s-1}-1\right)}\left(\frac{w_{Li}}{w_{Ri}}\right)^{\varepsilon_s-1}\right]^{-1}. \qquad (38)
\end{aligned}
$$

Moreover, (29) becomes:

$$
\begin{aligned}
P_{ijs} =& d_{ijs}[\gamma_s^{\varepsilon_s}\left(A_{Ris}\right)^{\delta(\varepsilon_s-1)+\frac{\varepsilon_s-1}{\mu_s-1}}\left(\frac{\mu_s}{\mu_s-1}\right)^{1-\varepsilon_s} w_{Rj}^{1-\varepsilon_s} + \\
& (1-\gamma_s)^{\varepsilon_s}\left(A_{Lis}\right)^{\delta(\varepsilon_s-1)+\frac{\varepsilon_s-1}{\mu_s-1}}\left(\frac{\mu_s}{\mu_s-1}\right)^{1-\varepsilon_s} w_{Lj}^{1-\varepsilon_s}]^{\frac{\phi_{is}}{1-\varepsilon_s}} \prod_{s'} P_{js}^{\phi_{jss'}}. \qquad (39)
\end{aligned}
$$

The remaining equilibrium conditions are unaffected.

5.4 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):

$$
\frac{Y_{Ris}}{Y_{Lis}} = \frac{E_{Ris}}{E_{Lis}}\left(\frac{A_{Ris}}{A_{Lis}}\right)^{\frac{\mu_s}{\mu_s-1}}\frac{r_{is}}{l_{is}}. \qquad (40)
$$

Next, combining this expression with the relative demand equation

$$
\frac{Y_{Ris}}{Y_{Lis}} = \left(\frac{\gamma_s}{1-\gamma_s}\right)^{\varepsilon}\left(\frac{P_{Ris}}{P_{Lis}}\right)^{-\varepsilon}, \qquad (41)
$$

we derive an expression for the relative revenues of firms in the R_{is} and L_{is} sectors:

$$
\frac{P_{Ris}Y_{Ris}}{P_{Lis}Y_{Lis}} = \frac{\gamma_s}{1-\gamma_s}\left(\frac{E_{Ris}}{E_{Lis}}\right)^{\frac{\varepsilon_s-1}{\varepsilon_s}}\left(\frac{A_{Ris}}{A_{Lis}}\right)^{\frac{\mu_s}{\mu_s-1}\frac{\varepsilon_s-1}{\varepsilon_s}}\left(\frac{r_{is}}{l_{is}}\right)^{\frac{\varepsilon_s-1}{\varepsilon_s}}. \qquad (42)
$$

Combining (42) with (15), and assuming that $E_{Ris}/E_{Lis} = (A_{Ris}/A_{Lis})^{\delta}$, we can solve for the relative technology bias as a function of the input ratio:

$$\frac{A_{Ris}}{A_{Lis}} = \left(\frac{f_{Li}}{f_{Ri}}\frac{\gamma_s}{1-\gamma_s}\right)^{\frac{(\mu_s-1)\varepsilon_s}{\kappa_s}} \left(\frac{r_{is}}{l_{is}}\right)^{\frac{(\mu_s-1)(\varepsilon_s-1)}{\kappa_s}} . \tag{43}$$

When $\mu_s > 1$ (a necessary condition to ensure well-defined profit maximization by monopolistic producers) and $\varepsilon_s < 1$ (indicating that REEs and labor are gross complements), the expression in (43) is decreasing in $\frac{r_{is}}{l_{is}}$ if $\delta \geq 0$, or if $|\delta| < \frac{\mu_s-\varepsilon_s}{(\mu_s-1)(\varepsilon_s-1)}$ when $\delta < 0$. 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.

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 relative revenue expression (44), which results from substituting (43) into (42):

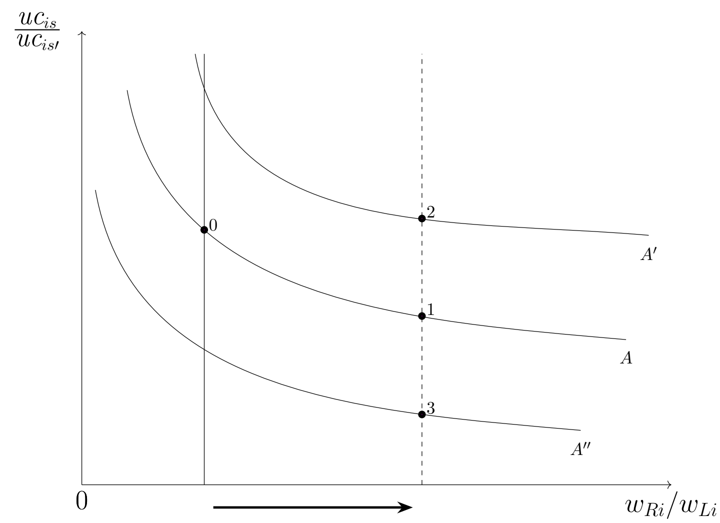
$$\frac{P_{Ris}Y_{Ris}}{P_{Lis}Y_{Lis}} = \left(\frac{f_{Li}}{f_{Ri}}\right)^{\frac{\mu_s(\varepsilon_s-1)\kappa_s+(\mu_s-1)^2\varepsilon_s\delta(\varepsilon_s-1)}{(\mu_s-\varepsilon_s)\kappa_s}} \left(\frac{\gamma_s}{1-\gamma_s}\right)^{\frac{\varepsilon_s(\mu_s-1)\kappa_s+(\mu_s-1)^2\varepsilon_s\delta(\varepsilon_s-1)}{(\mu_s-\varepsilon_s)\kappa_s}} \left(\frac{r_{is}}{l_{is}}\right)^{\frac{(\mu_s-1)(\varepsilon_s-1)\kappa_s+(\mu_s-1)^2(\varepsilon_s-1)^2\delta}{(\mu_s-\varepsilon_s)\kappa_s}} . \tag{44}$$

