Industrial Policy, Supply Chains and Directed Technological Change: Evidence from Rare Earths

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Abstract

Industrial policies, while often aimed at bolstering domestic industries, can unintentionally spur technological progress abroad. We document this mechanism in the case of rare earth elements (REE) – critical inputs for manufacturing and the green transformation, with low elasticity of substitution, inelastic supply, and high production and processing concentration in China. To assess the importance of REE across industries, we construct an input-output table incorporating individual REE inputs. Using REE-related patents classified by a large language model, sectoral TFP data, and matched trade data, we show that the introduction of REE export restrictions 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. Under endogenous technologies, input-supply restrictions shift the direction of innovation in downstream sectors toward scarce inputs when inputs are gross complements, which can lead to the expansion of these sectors.

Keywords: Trade and Industrial Policy, Global Value Chains, Rare Earths, Directed Technical Change
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1 Introduction

Governments traditionally use industrial policies to selectively promote economic activity in specific sectors. While industrial policy could aim at correcting market imperfections that misalign private and social marginal 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 (REE) have gained increased attention. Their distinct role as critical inputs for many manufacturing goods, with few possibilities of substitution, inelastic supply, and concentration 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. 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 focus on REEs, which are crucial inputs in many manufacturing products and pivotal for the green transformation. REEs capture our interest due to at least four characteristics. First, REEs have broad and diverse applications 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 are geographically dispersed, such as lithium.

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

[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).

in standard industry data and input-output (IO) tables. Therefore, the first contribution that this paper makes is the construction of a novel IO table that maps the use of REE 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 REE 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 REE. Following a WTO ruling, China relaxed its export restrictions on REE 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.

Using data on manufacturing industries across countries, we provide evidence for the impact of Chinese export restrictions on REE on downstream industries. We employ difference-in-difference estimates with a 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 by the substitutability of each chemical element. We observe outcomes for the period 2002-2018, with years since the introduction of Chinese export restrictions on REE in 2010 as the treatment period.

We focus on directed technological change, similar to the impact of historical oil price shocks on increased efforts to energy-saving innovation (see Hassler et al., 2021). We thus first study the impact of the REE supply shock on innovation in downstream industries. To measure innovation activities, we obtain the universe of granted patents across countries that mention REE, chemical compounds of REE, or REE-specific technologies from the Google Patent Research Database. We use a large language model (L.L.M.) to identify those patents within the corpus 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 REE or improving the efficiency of those technologies. 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 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 using 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 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 REE 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 effect of China's export restriction using a novel quantitative general-equilibrium trade model with directed technological change. The model combines a structural gravity model of trade with an IO structure (see Caliendo and Parro, 2015, Fadinger et al., 2024) with a static version of Acemoglu's (2002) model of directed technological change. In the model, the factor bias of production is an endogenous outcome that is caused by firms' deliberate innovation activity in the REE and the labor-input layers. A key parameter determining the direction of technological change in response to an input-supply shock is the elasticity of substitution between REE and labor in producing industry-level output. If labor and REE are gross substitutes, an adverse REE supply shock causes a shift in the technological bias towards labor-augmenting technologies. In this case, the market-size effect dominates the price effect and it becomes more profitable for innovators to develop new technologies that complement labor. If however labor and REE are gross complements, a negative REE supply shock will shift the direction of technological change towards innovation in REE in order to save input costs. In this case, higher prices of REE-intensive sectors provide the key incentive to invent new technologies that increase the efficiency of REE inputs. Depending on the strength of externalities in production

technologies, this change in the direction of technologies can be strong enough to outweigh the increase in the REE factor price such that sectors that are REE-intensive expand production while sectors that are not REE-intensive contract.

We calibrate our model using detailed trade and production data from the World Input-Output Database (WIOD). Since standard estimation techniques for substitution elasticities require granular industry-level input expenditure data—which are unavailable for rare earth elements (REE)—we develop a novel method to estimate the elasticity of substitution between REE and labor within our model. This approach leverages observable relative innovation activities, using the relative number of patents and relative factor prices as proxies.

Our estimates indicate that the elasticity of substitution for REE is significantly below unity in most industries. This finding provides further support for our proposed mechanism, as a low elasticity can explain the effects on the direction of innovation observed in our reduced-form empirical analysis.

In our quantitative analysis, which examines the impact of a Chinese export tax on REE, we demonstrate that the model qualitatively replicates the patterns identified in our empirical evidence. When technologies adjust endogenously, an increase in global REE prices—driven by the export tax—induces a sufficiently strong technological response, leading REE-intensive industries to expand relative to other industries outside China. Additionally, we show that directed technological change is crucial for this outcome: in a model variant with fixed technologies, global sales and exports in REE-intensive industries shift strongly in favor of China.

Related Literature: The academic literature on trade and industrial policy is vast, as summarized in Harrison and Rodríguez-Clare (2010) and Juhász et al. (2023). Empirical evidence on the effect of industrial policy is mixed, fueling the debate. Criscuolo et al. (2019), for example, find positive effects on incumbent firms' investment and employment but not TFP for regional policies. Bartelme et al. (2019) 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. On the other hand, Juhász et al. (2023) 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 policy 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. 2024).

In the field of technological 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 tend to 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) highlights the complex relationship between offshoring and the direction of technological progress. The authors show that while offshoring can drive skill-biased technological change, it can spur innovations favoring unskilled labor.

More generally, there is a literature on biased technological change, where innovation favors a particular input due to its relative supply or price, with Kennedy (1964) being one seminal work. Popp (2002) offers empirical evidence for the case of energy inputs using patent data, finding that higher energy prices induced more innovation in energy-saving technology. Hassler et al. (2021) model energy-saving technological change to estimate the elasticity of substitution between energy and labor or capital inputs. Similar to our work, Hanlon (2015) exploits a trade policy episode to show that innovation was directed towards augmenting the inputs that are relatively less scarce. Specifically, he finds that the blockade on cotton from the Southern U.S. during the U.S. Civil War spurred technological progress in the use of lower-quality cotton inputs from India. 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.

The paper also relates to the growing literature on the role of sanctions (Hirschman, 1945; Felbermayr et al., 2020). A growing 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 differs in that we stress the importance of directed technological change in addition to these adjustments.

The remainder of the paper is organized as follows. Section 2 describes the context and policies around REE. Section 3 presents the data and describes in detail the construction of the input-output rare elements tables and the construction of the REE 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 REE Differentiating Characteristics

The U.S. Geological Survey (USGS) defines the REE as a group of 17 elements composed of Scandium, Yttrium, and the lanthanides.[2] 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.[3]

Second, their applications usually involve small quantities but 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).

[2]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).

[3]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.

This characteristic affects 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 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.[4]

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 rare-earth 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 rare earths as a strategic resource, barring foreign investors from ownership of mines and limiting their involvement to rare-earth smelting and separation projects unless through joint ventures with Chinese companies. Every rare-earth mining, 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

[4]Most REE mines have Thorium, for example, which is radioactive. Cerium, Lanthanum, and Dysprosium, like the other lanthanides, easily react 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 rare earth metals are classified as mild to moderate toxic, Harbison and Johnson (2015).

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 rare-earth output surged from 27% in 1990 to over 90% by 2008, supplying more than 80% of the world's rare earths in the form of concentrates, intermediate products, and chemicals during this period. In 2009, China's market share in global rare earth mine production reached 98% (see Figure A.3 in the Data Appendix).

2.3 The 2010 REE Supply Shock

We exploit the extreme and unprecedented 2010-2011 REE prices surge: by a factor of 10 (Terbium and Europium) to 45 (Cerium) as a supply shock for our empirical analysis (see Figure 1).[5] 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.

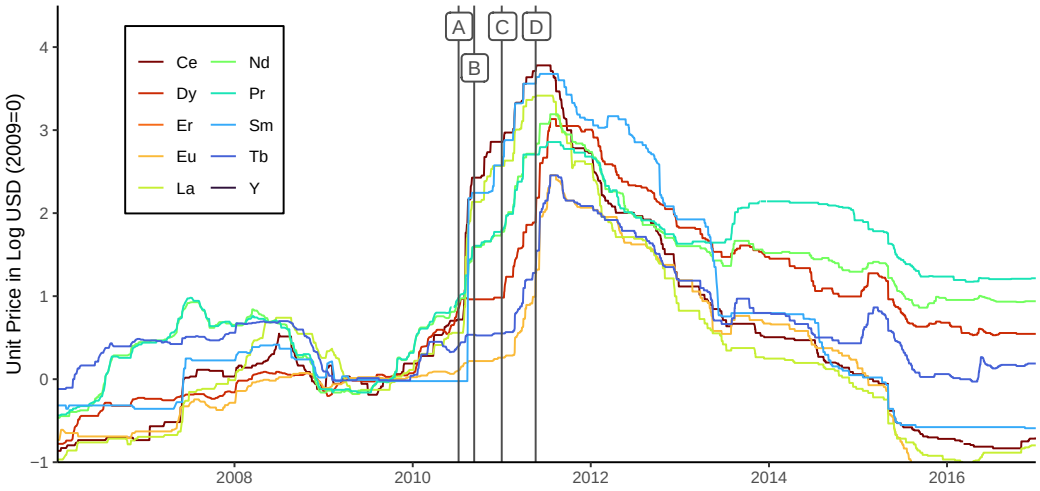
The 2010 crisis made the risk of future disruptions evident, creating a lasting shock to REE supply uncertainty, which we focus on in our analysis. In July 2010, China drastically reduced the REE export quota for the second half of the year by 72%, with a stated motive of combating illegal mining and environmental pollution (Müller et al., 2016).[6] 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 2022). 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

[5]REE markets are highly illiquid, making yearly price changes more discernible than higher-frequency movements, which tend to be extremely noisy.