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

In contrast, the relative output of the REE sector Y_{Ris}/Y_{Lis} increases with the input ratio:

$$\frac{Y_{Ris}}{Y_{Lis}} = \left(\frac{f_{Li}}{f_{Ri}}\frac{\gamma_s}{1-\gamma_s}\right)^{\frac{\mu_s\varepsilon_s\kappa_s+\delta(\mu_s-1)^2\varepsilon_s^2}{(\mu_s-\varepsilon_s)\kappa_s}} \left(\frac{r_{is}}{l_{is}}\right)^{\frac{\delta(\mu_s-1)^2\varepsilon_s(\varepsilon_s-1)+(\mu_s-1)\varepsilon_s\kappa_s}{(\mu_s-\varepsilon_s)\kappa_s}} . \tag{45}$$

Figure 5: Factor Prices and the Direction of Technological Change



Notes: The figure plots possible adjustments in response to an increase in the relative REE factor price for two industries s and $s\prime$, where industry $s\prime$ is more reliant on REE. Curves A, A' and A'' depict different relative unit costs depending on the direction of technological change.

Finally, the optimal factor input ratio is inversely related to the relative price of REEs:

$$\frac{r_{is}}{l_{is}} = \frac{f_{Ri}}{f_{Li}} \frac{w_{Li}}{w_{Ri}}.$$

Impact on Productivity: By comparing the expressions for unit costs under endogenous (29) and exogenous technologies (39), we gain insight into how the competitiveness of downstream industries responds to an increase in the price of REEs. Under exogenous technology, an increase in w_{Rj} raises production costs — an effect that is more pronounced in industries with higher REE intensity. According to the trade-share equation (20), this increase in costs reduces bilateral exports.

In contrast, under endogenous technology, an increase in w_{Rj} also induces a technological response via an associated increase in $P_{Rjs}Y_{Rjs}$ (the *technology effect*). If this effect is sufficiently strong, it can outweigh the *factor cost effect*, enhancing the relative competitiveness of REE-intensive industries. As a result, exports from these sectors may increase despite the rise in input costs.

This can be illustrated with the help of Figure 5. The figure shows relative unit costs for two industries s and s' and highlights potential equilibrium adjustments in response to an increase in the relative price of REE. Since these relative unit-cost curves are downward sloping in the relative price of REE w_{Ri}/w_{Li}, sector s' is relatively more REE-intensive. 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 exogenously fixed, the adjustment occurs along the A curve to the new equilibrium point 1: the REE-intensive sector loses some of its competitiveness due to the relatively intensive use of the REE factor, whose relative price has risen. However, if there is a sufficiently strong response in the direction of technological change biased towards REE, 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. Alternatively, if the bias of innovation were to shift in the opposite direction, the relative unit costs would become A''. In this alternative equilibrium (point 3), the REE-intensive industry would further lose relative competitiveness compared to the case of exogenous technology.

6 Quantification

6.1 Taking the Model to the Data

Matching World Input-Output Data: We calibrate the model to a baseline economy in 2009 – the year before the REE supply shock – using trade and production data from the World Input-Output Tables (WIOD, 2012 release). We aggregate the world IO tables to 5 regions: China, Europe, Japan, the U.S., and the rest of the world (RoW), including all remaining countries. We consider 14 industries: twelve inmanufacturing, agriculture and services. For each country-industry pair, we perfectly match (i) bilateral trade shares λ_{ijs} and (ii) consumption expenditure shares $\alpha_{js}\left(P_{js}/P_j\right)^{1-\rho}$. Moreover, we take (iii) the value-added shares in gross output ϕ_{is} and (iv) the direct requirement shares in gross output $\phi_{jss'}$ directly from the data. Additionally, we obtain exogenous trade imbalances (TB_i) for each region.

Calibration of Aggregate 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_s of 6.5, implying a markup of 18%, consistent with estimates from De Loecker and Eeckhout (2018). We choose the size of labor endowments across countries according to country-level employment data from WIOD adjusted for human-capital differences from the Penn World Tables. The elasticity of final demand is set to equal the trade elasticity. Finally, we calibrate the value of parameter governing the innovation spillover effects, δ, to ensure that the signs of the regression coefficients for innovation bias, productivity, and exports with respect to REE prices align between the model and the empirical data. Based on this, we set the externality δ to -1. We normalize the level of global real GDP to unity.

Estimating the Substitution Elasticity for REE ε_s: The industry-specific substitution elasticity between REE and labor ε_s is a key parameter in our calibration since it governs the response of input costs and innovation to a REE supply shock. For a positive REEs price shock to shift the direction of innovation towards REEs, like in the empirical findings, REEs need to be a complementary input ($\varepsilon_s < 1$). Typically, the elasticity of substitution can be estimated from expenditure shares on inputs. However, for the case of REEs, this information is not available at the industry-country level. We therefore exploit the model structure to estimate the elasticity of substitution between REE and labor from the relation between relative factor prices and the direction of innovation (REE-related patents relative to other patents) in a given industry.

Suppose we have data on A_{Ris}/A_{Lis} (REE patents relative to other patents) and w_{Ri}/w_{Li} (relative factor prices) for many countries i and industries s. Our model implies the following structural relationship between patents and factor prices that we exploit to estimate ε_s:

$$\log\left(\frac{A_{Ris}}{A_{Lis}}\right) = \beta_s \log\left(\frac{w_{Ri}}{w_{Li}}\right) + \delta_s + u_{is}, \tag{46}$$

where $\beta_s \equiv \frac{(1-\varepsilon_s)(\mu_s-1)}{\kappa_s}$, $\delta_s \equiv \frac{\varepsilon_s(\mu_s-1)}{\kappa_s}\log\left(\frac{\gamma_s}{1-\gamma_s}\right)$ is an industry fixed effect and $u_{is} \equiv \frac{\mu_s-1}{\kappa_s}\log\left(\frac{f_{Li}}{f_{Ri}}\right)$ is a residual.[18] This equation can be estimated from data on the relative number of patents in each industry, REE unit values and wages. We use our patent count data, classified with the LLM algorithm described in Section 3.2. The REE unit value for each country is obtained by dividing the value of REE imports by that country with the physical quantity. Finally, labor costs for each country are calculated from the Penn World Tables. We estimate (46) separately for each 2-digit manufacturing SIC code, using a panel of our 5 regions over the sample period from 2002 to 2018. We then aggregate the resulting REE elasticity of substitution estimates to the level of WIOD industries by taking averages weighted by value added. Table 4 reports the estimates of ε_s by industry. We estimate $\varepsilon_s \in [0.75, 1.28]$, with point estimates below unity in most industries.

Calibrating the REE intensity γ_s: Another important parameter in the quantification exercise 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:

$$\frac{P_{Ris}Y_{Ris}}{P_{VAis}VA_{is}} = \frac{1}{1+\left(\frac{1-\gamma_s}{\gamma_s}\right)^{1/\varepsilon_s}\left(\frac{P_{Lis}}{P_{Ris}}\right)^{1-\varepsilon_s}}. \tag{47}$$

Given the sectoral total requirements of REE for the U.S. from our IO table presented in Section 3.1, combined with data on value added, prices P_{Ris}, P_{Lis}, and estimates for ε_s, we can back out

[18] We refer to Appendix B.1 for a derivation.

Table 4: Estimates of ε_s and γ_s

WIOD Manufacturing Industry	ε_s	γ_s
Transport equipment	0.75	0.0071
Basic metals and fabricated metal	0.80	0.0074
Mining, petroleum and coal products	0.86	0.0021
Rubber and plastics	0.86	0.0005
Chemicals and chemical products	0.94	0.0004
Other non-metallic mineral products	0.96	0.0001
Machinery	0.98	0.0006
Computer and electronic products	0.99	0.0003
Wood and paper products	1.12	0.0003
Food, beverages and tobacco	1.16	0.0000
Furniture and misc. manufacturing	1.25	0.0000
Textiles and textile products	1.28	0.0000

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

γ_s for all industries s.[19]

Table 4 presents the estimates of ε_s and γ_s by industry, sorted by descending values of ε_s. It stands out that those industries with the lowest values of the elasticity of substitution are also the most REE-intensive industries.

6.2 Quantitative Exercise

We simulate the introduction of a 400% tax on exports of REEs by China ($\tau_{XC} = 5$), motivated by the observation that unit import values of REE-related HS codes increased by a factor of approximately 5 on average around the year 2010.[20] The introduction of this tax raises the relative difference in factor prices w_{Ri}/w_{Li} between China and the other regions by a factor of 5.06 in our model with endogenous innovation.

Figure 6 visualizes each industry's innovation response to China's export tax for countries outside of China, as measured by the relative change in the industry-level innovation bias $\Delta(A_{Ris}/A_{Lis})$.

[19] 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}.

[20] Compared to the price increases in the element-level price series presented in Figure 1, this tax rate is a rather conservative choice for τ_{XC}.

Table 5: Simulated Regressions

	$\Delta(A_{Ris}/A_{Lis})$		$\Delta(\textit{VA productivity})_{is}$		ΔExp_{is}	
	NONCHN (1)	CHN (2)	NONCHN (3)	CHN (4)	NONCHN (5)	CHN (6)
$1/\varepsilon_s$	0.125	-2.203	0.159	-0.0262	0.0687	-0.134
	(0.000485)	(0.115)	(0.127)	(0.509)	(0.0399)	(0.266)
Observations	48	12	48	12	48	12

Notes: The table presents coefficient estimates from the regression: $\Delta y_{is} = \alpha + \beta\,(1/\varepsilon_s) + \epsilon_{ist}$, where the outcome variable is either $\frac{(A_{Ris}/A_{Lis})^{post}}{(A_{Ris}/A_{Lis})^{pre}}$ or $\frac{(\textit{VA productivity})^{post}_{is}}{(\textit{VA productivity})^{pre}_{is}}$ or $\frac{Exp^{post}_{is}}{Exp^{pre}_{is}}$. All coefficients are reported in units of standard-deviation changes.

The lower the elasticity of substitution ε_s of any given industry, the stronger is the observed shift in the innovation bias towards the REE factor. The shift in the innovation bias ranges between 2.7 p.p. (for transport equipment) and -2.0 p.p. (for textiles).