[6]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: Index of Unit Prices of Selected REEs



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.

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 REE 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 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.[7] Production and processing remained reliant on China. Uncertainty constrained inventory use. Many Japanese firms, for example, stockpiled rather than released REEs, fearing depletion with-

[7]Mountain Pass, sold to Molycorp in 2009, reopened in 2015 but soon shut down due to Molycorp's 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).

out fresh imports from China (Gholz and Hughes, 2021).[8] 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 REE (Banner, 2022; Reuters, 2021; Bomgardner, 2018; Owano, 2018; Halvorson, 2022; Houser, 2023).[9]

3 Data Sources and Descriptive Statistics

3.1 Building an Input-Output Table with Rare Earths

To construct an IO table with REE, we combine and complement different datasets, capturing the use of rare elements from USGS and prices from BCC and Asian Metal. In the Data Appendix, we describe sources and the methodology in detail.

Use of Rare Elements: To account for the use of rare elements, we first 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 of 405 BEA industry groups, which are a slightly more aggregated version of the 6-digit 2012 NAICS codes. We then combine this data with USGS data on REE inputs consumed by the U.S. in 2010 for seven "General Application" categories. These categories are alloys, batteries, automobile catalysts, fluid catalyst cracking, phosphors and diodes, and solutions (Table 1), which are the most upstream available.[10] We focus on the estimates of the use of five broadly used REEs: Lanthanum, Cerium, Praseodymium, Neodymium, and Dysprosium.

[8] 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.

[9] 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 motor magnets by 20%. Volkswagen followed, while Nissan and BMW unveiled magnet-free motor prototypes in 2022-2023. Other industries also sought REE-use reductions, such as catalysts using less Cerium (Machida et al., 2017). See appendix B.3 for other examples.

[10] 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 excluded solutions because the report provided no precise point estimates for this category's input element.

Table 1: Categories of Rare Earth Elements Applications from USGS

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)

We impute raw data of rare earth input amounts from a USGS report (Bleiwas and Gambogi, 2013) into the supply-use table. The 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, while aligning U.S. data with the BEA's IO table around 2010. The report multiplies the number of each REE per product by the total number of the products consumed in the U.S. obtained from consumption and trade statistics. For imputation into the supply-use table, we first match each general category into its corresponding NAICS code, which the BEA's SUT uses. This matching determines which using sectors (columns) are assigned the numbers. We detail the procedure in the Data Appendix.

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 imputed with REEs to calculate the total requirements matrix (the Leontief inverse), whose values denote how much each using sector takes inputs from another sector, accounting for indirect backward linkages.

The top using sector of REE is SIC 3691 (Storage batteries), which uses Lanthanum. Another REE-intensive industry is SIC 3625 (Relays and Industrial Controls), which employs Neodymium, Praseodymium, and Dysprosium.

3.2 Patent Data

Our primary measure for shifts in the direction of technological change is based on patent data. We obtain the universe of granted patents related to 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 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.3 in the Data Appendix lists the keywords). By the end of the sample period, around 30,000 unique REE patents were granted globally. We assign the country of the patent based on the country of the patent assignee, considering the top 50 countries by GDP that we pool to the regions Europe, U.S. and Canada, China, Russia, Korea, Japan, Australia and the Rest of World. Table A.4 in the Appendix details the countries in the sample.

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. Given the large fraction of non-corporate entities' patents filed and the lack of a global matched patent-firm database, we use an L.L.M. 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 L.L.M. and let the L.L.M. suggest the SIC industry that fits best to the patent.[11] 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 that REE by the end of the sample period. Additionally, we further refine the sample of REE patents by asking the L.L.M. to classify whether each patent describes a technology that improves the use of REEs or helps to substitute away from the use of REE. We present examples of the patents in Appendix A.6.

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 REE. We address that concern by controlling for the overall stock of patents in a 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 L.L.M. 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.

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

[11] 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 L.L.M. 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. For this approach, we use the model GPT4 from OpenAI.

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 country-industry relative to the total number of subsidy policies worldwide.

3.4 Descriptive Patterns

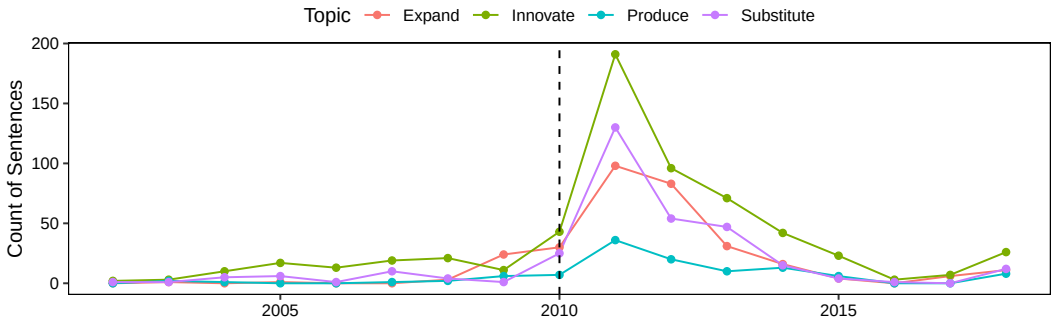
Figure 1 shows composite REE price indices (log USD) over the sample period. Prices surged around 2010, peaked shortly after, then declined sharply and stabilized at a lower level. At the individual REE level, prices rose by a factor of 10 to 45. This spike reflects the global supply shock triggered by Chinese policy interventions in the REE market. While prices did not remain permanently high, their decline was driven by both a medium-run supply increase—primarily from the easing of Chinese export restrictions and, to a lesser extent, limited foreign market entry—and a demand reduction due 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 reoccur in the future.

Figure 2 depicts additional descriptive patterns 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 L.L.M. to categorize those sentences. *"Expand"* denotes sentences about the expansion of REE production (including mining and refining), *"Innovate"* denotes innovations in REE which are further subdivided into production of REE (*"Produce"*) or usage substitution (*"Substitute"*). The mentions rose 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.

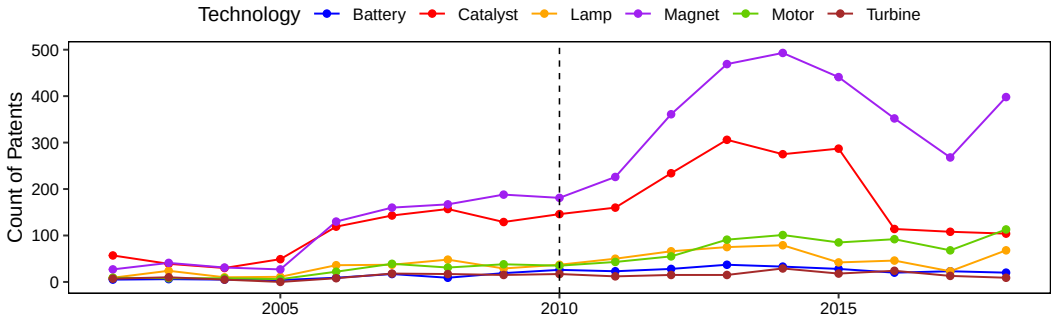
Panel (b) depicts that counts of newly granted patents that relate to REE generally increase over time, particularly in magnet and catalyst technologies, indicating a growing emphasis on innovation in these areas. The trend strongly accelerated after 2010, in line with the idea that the price spike may have catalyzed greater investment in technological development and innovation related to

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 REE in firms' earnings calls *(a)*, and patents related to REE *(b)*. Subfigure *(a)* depicts the count of REE mentions in global firms' earnings calls, categorized by topic using an L.L.M. 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.