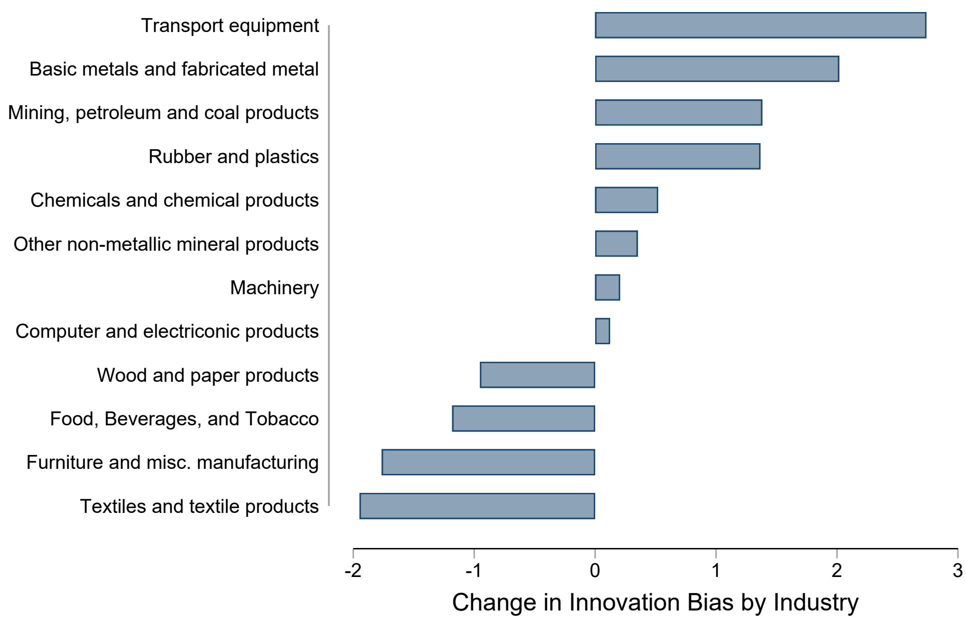
In a next step, we assess if our quantitative model can reproduce the industry-level innovation, productivity and export response to the REE supply shock. We thus regress (i) the change in the innovation bias $\Delta(A_{Ris}/A_{Lis})$, (ii) the change in value-added productivity, measured as the inverse cost of producing one unit of industry value added, and (iii) the change in exports ΔExp_{is} of manufacturing industry s in country i on a proxy for how sensitive industry s is to the REE supply shock. We use the inverse of ε_s to proxy for how susceptible each industry is.

Table 5 presents the results of this exercise. Column (1) confirms that, in response to the introduction of the export tax, the innovation bias outside of China shifts towards REEs in those sectors that are more REE-sensitive. By contrast, the opposite adjustment occurs within China, where the technology bias A_{Ris}/A_{Lis} falls in REE-sensitive industries, as can be seen in column (2). In terms of magnitude, a one-standard-deviation increase in REE sensitivity increases the technology bias by 0.12 standard deviations.

Column (3) shows that, outside of China, the shift in the innovation bias towards REEs is sufficiently strong to increase productivity more strongly in REE-sensitive industries compared to other industries, even though the relative factor price of REEs outside of China increases. The point estimate implies that a one-standard-deviation increase in REE sensitivity increases relative industry productivity by 0.16 standard deviations. Column (4) shows that, in China, the productivity of REE-sensitive industries decreases instead. These changes in relative productivities have a direct impact on downstream-industry exports Exp_{is}.

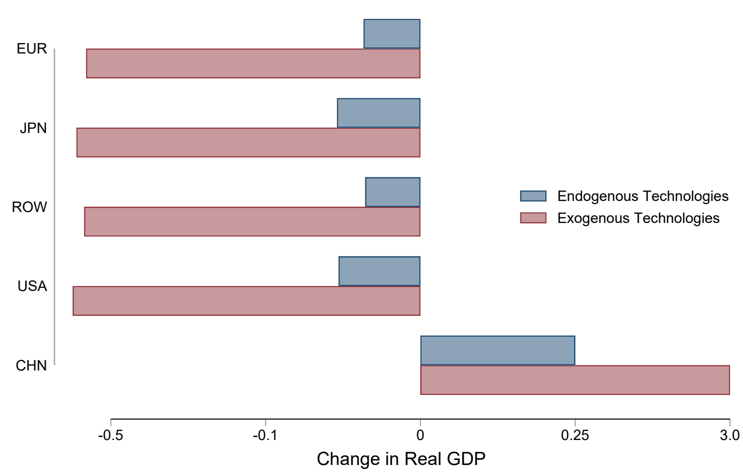
Columns (5) and (6) show that exports of REE-sensitive industries expand outside China, while the exports of these industries contract in China. Quantitatively, a one-standard deviation increase

Figure 6: Change in the Innovation Bias



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 the Chinese REE export tax. Regions are weighted according to real GDP in the baseline economy.

Figure 7: Effect of a Rare-Earth Export Tax 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 the Chinese REE export tax.

in REE sensitivity is associated with a 0.07 s.d. stronger export outside China.

We now turn to a discussion of the GE effects of China's export tax on real GDP. We present the results in Figure 7. The global response of value added highlights the importance of directed technological change in cushioning the response to China's REE export tax; real GDP losses outside China are very small (in the range of 0.04% to 0.05%). By contrast, in a counterfactual world where technologies are exogenously held fixed, the global effect of China's policy on other countries' real GDP would have been very different. Without directed technological change, all regions outside of China would have incurred more than ten times larger real GDP losses, ranging between 0.54% and 0.56%.