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 manufacturing industries across the world and in China, using patent data. We estimate the following count model for patents:

$$y_{rst} = \beta RE\ Sensitivity_s \times post_t + \gamma \Delta_{rst} + \eta_{rs} + \eta_{rt} + \epsilon_{rst}. \tag{1}$$

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 REE sensitivity measure $RE\ Sensitivity_s$ 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 REE. 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). 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—where no substitute exists—are more exposed than those using REEs in nickel-metal hydride batteries, which can be replaced by lithium-ion alternatives. This complementarity stems from the physical and chemical properties of elements, not economic factors. We proxy this using the complementarity index from Graedel et al. (2015), which evaluates potential substitutes based on expert assessment. Dysprosium ranks as the least substitutable, while Samarium is the most. To construct the exposure variable $RE\ Sensitivity_s$, 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:

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

This variable measures the exposure of industry s to the REE supply shock. $RE\ Sensitivity_s$ 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 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 RE 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 2 reports our estimates of (1). The sample only counts those patents that the L.L.M. identifies as patents that either improve the efficiency of REE or help to substitute for REE usage. We find that industries that are more sensitive to the REE supply shock innovated more in the treatment 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 7.5% 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 rare-earth inputs also patented more REE technologies in China during the treatment period compared to other sectors. 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 direct measures of productivity growth of REE-using industries. We estimate the following difference-in-differences specification, using productivity as the outcome variable:

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

Table 2: Patents in Rare-Earth Intense Manufacturing Industries

	REE-Enhancing Patents					
	NONCHN	ALL	USA	EUR	JPN	CHN
	(1)	(2)	(3)	(4)	(5)	(6)
RE Sens. × Post	15.69***	14.55***	18.18***	18.08***	25.54**	2.603
	(4.798)	(4.918)	(6.862)	(6.041)	(10.88)	(17.97)
Observations	5,796	7,925	1,264	1,196	1,022	2,129
Clusters	386	530	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: $y_{rst} = \beta\, RE\ Sens._s \times post_t + \gamma \Delta_{rst} + \eta_{rs} + \eta_{rt} + \epsilon_{rst}$ 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 $RE\ Sens._s$ 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: $RE\ Sens._s = \sum_e tr_{es} \times compl_e$. $post_t$ 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 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The outcome variable y_{ist} is the annualized growth rate of productivity for the 4-digit SIC manufacturing industry s by country i during year t, again considering the sample window from 2002 until 2018. The annualized productivity growth rate for the period t is computed using the midpoint of t and $t-1$ as the denominator. The coefficient of interest β is again the coefficient on an interaction term of our REE sensitivity measure $RE\ Sensitivity_s$ 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[12] and cluster standard errors at the country-industry level.

The regression results in Table 3 highlight the impact of the REE supply shock on the 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 on both TFP and labor productivity growth. A one standard-deviation higher value in RE sensitivity is associated with 0.19 and 0.15 percentage-point higher growth rate of TFP and labor productivity, respectively, after the REE supply shock. European and Japanese industries in particular experience a significant increase in TFP (columns 4 and 5).[13] Japanese industries with a one standard-deviation higher REE sensitivity boast 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 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, might have 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,

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

[13] 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 3: 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)
RE Sens. × Post	0.468*	0.438*	0.440	0.521**	1.232***	-2.255***
	(0.244)	(0.244)	(0.293)	(0.227)	(0.405)	(0.740)
Observations	183,818	186,770	4,978	88,055	4,978	2,952
Clusters	14,981	15,350	378	6,306	363	369
	Annualized Growth: Labor Productivity					
	NONCHN	ALL	USA	EUR	JPN	CHN
	(7)	(8)	(9)	(10)	(11)	(12)
RE Sens. × Post	0.365**	0.354**	0.0148	0.188	1.168***	-0.911
	(0.165)	(0.164)	(0.576)	(0.150)	(0.403)	(0.638)
Observations	183,818	186,770	5,292	88,055	5,685	2,952
Clusters	14,981	15,350	378	6,306	383	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: $y_{ist} = \beta\, RE\ Sens._s \times post_t + \gamma\Delta_{ist} + \eta_{is} + \eta_{it} + \epsilon_{ist}$, 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 $RE\ Sens._s$ is a weighted sum of an RE element-specific complementarity index (ranging from 0 to 100), with weights based on total requirement shares for industry s: $RE\ Sens._s = \sum_e tr_{es} \times compl_e$. $post_t$ 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 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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 4 presents the results from specification (3) using export growth as the outcome variable. The coefficient β on the interaction term $RE\ Sensitivity_s \times post_t$ is positive and statistically significant at the 1% level in column (1) for the sample of countries excluding China. This indicates that, outside China, exports from 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 in European countries and Japan, while they are more moderate in the U.S.[14]

The bottom panel of Table 4 presents results from similar specifications but with the outcome variable 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 from more exposed industries outside of China grew significantly more in response to the REE supply shock.

To make sure that our results are not driven by pre-trends in REE intensive industries compared to other industries, Figure 3 visualizes the time-varying effects of the REE supply shock (weighted High REE/Low REE). There is no clear trend in the effect of $RE\ sensitivity_s$ on the level of exports before 2009 besides the trade collapse during the Global Financial Crisis. Moreover, in line with the results in Table 4, we do observe an increase in REE-intensive manufacturing exports starting after the Chinese REE export restrictions.

Alternative Treatment Measures: While using the index of complementarity in (2) has the appeal that it directly relates to the production function of industries and 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

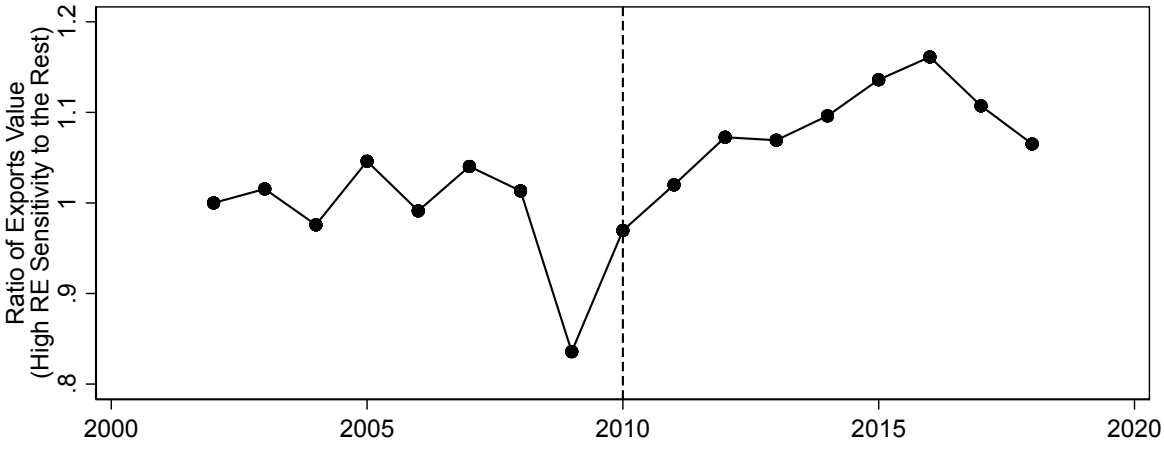
[14] In Appendix A.5, we use UN Comtrade trade data disaggregated at the finer 6-digit HS product code level. At this level, we can separate the effect on the growth of export values into price growth and the growth of physical quantities, to confirm that the positive effect on exports outside China was not merely driven by price increases.

Table 4: Downstream Export Growth – Rare-Earth Intense Manufacturing Industries

	Annualized Growth: Exports Value					
	NONCHN	ALL	USA	EUR	JPN	CHN
	(1)	(2)	(3)	(4)	(5)	(6)
RE Sens. × Post	0.808***	0.750***	0.309	0.624**	1.454**	-0.657
	(0.234)	(0.226)	(0.712)	(0.312)	(0.721)	(0.753)
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)	
RE Sens. × Post	3.309***	3.154***	3.051***	3.347***	2.675*	
	(0.463)	(0.445)	(0.879)	(0.652)	(1.378)	
Observations	270,342	276,325	5,987	107,321	5,951	
Clusters	17,159	17,533	376	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: $y_{ist} = \beta\, RE\ Sens._s \times post_t + \gamma \Delta_{ist} + \eta_{is} + \eta_{it} + \epsilon_{ist}$, 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 $RE\ Sens._s$ 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: $RE\ Sens._s = \sum_e tr_{es} \times compl_e$. $post_t$ 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 weighted average growth rate of GDP of the ten largest importers from is. Regressions are weighted by the share of export values $w_{is} = exports_{is} / \sum_{i,s} exports_{is}$ from 2002-2004. Standard errors (in parentheses) are clustered at the country-industry level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 3: Relative Exports of High RE sensitivity to Low RE sensitivity Manufacturing Industries



Notes: The figure plots the yearly ratio of exports value by manufacturing industries that are classified in the top 25 percentile of RE sensitivity to exports value by all other manufacturing industries. RE sensitivity is constructed following equation (2). The sample consists of the top 50 countries by GDP excluding China, where each country is weighted by their share of initial exports value in 2002-2004 as in our downstream exports regressions. The ratio has been normalized to 1 for the year 2002.

values of REE imports interacted with the total requirements of REE of each industry (aggregated across elements):[15]

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

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 REE sourced from a larger set of countries (China, the U.S., Australia, Russia or India) again interacted with the total requirement of REE of industry s:

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

For both shock measures, we consider HS codes 284690, 284610, and 280530 as REE relevant and weigh them by initial import shares. Table 5 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.

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

Table 5: Downstream Export Growth—Rare-Earth Import Intensity of Manufacturing Industries

	Annualized Growth: Exports Value				
	NONCHN	ALL	USA	EUR	JPN
	(1)	(2)	(3)	(4)	(5)
	RE Sens.$_{is}$ based on REE import price surge				
RE Sens. × Post	24.32***	24.77***	7.007	27.98***	49.85**
	(7.582)	(7.513)	(17.41)	(10.47)	(25.15)
Observations	155,820	161,803	6,048	72,030	5,979
Clusters	9,764	10,138	378	4,508	375
	Annualized Growth: Exports Value				
	NONCHN	ALL	USA	EUR	JPN
	(6)	(7)	(8)	(9)	(10)
	RE Sens.$_{is}$ based on the REE import share from CHN				
RE Sens. × Post	71.38***	72.78***	18.97	73.07***	112.0**
	(19.29)	(19.28)	(50.57)	(25.11)	(50.46)
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: $y_{ist} = \beta\, RE\ Sens._{is} \times post_t + \gamma\Delta_{ist} + \eta_{is} + \eta_{it} + \epsilon_{ist}$, 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, $RE\ Sens._{is}$ 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. $RE\ Sens._{is} = (\sum_e tr_{es}) \times (\ln(max\ REE\ import\ price_i) - \ln(REE\ import\ price\ 2009_i))$. In the bottom panel, $RE\ Sens._{is}$ 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. $RE\ Sens._{is} = (\sum_e tr_{es}) \times (REE\ imports\ from\ CHN_i / REE\ imports\ from\ CHN,\ USA,\ AUS,\ RUS,\ IND_i)$. $post_t$ 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 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5 A Quantitative Model of Trade and Directed Technological Change

In this section, we present a model that can generate rare-earth 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 $s\prime$). The production function for

gross output and the resource constraint of the industry goods are given by

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

where $\Psi_{is} \equiv \phi_{is}^{-\phi_{is}} \prod_{s'} \phi_{iss'}^{-\phi_{iss'}}$ is a constant normalizing the production function. Production output Y_{is} is used across 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 Technical 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 rare-earth 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 innovation externalities from the measures A_{Ris}, A_{Lis} of input firms on sectoral productivity. If $\delta > 0$, there are positive spillovers such that sectoral productivity increases in the measure of input firms, while if $\delta < 0$ there are negative spillovers. If $\delta = 0$ spillover effects are absent.[16]

The corresponding price indices for the rare-earth 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, are endogenous and determined by free entry. Input firms only sell domestically, operate under monopolistic competition, and hold a patent for their variety. For simplicity, input firms and their

[16] These spillover affects are absent in Acemoglu (2002) and not necessary for the results relating to the direction of technological change in response to changes in factor prices. However, they determine the strength of the technology response and hence the response of revenue in downstream industries.

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 input variety is produced with a linear technology with the factor REE r_{is} as input, while each labor input variety is produced with the factor labor 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), production technology (11) and production taxes or subsidies τ_{Ris}, τ_{Lis} as given. Solving their profit-maximization problem yields the optimal prices of inputs

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

and the variable profits of input monopolists:

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

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:

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

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 these 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 each country i has the following policy instruments available: Bilateral ad-valorem tariffs τ_{ijs} on imports of goods in industry s from country j; industry-specific taxes/subsidies τ_{Ris} and τ_{Lis} on production of monopolistic input varieties in input layers R_{is} and L_{is}. Importantly, China is the only country that has endowments of rare earths R_C that can be sold across the global economy. It additionally disposes of an export tax τ_{XC} on the exports of the rare-earth factor.

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:

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

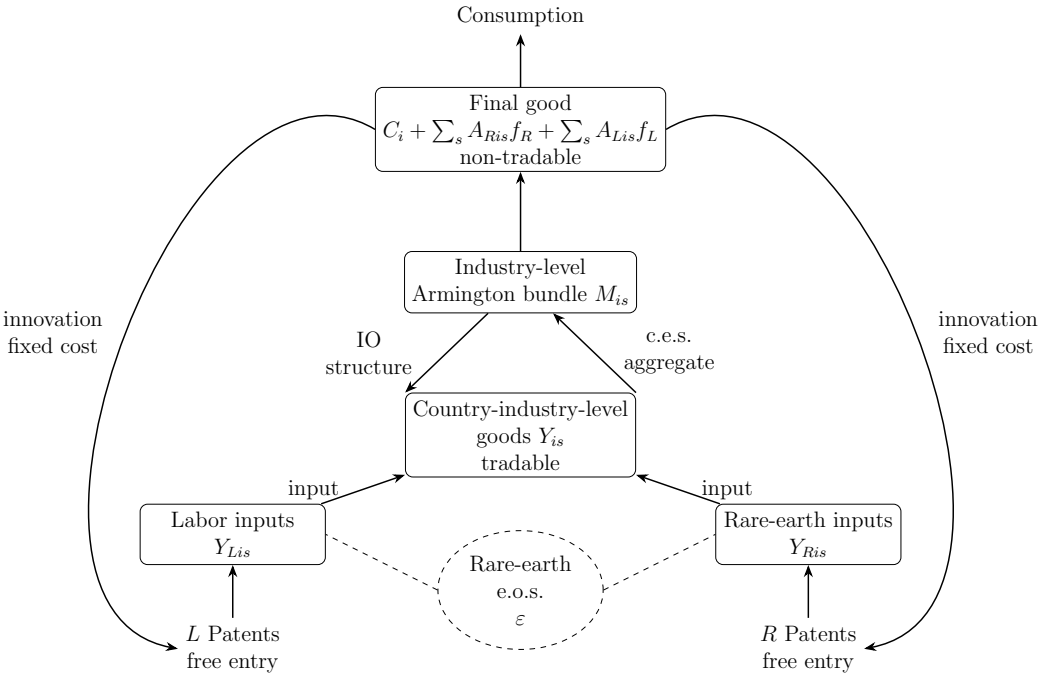
Here, I_C is an indicator variable that equals unity when j is China and zero for all other countries j. TB_j is the (exogenous) trade imbalance and

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

are net factor incomes from abroad arising from the use of the REE factor for countries other than China and for China, respectively. Revenues on production taxes and as well as tariffs are fully rebated to consumers with lump-sum transfers T_j. These transfers equal total export tax revenue on net exports of rare earths plus net revenue from taxes/subsidies on marginal costs of monopolistic producers plus total tariff revenue from imports of the Armington goods:

$$\begin{aligned} T_j =& I_C \times (\tau_{XC} - 1)w_{RC}(R_C - \sum_s A_{RjC}r_{Cs}) + \sum_s(\tau_{Rjs} - 1)A_{Rjs}r_{js}w_{Rj} + \\ & \sum_s(\tau_{Ljs} - 1)A_{Ljs}l_{js}w_{Lj} + \sum_i\sum_s(\tau_{jis} - 1)\tau_{jis}^{-1}P_{jis}Y_{jis}. \end{aligned} \tag{23}$$

Figure 4: Model Structure



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

The factor labor is immobile across countries and labor markets clear for each country:

$$\sum_s \int_0^{A_{Lsi}} l_s(a)da = L_i. \tag{24}$$

By contrast, the rare-earth factor is tradable and homogeneous with China being its sole supplier with endowment R_C. Importantly, China may impose non-discriminatory gross ad-valorem export taxes on rare earths $\tau_{XC} \geq 1$. Therefore, the price paid for REE in country j is equal to $w_{Rj} = \tau_{XC} w_{RC}$ and the REE market clears at the global level:

$$\sum_j \sum_s \int_0^{A_{Rjs}} r_{js}(a)da = R_C. \tag{25}$$

5.3 Equilibrium

An equilibrium in this model determines a solution for *(i)* all factor prices w_{RC} for China and w_{Li} $\forall i$; *(ii)* revenues, prices and trade shares for all 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 (26), determining Rev_{is}; *(ii)* $I \times J \times S$ equations (30) determining λ_{ijs}; *(iii)* $I \times J \times S$ equations (31) determining P_{ijs}; *(iv)* $I \times S$ equations (32) determining P_{is}; *(v)* I equations (33) determining P_i; *(vi)* $2 \times I \times S$ equations of type (34) determining $P_{Ris}Y_{Ris}$ and $P_{Lis}Y_{Lis}$; *(vii)* I equations (37) determining w_{Li} and *(viii)* 1 equation (38), determining w_{RC}. We use world GDP as the numéraire good such that all expenditure and income terms are expressed in units of global value added. Further, note that $w_{Ri} = w_{RC}\tau_{XC}$.