Conversely, China gains much less from the policy under directed technological change than in a world without endogenous technology response: China's real GDP increases by 0.25%, which is driven by cheaper domestic factors. By contrast, with exogenous technology, China's real GDP gain from the same policy would have been substantially larger, at around 3%.

Lastly, we use our model quantification to back out the welfare consequences of China's policy. We measure welfare in terms of real consumption of the final good. Thus, changes in real value added need to be adjusted for primary incomes from tradable factor inputs and REE tax revenues to obtain real gross national expenditures of each region on the non-tradable final good. We deduct investment for innovation from gross national expenditure to obtain real consumption.[21] The REE tax increases China's real consumption by about 2.6% while it has small welfare costs on regions outside China. In Europe, the technological response in combination with GE price changes is even sufficiently strong to generate a small welfare increase. When contrasting these outcomes with welfare changes in a world with fixed technologies, we again observe very large differences. Chinese welfare would have increased almost twice as much due to strong positive terms-of-trade effects of the REE export tax while welfare losses in the other regions would have been substantial, between 0.45% in Europe and 0.62% in Japan (see Appendix Figure A.8).

7 Conclusion

How did export restrictions on REEs affect downstream industries both globally and domestically? To address this question, we construct a detailed IO table that accounts for individual REE inputs, allowing us to assess their significance for specific industries. Our empirical analysis provides robust evidence that the export restrictions imposed by China between 2010 and 2015 stimulated a strong innovation response in REE-intensive downstream industries outside of China. To measure

[21]Consequently, while more innovation raises GDP, it also reduces the part of gross national expenditures that is available for consumption due to the presence of innovation fix costs.

REE-biased innovation, we classify patents from downstream industries across the world based on whether they substitute for or enhance the efficiency of REE usage. Our findings further indicate a significant increase in total factor productivity and exports in the most exposed industries outside of China, relative to less affected industries. Furthermore, we do not observe a comparable increase in total factor productivity or exports within the respective Chinese industries.

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 and production data. Leveraging the model structure, we estimate the elasticity of substitution between REEs and 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 Empirical 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.

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.2).

A.3 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 REE from the Google Patent Research database.

REE Patents: As a first step, we identify patents as broadly related to REE and link them to individual elements when their title or abstract contains certain 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.[22] By the end of the sample period, there exist around 30,000 granted unique REE patents, globally. We assign the country of the patent based on the country of the patent assignee, considering the same set of top 50 countries as in the other analyses that we pool to the regions Europe, U.S. and Canada, China, Russia, Korea, Japan, Australia and the Rest of World.

Classifying Patents in a LLM: In the next step, we link each patent in our sample to an industry. This is not a straightforward task, as patents are categorized in technology classes instead of industries. To assign a patent to an industry, researchers have previously created and used concordance tables linking technology classes to their sectors of use.[23]

While this method is in principle feasible for our classification, a concern is that REE-related technologies are generally much younger than concordances between IPC technology classes and the SIC industry classification. Furthermore, technologies usually map into large groups of industries, and this mapping is not specific to REE. Alternatively, patents have been linked to industries via the industry affiliation of the firm holding the patent.[24] Linking patents via firms has two caveats. First, a large fraction of REE patents is filed by non-corporate entities such as universities and other research institutions or by non-public firms. Neglecting these patents could bias our results if REE-related research were systematically more prevalent in the corporate or non-corporate sectors. Second, while patent-firm matches exist for some countries (such as the NBER/Compustat patent matches for the U.S.), a global matched patent-firm database is not readily available.

Instead of following these paths, we use an LLM to assign the patents in our sample to industries. For that purpose, we parse the title and abstract text of each individual patent to the LLM and let the LLM suggest the SIC industry that fits best to the patent.For this approach, we use the model GPT4 from OpenAI. We refine the sample of REE patents by asking the LLM to classify

[22] See Table A.5 for the list of keywords.
[23] See, e.g., Silverman (2002).
[24] See e.g. Bloom et al. (2013).

whether each patent describes a technology that improves the use of REEs or helps to substitute away from the use of REE.

Other Patents: We draw a large random sample of patents and let the LLM allocate the SIC manufacturing industry codes. We then scale these numbers for each year across regions by the observable number of granted patents that each region has in the total sample of manufacturing patents for that year.

A.4 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. 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.

A.5 Trade and Other 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 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). This proxy is the share of subsidies (counted in the number of policy measures) going to a country-industry relative to the total number of subsidy policies worldwide.

A.6 Results with Alternative REE Sensitivity Measures

For our regressions of exports growth, 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 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):

$$\textit{REE Sensitivity}_{is} = \left(\sum_e tr_{es}\right) \times (\ln(\textit{max REE import price}_i) - \ln(\textit{REE import price 2009}_i)) \,.$$

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:

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

.

Table A.6 shows that export growth of downstream industries increased relatively more in those country-industries where the REE supply shock was relatively more important.

A.7 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 exports value, we find that the results are qualitatively similar to our baseline regressions at the SIC level. Specifically, for all our sub-samples except for 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 exports quantity and unit value confirm that the effects for non-China countries are driven more by quantity of exports than just by passing through higher prices. This is demonstrated by the coefficients for non-China and all countries 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.

A.8 Examples of Patents

This appendix presents 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.