Market clearing for Armington goods is given by:

$$Rev_{is} = \sum_j \tau_{jis}^{-1}\lambda_{jis} \times \left[\alpha_{js}\left(\frac{P_{js}}{P_j}\right)^{1-\rho}(w_{Lj}L_j + I_C \times w_{RC}R_C + T_j - TB_j - NFIA_j) + \sum_s \phi_{ss'j}Rev_{js}\right] \quad \forall i, s, \tag{26}$$

with net factor incomes from abroad being

$$NFIA_j = \begin{cases} -\sum_{s=1}^{S}\left(\frac{\mu_s - 1}{\mu_s}\right)\tau_{Rjs}^{-1}(P_{Rjs}Y_{Rjs}), & \forall j \neq C \\ \sum_{j \neq C}\sum_{s=1}^{S}\left(\frac{\mu_s - 1}{\mu_s}\right)\tau_{Rjs}^{-1}(P_{Rjs}Y_{Rjs}), & \forall j = C. \end{cases} \tag{27}$$

Transfers T_j are given by:

$$\begin{aligned} T_j =& I_C \times (\tau_{XC} - 1)[w_{RC}R_C - \sum_s \left(\frac{\mu_s - 1}{\mu_s}\right)\tau_{RCs}^{-1}(P_{RCs}Y_{RCs})] + \sum_i \sum_s (\tau_{jis} - 1)\tau_{jis}^{-1}P_{jis}Y_{jis} \\ &+ \sum_s (\tau_{Rjs} - 1)\left(\frac{\mu_s - 1}{\mu_s}\right)\tau_{Rjs}^{-1}(P_{Rjs}Y_{Rjs}) \\ &+ \sum_s (\tau_{Ljs} - 1)\left(\frac{\mu_s - 1}{\mu_s}\right)\tau_{Ljs}^{-1}(P_{Ljs}Y_{Ljs}) \quad \forall j, \end{aligned} \tag{28}$$

where I_C is an indicator that equals unity for if $j = China$ and 0 otherwise and where

$$\tau_{jis}^{-1}P_{jis}Y_{jis} = \tau_{jis}^{-1}\lambda_{jis}\left[\alpha_{js}\left(\frac{P_{js}}{P_j}\right)^{1-\rho}(w_{Lj}L_j + w_{Rj}R_j + T_j - TB_j) + \sum_{s\prime}\phi_{jss\prime}Rev_{js}\right] \quad \forall i, j, s. \tag{29}$$

Bilateral trade shares are:

$$\lambda_{ijs} = \left(\frac{P_{ijs}}{P_{is}}\right)^{1-\sigma_s} \quad \forall i, j, s. \tag{30}$$

Bilateral prices are given by:

$$P_{ijs} = \tau_{ijs} d_{ijs} [\gamma_s^{\varepsilon} \left(\frac{P_{Rjs} Y_{Rjs}}{\mu_s f_R P_j} \right)^{\delta(\varepsilon-1)+\frac{\varepsilon-1}{\mu_s-1}} \left(\frac{\mu_s}{\mu_s - 1} \right)^{1-\varepsilon} (\tau_{Rjs} w_{Rj})^{1-\varepsilon} + \\ (1-\gamma_s)^{\varepsilon} \left(\frac{P_{Ljs} Y_{Ljs}}{\mu_s f_L P_j} \right)^{\delta(\varepsilon-1)+\frac{\varepsilon-1}{\mu_s-1}} \left(\frac{\mu_s}{\mu_s - 1} \right)^{1-\varepsilon} (\tau_{Lj} w_{Lj})^{1-\varepsilon}]^{\frac{\phi_{is}}{1-\varepsilon}} \prod_{s'} P_{js}^{\phi_{jss'}} \quad \forall i, j, s. \tag{31}$$

Industry-level price indices are defined as:

$$P_{is} = \left[\sum_j P_{ijs}^{1-\sigma_s} \right]^{\frac{1}{1-\sigma_s}} \quad \forall i, s. \tag{32}$$

Aggregate price levels are given by:

$$P_i = \left[\sum_s \alpha_{is} P_{is}^{1-\rho} \right]^{\frac{1}{1-\rho}} \quad \forall i. \tag{33}$$

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

$$P_{Ris} Y_{Ris} = \gamma_s \phi_{is} Rev_{is} \times \\ \left[\gamma_s + (1-\gamma_s) \left(\frac{(1-\gamma_s) f_{Ri}}{\gamma_s f_{Li}} \right)^{\frac{(\varepsilon_s-1)\{\mu_s\kappa_s+(\mu_s-1)^2\varepsilon_s\delta\}}{(\mu_s-\varepsilon_s)[\mu_s-\varepsilon_s-\delta(\mu_s-1)(\varepsilon_s-1)]}} \left(\frac{r_{is}}{l_{is}} \right)^{\frac{(1-\varepsilon_s)\{\delta(\mu_s-1)^2(\varepsilon_s-1)+(\mu_s-1)\kappa_s\}}{(\mu_s-\varepsilon_s)\kappa_s}} \right]^{-1} \quad \forall i, s, \tag{34}$$

$$P_{Lis} Y_{Lis} = (1-\gamma_s) \phi_{is} Rev_{is} \times \\ \left[\gamma_s \left(\frac{(1-\gamma_s) f_{Ri}}{\gamma_s f_{Li}} \right)^{\frac{(1-\varepsilon_s)\{\mu_s\kappa_s+(\mu_s-1)^2\varepsilon_s\delta\}}{(\mu_s-\varepsilon_s)\kappa_s}} \left(\frac{r_{is}}{l_{is}} \right)^{\frac{(\varepsilon_s-1)\{\delta(\mu_s-1)^2(\varepsilon_s-1)+(\mu_s-1)\kappa_s\}}{(\mu_s-\varepsilon_s)\kappa_s}} + (1-\gamma_s) \right]^{-1} \quad \forall i, s, \tag{35}$$

where

$$\frac{r_{is}}{l_{is}} = \frac{f_{Ri}}{f_{Li}} \frac{w_{Li}}{w_{Ri}} \frac{\tau_{Lis}}{\tau_{Ris}} \quad \forall i, s. \tag{36}$$

Labor markets clear in each country:

$$\sum_s \left(\frac{\mu_s - 1}{\mu_s} \right) \tau_{Lis}^{-1} (P_{Lis} Y_{Lis}) = w_{Li} L_i \quad \forall i. \tag{37}$$

The REE market clears at the world level:

$$\sum_j \sum_s \left(\frac{\mu_s - 1}{\mu_s}\right) \tau_{Rjs}^{-1} (P_{Rjs} Y_{Rjs}) \tau_{XC}^{-1} = w_{RC} R_C. \tag{38}$$

5.4 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 (34) need to be replaced by:

$$\begin{aligned} P_{Ris} Y_{Ris} =& \gamma_s \phi_{is} Rev_{is} \times \\ & \left[\gamma_s + (1-\gamma_s)\left(\frac{\gamma_s}{1-\gamma_s}\right)^{1-\varepsilon_s}\left(\frac{A_{Ris}}{A_{Lis}}\right)^{(1-\varepsilon_s)\left(\delta+\frac{\mu_s}{\mu_s-1}-1\right)}\left(\frac{w_{Li}}{w_{Ri}}\right)^{1-\varepsilon_s}\left(\frac{\tau_{Lis}}{\tau_{Ris}}\right)^{1-\varepsilon_s}\right]^{-1} \end{aligned} \tag{39}$$

$$\begin{aligned} P_{Lis} Y_{Lis} =& (1-\gamma_s) \phi_{is} Rev_{is} \times \\ & \left[\gamma_s \left(\frac{\gamma_s}{1-\gamma_s}\right)^{\varepsilon_s - 1}\left(\frac{A_{Ris}}{A_{Lis}}\right)^{(\varepsilon_s-1)\left(\delta+\frac{\mu_s}{\mu_s-1}-1\right)}\left(\frac{w_{Li}}{w_{Ri}}\right)^{\varepsilon_s-1}\left(\frac{\tau_{Lis}}{\tau_{Ris}}\right)^{\varepsilon_s-1} + (1-\gamma_s)\right]^{-1}. \end{aligned} \tag{40}$$

Moreover, (31) becomes:

$$\begin{aligned} P_{ijs} =& \tau_{ijs} d_{ijs} [\gamma_s^{\varepsilon_s} (A_{Ris})^{\delta(\varepsilon_s-1)+\frac{\varepsilon_s-1}{\mu_s-1}} \left(\frac{\mu_s}{\mu_s-1}\right)^{1-\varepsilon_s} (\tau_{Rjs} w_{Rj})^{1-\varepsilon_s} + \\ & (1-\gamma_s)^{\varepsilon_s} (A_{Lis})^{\delta(\varepsilon_s-1)+\frac{\varepsilon_s-1}{\mu_s-1}} \left(\frac{\mu_s}{\mu_s-1}\right)^{1-\varepsilon_s} (\tau_{Lj} w_{Lj})^{1-\varepsilon_s}]^{\frac{\phi_{is}}{1-\varepsilon_s}} \prod_{s'} P_{js}^{\phi_{jss'}}. \end{aligned} \tag{41}$$

The remaining equilibrium conditions are unaffected.

5.5 Discussion

Direction of Innovation Bias: Using the model, we can show analytically in which direction the innovation bias A_{Ris}/A_{Lis} shifts when the factor bias r_{is}/l_{is} of country-industry is shifts. To see that, first take ratios of the production functions for the R_{is} and L_{is} input layers (8):

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

From this relative demand for Y_{Ris}/Y_{Lis}, we obtain the relative revenues of firms in the R_{is} compared to those of firms in the L_{is} sector:

$$\frac{P_{Ris}Y_{Ris}}{P_{Lis}Y_{Lis}} = \frac{\gamma_s}{1-\gamma_s}\left(\frac{E_{Ris}}{E_{Lis}}\right)^{\frac{\varepsilon_s-1}{\varepsilon_s}}\left(\frac{A_{Ris}}{A_{Lis}}\right)^{\frac{\mu_s}{\mu_s-1}\frac{\varepsilon_s-1}{\varepsilon_s}}\left(\frac{r_{is}}{l_{is}}\right)^{\frac{\varepsilon_s-1}{\varepsilon_s}}. \tag{43}$$

Combining (43) with (15), we can solve for the relative technology bias for a given level of factor inputs r_{is}/l_{is} under the assumption that $E_{Ris}/E_{Lis} = (A_{Ris}/A_{Lis})^{\delta}$:

$$\frac{A_{Ris}}{A_{Lis}} = \left(\frac{f_{Li}}{f_{Ri}}\frac{\gamma_s}{1-\gamma_s}\right)^{\frac{(\mu_s-1)\varepsilon_s}{\kappa_s}}\left(\frac{r_{is}}{l_{is}}\right)^{\frac{(\mu_s-1)(\varepsilon_s-1)}{\kappa_s}}, \tag{44}$$

where $\kappa_s \equiv \mu_s - \varepsilon_s + \delta(\mu_s-1)(1-\varepsilon_s)$. Note that when $\mu_s > 1$ (a necessary condition for the profit maximization of monopolistic producers to be well defined) and $\varepsilon_s < 1$ (REE and labor are gross complements), this expression is decreasing in relative inputs r_{is}/l_{is} when $\delta \geq 0$ or for $|\delta| < \frac{\mu_s-\varepsilon_s}{(\mu_s-1)(\varepsilon_s-1)}$ when $\delta < 0$. In this case, a negative REE supply shock that reduces r_{is}/l_{is} biases technology towards increasing the efficiency of REE inputs. Intuitively, the price effect via larger P_{Ris}/P_{Lis} will dominate the negative market-size effect via smaller r_{is}/l_{is} such that it becomes relatively more profitable to invent varieties that enhance the efficiency of the R_{is} sector compared to the L_{is} sector. Moreover, as long as $\kappa_s > 0$, the technology bias responds more strongly to changes in r_{is}/l_{is} the more negative the value of δ. Intuitively, negative spillover effects on the productivity of competitors increase the profitability of inventing a a patent by reducing the profit destruction effect of entry. This effect can be seen in (45), which can be obtained from substituting (44) back into (43):

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

This expression is decreasing in r_{is}/l_{is} under similar conditions as A_{Ris}/A_{Lis} so that a negative supply shock of REE increases the relative profitability of the R_{is} sector. By contrast, relative output of the R_{is} sector is increasing in r_{is}/l_{is} when revenue is decreasing:

$$\frac{Y_{Ris}}{Y_{Lis}} = \left(\frac{f_{Li}}{f_{Ri}}\frac{\gamma_s}{1-\gamma_s}\right)^{\frac{\mu_s\varepsilon_s\kappa_s+\delta(\mu_s-1)^2\varepsilon_s^2}{(\mu_s-\varepsilon_s)\kappa_s}}\left(\frac{r_{is}}{l_{is}}\right)^{\frac{\delta(\mu_s-1)^2\varepsilon_s(\varepsilon_s-1)+(\mu_s-1)\varepsilon_s\kappa_s}{(\mu_s-\varepsilon_s)\kappa_s}}. \tag{46}$$

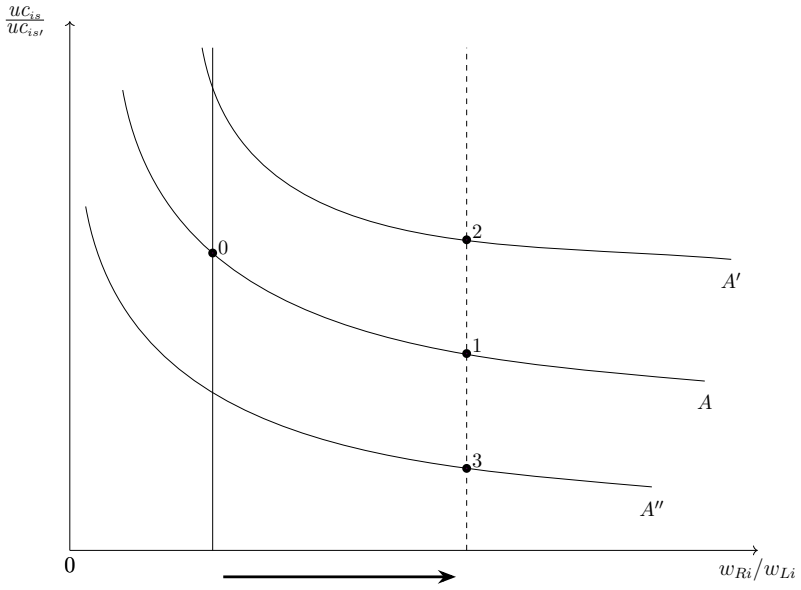
Finally, one can show that relative factor inputs are decreasing in the relative price of REE w_{Ri}/w_{Li}:

$$\frac{r_{is}}{l_{is}} = \frac{f_{Ri}}{f_{Li}} \frac{w_{Li}}{w_{Ri}} \frac{\tau_{Lis}}{\tau_{Ris}}. \tag{47}$$

Impact on Productivity: By comparing the expressions for unit costs with endogenous (31) and exogenous technologies (41), we can gain intuition for how competitiveness of downstream industries responds to an increase in the price of REE. Under exogenous technology, an increase in w_{Rj} increases production costs (factor cost effect) and more so in industries with higher values of γ_s. Then, from the expression for trade shares (20), it follows that this reduces bilateral exports. By contrast, under endogenous technology, the increase in w_{Rj} also triggers a technology response because it is associated with a rise in $P_{Rjs}Y_{Rjs}$ (technology effect). If the technology effect is sufficiently strong, it dominates the factor cost effect, thereby leading to a larger increase in competitiveness in more REE intensive sectors and a corresponding increase in their exports.

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.

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.

6 Quantification *(Preliminary)*

6.1 Taking the Model to the Data

World Input-Output Tables: We use trade and production data from the World Input-Output Tabes (WIOD) (2012 release). We aggregate the world IO tables to 5 regions: China, Europe, Japan, the U.S. and a rest of the world (RoW) including all remaining countries. We consider 14 sectors. 12 of these are in manufacturing, one correspond to agriculture and one aggregate sector for all service industries. For each country-sector pair, we obtain the value-added share in gross output ϕ_{is} and the direct requirement shares in gross output $\phi_{jss\prime}$. Additionally, we obtain trade imbalances (TB_i) for each country.

Estimating the Substitution Elasticity for REE ε_s: A key parameter in our calibration is the sectoral substitution elasticity for REE ε_s because 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/other patents) and w_{Ri}/w_{Li} (factor prices) for many countries i and industries s. Combining (15) and relative demand

$$\left(\frac{\gamma_s}{1-\gamma_s}\right)^{\varepsilon}\left(\frac{P_{Ris}}{P_{Lis}}\right)^{-\varepsilon}=\frac{Y_{Ris}}{Y_{Lis}}, \tag{48}$$

yields

$$\begin{aligned}\frac{A_{Ris}}{A_{Lis}}&=\left(\frac{\gamma_s}{1-\gamma_s}\right)^{\varepsilon_s}\left(\frac{P_{Ris}}{P_{Lis}}\right)^{1-\varepsilon_s}\frac{f_{Li}}{f_{Ri}}\\&=\left(\frac{\gamma_s}{1-\gamma_s}\right)^{\varepsilon_s}\left(\frac{A_{Ris}}{A_{Lis}}\right)^{(1-\varepsilon_s)(\frac{1}{1-\mu_s}-\delta)}\left(\frac{w_{Ri}\tau_{Ris}}{w_{Li}\tau_{Lis}}\right)^{1-\varepsilon_s}\frac{f_{Li}}{f_{Ri}},\end{aligned} \tag{49}$$

where the last equality uses $P_{Ris}=A_{Ris}^{\frac{1}{1-\mu_s}-\delta}\frac{\mu_s}{1-\mu_s}w_{Ri}\tau_{Ris}$ 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}:

$$\frac{A_{Ris}}{A_{Lis}}=\left(\frac{\gamma_s}{1-\gamma_s}\right)^{\frac{\varepsilon_s(\mu-1)}{\kappa_s}}\left(\frac{w_{Ri}\tau_{Ris}}{w_{Li}\tau_{Lis}}\right)^{\frac{(1-\varepsilon_s)(\mu_s-1)}{\kappa_s}}\left(\frac{f_{Li}}{f_{Ri}}\right)^{\frac{\mu_s-1}{\kappa_s}}. \tag{50}$$

Taking logs, we obtain the following regression specification:

$$\log\left(\frac{A_{Ris}}{A_{Lis}}\right)=\beta_s\log\left(\frac{\tau_{Ris}w_{Ri}}{\tau_{Lis}w_{Li}}\right)+\delta_s+u_{is}, \tag{51}$$

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. This equation can be estimated from observable data on the relative number of patents in each industry, REE unit values and wages. Depending on the industry, we estimate $\varepsilon_s\in[0.3,1.3]$, with point estimates below unity in most industries.