Table A.1: List of Sample Countries in Empirical Analysis

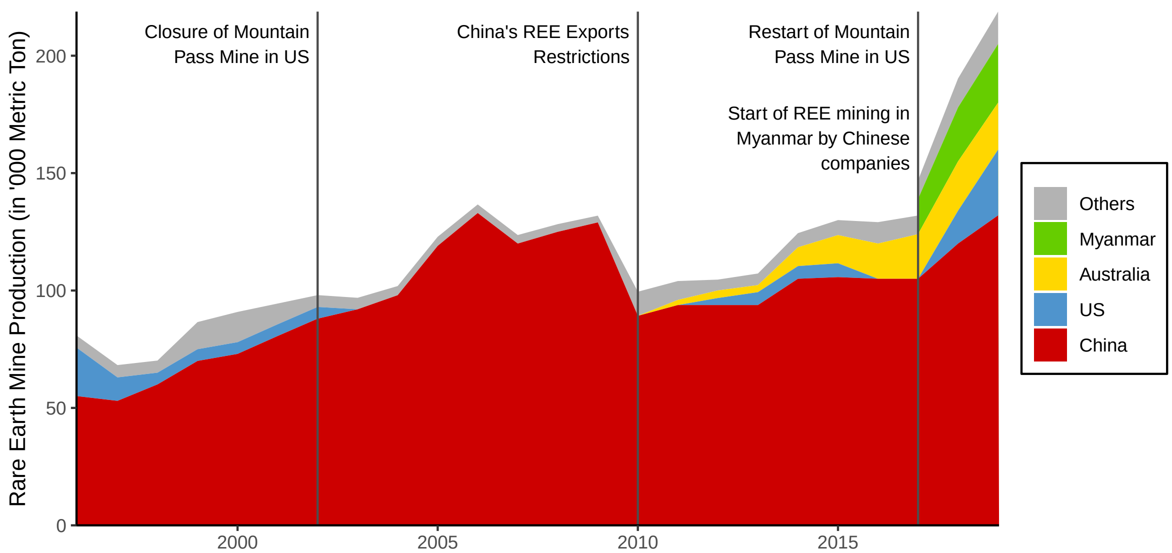
ISO Code	Country Name	ISO Code	Country Name
ARE	United Arab Emirates	ISR	Israel
ARG	Argentina	ITA	Italy
AUS	Australia	JPN	Japan
AUT	Austria	KOR	South Korea
BEL	Belgium	MEX	Mexico
BGD	Bangladesh	MYS	Malaysia
BRA	Brazil	NGA	Nigeria
CAN	Canada	NLD	Netherlands
CHE	Switzerland	NOR	Norway
CHL	Chile	NZL	New 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.

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)

Figure A.1: 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.

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: 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

Figure A.2: Index of Complementarity by Element

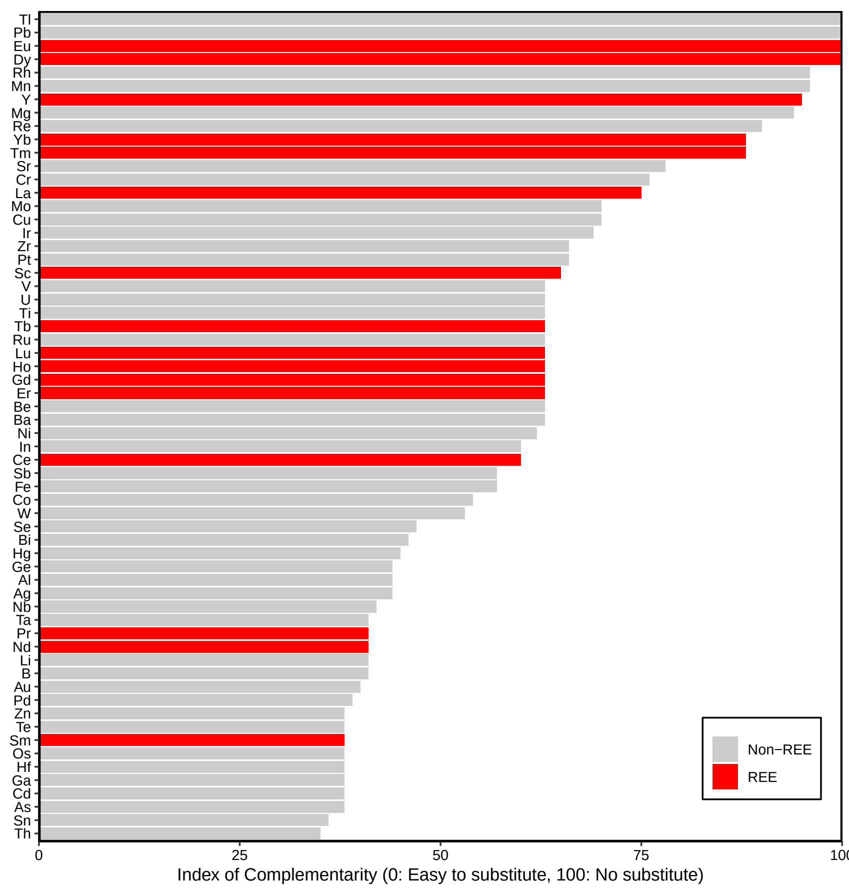


Table A.5: Keywords for the Rare-Earth Patent Search

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.

Table A.6: Manufacturing Industries Downstream Export Growth—Rare-Earth Import Intensity

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

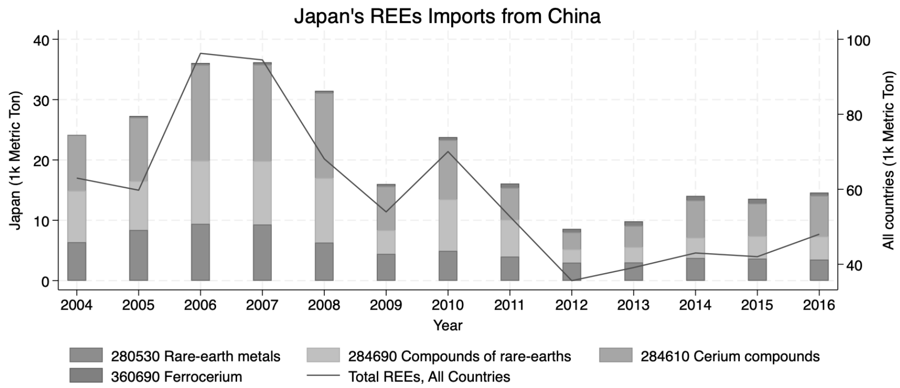
Notes: The table presents coefficient estimates of β from the regression: $y_{ist} = \beta\, REE\ Sens._{is} \times post_t + \gamma \Delta_{ist} + \eta_{is} + \eta_{it} + \epsilon_{ist}$, where y_{ist} represents the annualized growth rate of export values for country-industry is in year t. The annualized 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. $REE\ Sens._{is} = (\sum_e tr_{es}) \times (\ln(max\ REE\ import\ price_i) - \ln(REE\ import\ price\ 2009_i))$. 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, all countries, the U.S., European economies, and Japan. 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 Global Trade Alert 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.7: Downstream Export Growth – Rare-Earth Intense Manufacturing Industries (HS-Level Data)

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

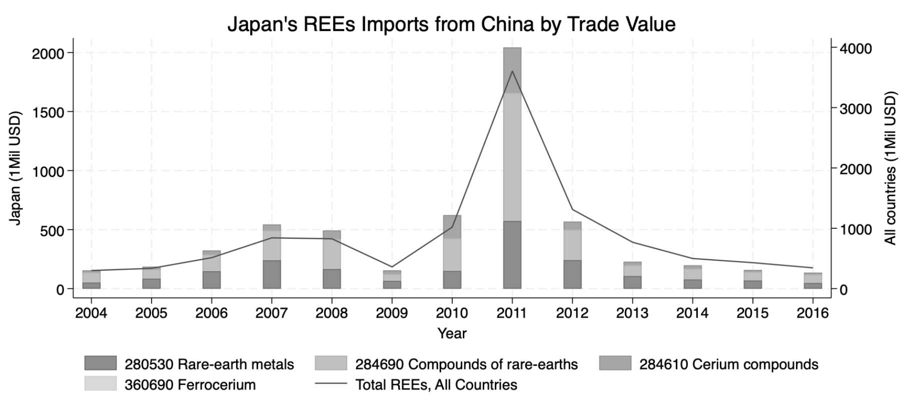
Notes: The table presents coefficient estimates of β from the regression: $y_{ist} = \beta\, REE\ Sens._s \times post_t + \gamma \Delta_{st} + \eta_{is} + \eta_{it} + \epsilon_{ist}$, where y_{ist} represents the annualized growth rate of export values, quantity and unit price for country-industry is 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, all countries, the U.S., European economies, Japan, 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure A.3: Annual REE Imports From China, Quantity (1K Metric Tons)



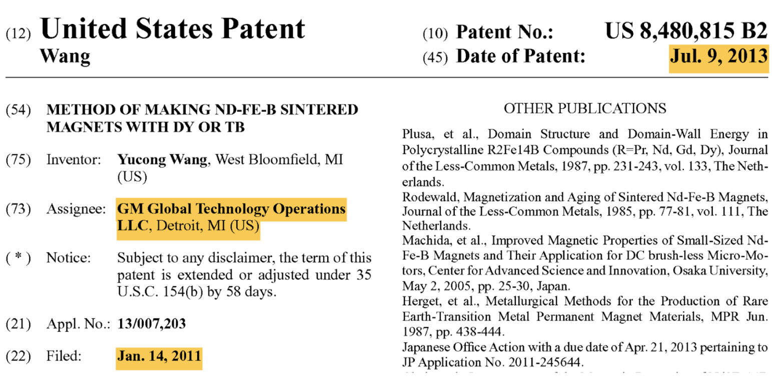
Notes: The figure plots production yearly imports of REEs (HS Codes 280530, 284610, 284690, 60690) to all countries (line) and Japan (bar lines) using data from UN Comtrade.

Figure A.4: Annual REE Imports From China, Value (1M US Dollars)



Notes: The figure plots production yearly imports of REEs (HS Codes 280530, 284610, 284690, 60690) to all countries (line) and Japan (bar lines) using data from UN Comtrade.