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

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

Given data on the sectoral total requirements of REE for the US, value added, prices P_{Ris}, P_{Lis}, and estimates for ε_s we can back out γ_s for all industries s.

Other Parameters: Using data on sectoral bilateral trade flows from WIOD, we proxy transport costs d_{ijs} by estimating a gravity equation and leveraging CEPII gravity data. We set the externality δ to -1.5 such that a shift in the factor bias towards REE improves the relative unit costs of REE-intensive sectors. We set the elasticity of substitution σ_s to 4 and the scale elasticity in the innovation layer μ_s to 2.5. We choose the relative size of labor endowments across countries according to country-level employment data from WIOD.

6.2 Quantitative Exercise

To assess whether our model mechanism can replicate the effects observed in our empirical analysis, we conduct a numerical exercise and simulate the introduction of a 100% tax on exports of REEs by China (τ_{XC}). The introduction of this tax raises the price of the REE factor outside China by 75% and lowers the REE factor price within China by 12.5%.

In analogy to the empirical regressions, we regress the relative change in industry factor bias $\Delta(A_{Ris}/A_{Lis})$, coresponding to the change in REE patents relative to other patents, the relative change in productivity measured in terms of unit costs and the relative change in revenue of downstream industries ΔRev_{is} on a proxy for how sensitive sector s is to REE usage.

We calculate REE sensitivity of each industry as the product of the REE intensity γ_s and the inverse of the elasticity of substitution ε_s^{-1}. Column (1) in the upper panel of Table 6 shows that, in response to the introduction of the export tax, the technology bias (patenting) outside China shifts towards REE in those sectors that are REE-intensive. 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). Column (3) shows that this shift in the technology bias towards REE is sufficiently strong to reduce unit costs more in REE-sensitive industries compared to other industries, even though the price of REE has increased outside of China. Column (4) shows that in China the relative unit costs of REE-sensitive sectors increase instead. These changes in the relative unit costs have a direct effect on industry revenue Rev_{is}. Columns (5) and (6) show that REE-sensitive industries outside of China expand their sales, while they contract in China.

Table 6: Introduction of a REE Export Tax

	$\Delta(A_{Ris}/A_{Lis})$		$\Delta(\textit{unit costs})_{is}^{-1}$		ΔRev_{is}	
	NONCHN	CHN	NONCHN	CHN	NONCHN	CHN
	(1)	(2)	(3)	(4)	(5)	(6)
	Model with Directed Technological Change					
RE sens.	12.35***	-0.705	0.0130***	-0.00465	0.0259***	-0.00552
	Model with Exogenous Technologies					
RE sens.			-0.130***	-0.00253	-0.270***	0.107***
Observations	56	14	56	14	56	14

Notes: The table presents coefficient estimates of β from the regression: $\Delta y_{ist} = \alpha + \beta\, RE\ sens._s + \epsilon_{ist}$, where the outcome variable is either $\frac{(A_{Ris}/A_{Lis})^{post}}{(A_{Ris}/A_{Lis})^{pre}}$ or $\frac{(1/\textit{unit costs})_{is}^{post}}{(1/\textit{unit costs})_{is}^{pre}}$ or $\frac{Rev_{is}^{post}}{Rev_{is}^{pre}}$ and $RE\ sens._i = \gamma_s \varepsilon_s^{-1}$ * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Furthermore, the introduction of the tax causes a global reallocation of value added. While Chinese GDP increases, there is a GDP loss in all other regions. This applies to both nominal and real GDP. Similarly, we find that consumption increases in China and decreases elsewhere.

To illustrate the force of directed technological change, we next conduct a second counterfactual where China also introduces a 100% export tax on REE but we assume that technologies A_{Ris} and A_{Lis} remain exogenously fixed, as described in Subsection 5.4. Then, the tax raises the price for the REE factor outside of China by less compared to the case if endogenous technologies (by 66% instead of 75%) and lowers the REE factor price within China by more (by 17% instead of 12.5%). The bottom panel of Table 6 shows that in this case productivity and revenues of REE-sensitive industries fall relative to those of other industries outside of China due to the factor cost effect. By contrast, in China REE sensitive industries expand relative to other industries.

7 Conclusion

How did export restrictions on rare earths affect downstream industries both globally and domestically? To address this question, we construct a detailed input-output 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, which led to an 10- to 45-fold increase in REE prices, stimulated a strong innovation response in REE-intensive downstream industries outside China.We measure REE-biased innovation by classifying patents from downstream industries 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 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 develop a novel quantitative trade model incorporating directed technological change and calibrate it 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. Consistent with our reduced-form evidence, our model predicts that in the presence of complementarities between REEs and labor, an increase in international REE prices—driven by a Chinese export tax—induces technological change aimed at reducing REE usage. When this technological response is sufficiently strong to offset the impact of rising input costs, REE-intensive industries outside China expand their exports relative to less REE-intensive industries. While innovation and export activity increase in REE-intensive industries outside China, this comes at the expense of reduced innovation and export activity in other industries, as well as negative terms-of-trade effects resulting from China's export tax on REEs.

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A Empirical Appendix

A.1 Matching REE into the Supply-Use Table:

For imputation into the supply-use table, we first match each general category into its corresponding NAICS code, which the BEA's SUT uses. This matching determines which using sectors (columns) are assigned the numbers. For instance, we match the "Fluid Cracking Catalysts" category with the NAICS code for "Petroleum Refineries". 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. 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 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.

On the supply side, 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". Figure A.4 in the Appendix provides a stylized illustration of these splits. 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. As a last step, we use a concordance mapping from NAICS to SIC as our other outcome data vary at the country and SIC levels.

REE Price Data and Input Values: 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. BCC reports global consumption of REE 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 USGS (2015).[17]

A.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 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.[18] 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 L.L.M.: 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.[19]

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.[20] Linking patents via firms has two caveats.

[17] REEs are often divided into light REEs (La, Ce, Pr, Nd, Pm, Sm, Eu, Gd) and heavy REEs (Tb, Dy, Ho, Er, Tm Yb, Lu, and Y). Heavy REEs tend to have higher unit prices but are considered to have smaller markets (Alonso et al., 2023).

[18] See Table A.3 in the Appendix for the list of keywords.

[19] See, e.g., Silverman (2002).

[20] See e.g. Bloom et al. (2013).

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 L.L.M. 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 L.L.M. and let the L.L.M. 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 L.L.M. to classify 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 L.L.M. 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.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 based on the UNIDO Indstat database to measure the effect on productivity across countries and industries. We take initial capital stocks from the OECD STAN database. To control for industry characteristics, we obtain the average capital and labor intensity from the NBER CES manufacturing database. Additionally, 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.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 US 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 HS Product Code-Level Results

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 was for robustness 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 includes the physical quantity of exports. We calculate unit price 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 of 2002-2018. For the REE sensitivity variable, we reconstructed it at the HS-level by converting NAICS-level total requirements to HS using the Pierce-Schott concordance instead of to SIC. We made use of the same concordance to convert our control variables.

For exports value, we find that the results are qualitatively identical to our baseline regressions at the SIC level. Specifically, for all our sub-samples except for US and China, exports of product codes that are more sensitive to rare earth inputs exhibited significantly greater growth during the treatment period 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 greater for physical quantity.