Figure A.5: 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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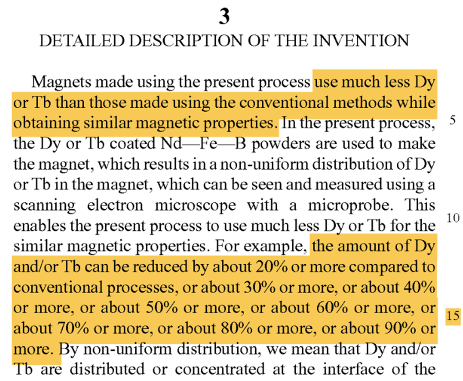
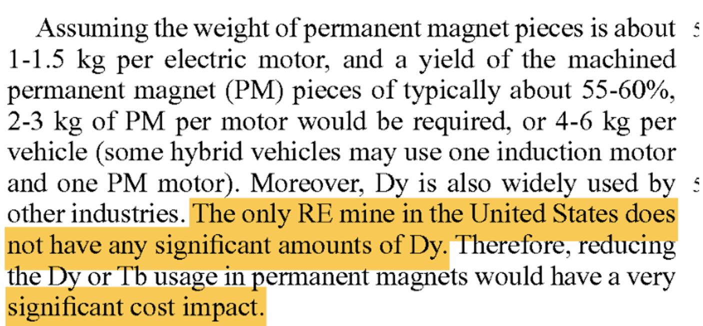


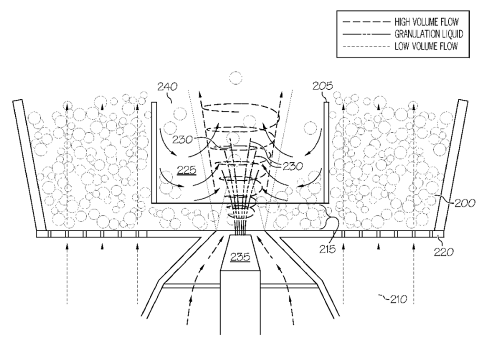
3

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.6: KR101281549B1: Position Sensors Without REE

(19) Korean Intellectual Property Office (KR)

(12) Patent Registration Publication (B1)

(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

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Total number of claims: 6 claims (54)

(45) Announcement date: July 3, 2013

(11) Registration number 10-1281549

(24) Registration date: June 27, 2013

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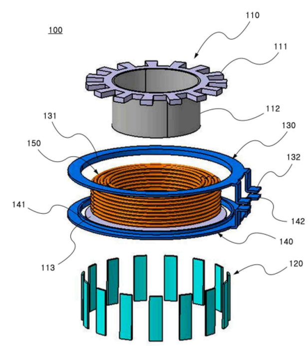
Examiner: Kim Hye-won



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.7: 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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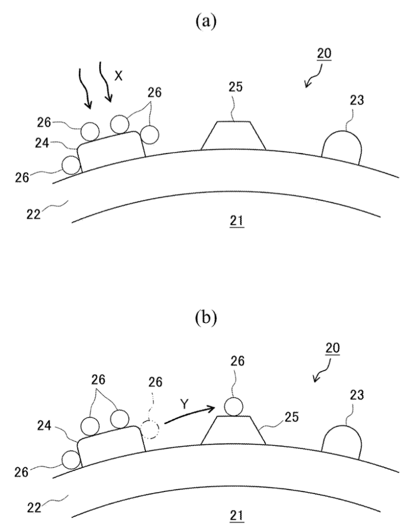
FIG. 38



(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 Model Appendix

B.1 Derivation of an Estimation Equation for ε_s

Combining (15) and relative demand (41) yields

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

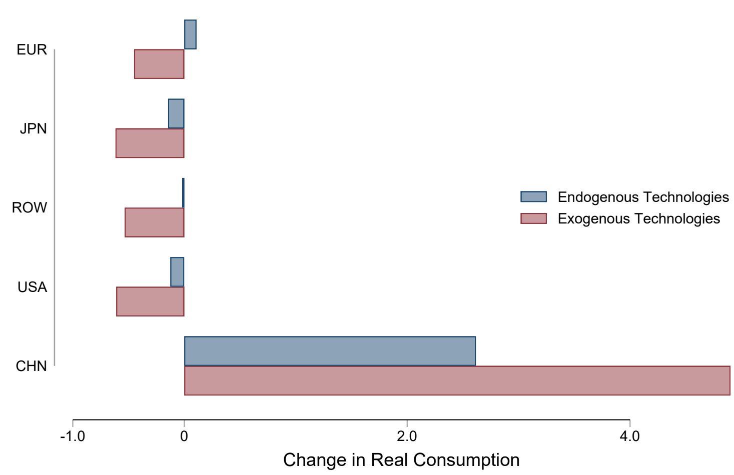
where the last equality uses $P_{Ris} = A_{Ris}^{\frac{1}{1-\mu_s}-\delta} \frac{\mu_s}{1-\mu_s} w_{Ri}$ and the corresponding expression for P_{Lis}. Solving for A_{Ris}/A_{Lis}, we obtain an expression of relative patents as a function of relative factor prices w_{Ri}/w_{Li}:

$$\frac{A_{Ris}}{A_{Lis}} = \left(\frac{\gamma_s}{1-\gamma_s}\right)^{\frac{\varepsilon_s(\mu-1)}{\kappa_s}} \left(\frac{w_{Ri}}{w_{Li}}\right)^{\frac{(1-\varepsilon_s)(\mu_s-1)}{\kappa_s}} \left(\frac{f_{Li}}{f_{Ri}}\right)^{\frac{\mu_s-1}{\kappa_s}}. \tag{A.2}$$

Taking logs, we obtain our regression specification:

$$\log\left(\frac{A_{Ris}}{A_{Lis}}\right) = \beta_s \log\left(\frac{w_{Ri}}{w_{Li}}\right) + \delta_s + u_{is}. \tag{A.3}$$

Figure A.8: Effect of a Rare-Earth Export Tax on Welfare



Notes: The figure plots relative changes in real consumption (measured in % change from the baseline economy) in response to the introduction of the Chinese REE export tax. To make the welfare effects under exogenous technologies comparable to the endogenous-technologies case, we deduct investments into innovation costs for the fix costs of innovation as if the free entry condition on patent firms would hold.