Table A.1: Downstream Export Growth – Rare-Earth Intense Manufacturing Industries

	Annualized Growth: Exports Value					
	NONCHN	ALL	USA	EUR	JPN	CHN
	(1)	(2)	(3)	(4)	(5)	(6)
RE 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)
RE 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)
RE 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 x Ind F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Country x Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes

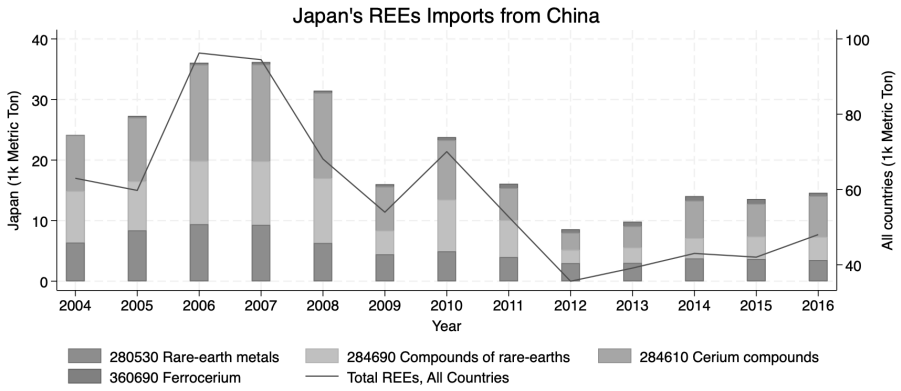
Notes: The table presents coefficient estimates of β from the regression: $y_{ist} = \beta\, RE\ Sens._s \times post_t + \gamma\Delta_{st} + \eta_{is} + \eta_{it} + \epsilon_{ist}$, where y_{ist} represents the annualized growth rate of export values, quantity and unit price for country-industry is in 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 $RE\ Sens._s$ 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: $RE\ Sens._s = \sum_e tr_{es} \times compl_e$. $post_t$ 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.2: 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

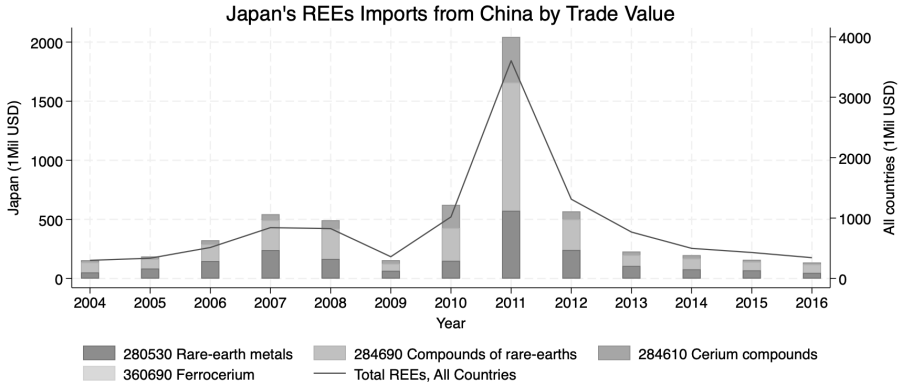
Notes: The table lists the weights we use for splitting the NAICS code for "Other fabricated metal manufacturing" into "magnets" and "non-magnets". For each NAICS code that uses USD x million input from "Other fabricated metal manufacturing" and has weight w, in the imputed input-output table it would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

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



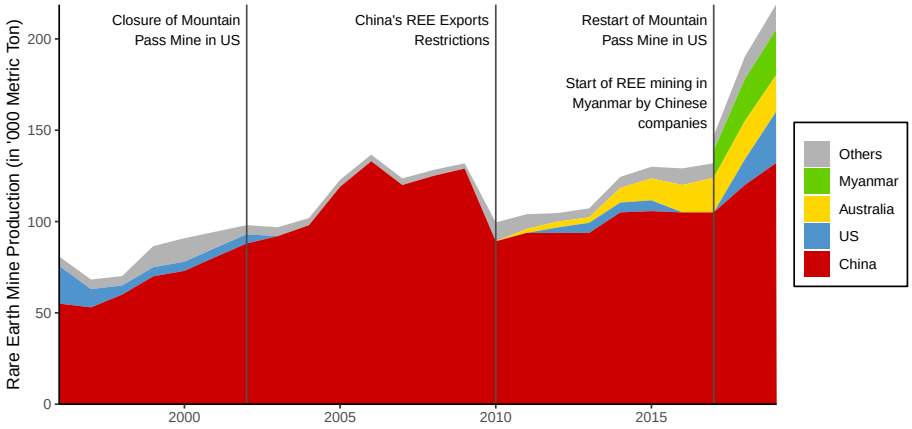
Notes: The Figure plots production yearly imports of REEs ((HS Codes 280530, 284610, 284690, 60690) to all countries (line) and Japan (bar lines) using data from the *Comtrade*.

Figure A.2: 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 the *Comtrade*.

Figure A.3: REE Mine Production Across Countries



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

Figure A.4: Stylized Illustration of Input-Output Split for Imputation

Before	...	OIC	PR	...
...				
OIC		3,231	753	
PR		1,709	20,331	
...				
Total Input		34,695	784,481	

After	...	OIC: Y	OIC: La	OIC: Ce	OIC: Nd	OIC: Dy	OIC: Other RE	OIC: Non-RE	PR	...
...										
OIC: Y		0	0	0	0	0	0	0	0	
OIC: La		0	0	0	0	0	0	0	38	
OIC: Ce		0	0	0	0	0	0	0	2	
OIC: Nd		0	0	0	0	0	0	0	34	
OIC: Dy		0	0	0	0	0	0	0	0	
OIC: Other RE		0	0	0	0	0	0	0	0	
OIC: Non-RE		0	0	0	0	0	0	3,231	679	
PR		0	0	0	0	0	0	1,709	20,331	
...										
Total Input		805	713	1,277	480	118	2,158	29,144	784,481	

Notes: OIC: Other Basic Inorganic Chemical Manufacturing, PR: Petroleum Refineries.

Table A.3: Keywords for REE 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.4: List of Sample Countries in Empirical Analysis

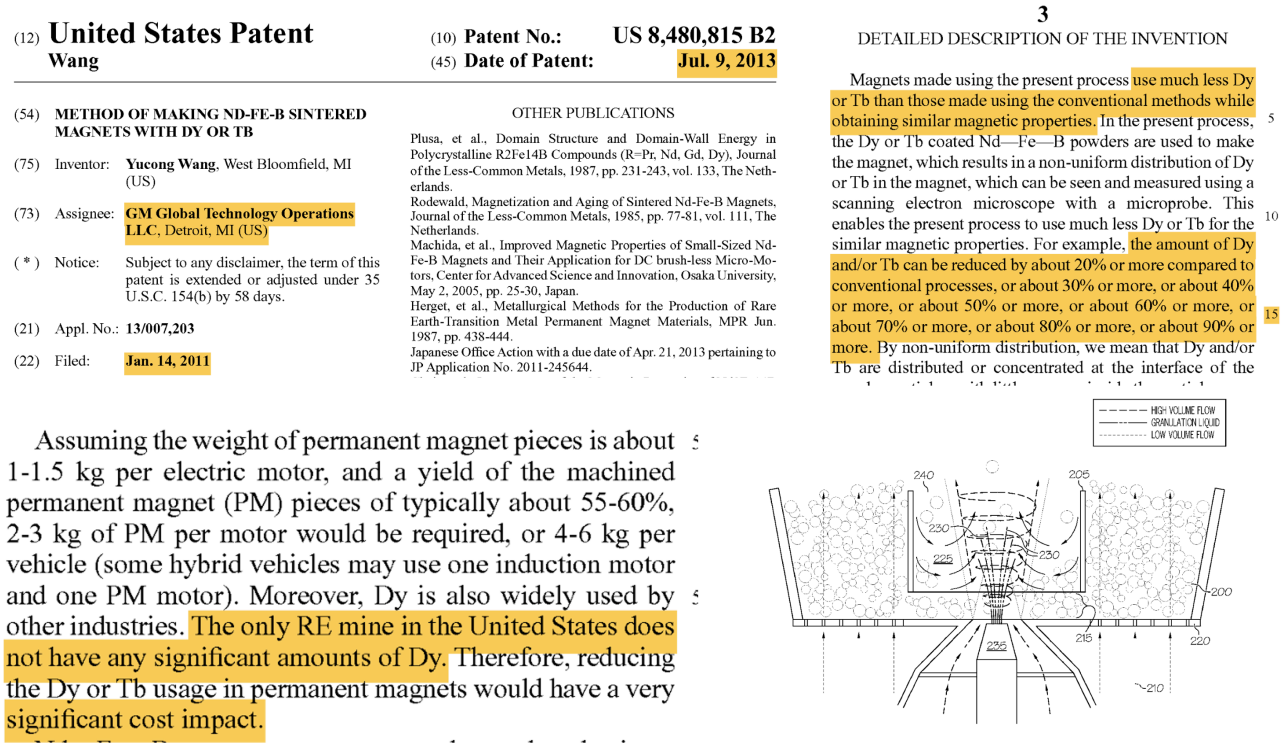
ISO Code	Country Name	ISO Code	Country Name
ARE	United Arab Emirates	ISR	Israel
ARG	Argentina	ITA	Italy
AUS	Australia	JPN	Japan
AUT	Austria	KOR	South Korea
BEL	Belgium	MEX	Mexico
BGD	Bangladesh	MYS	Malaysia
BRA	Brazil	NGA	Nigeria
CAN	Canada	NLD	Netherlands
CHE	Switzerland	NOR	Norway
CHL	Chile	NZL	New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

A.6 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 REE as inputs. They have also been handpicked to represent the variety of REE downstream uses.

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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Japanese Office Action with a due date of Apr. 21, 2013 pertaining to JP Application No. 2011-245644.

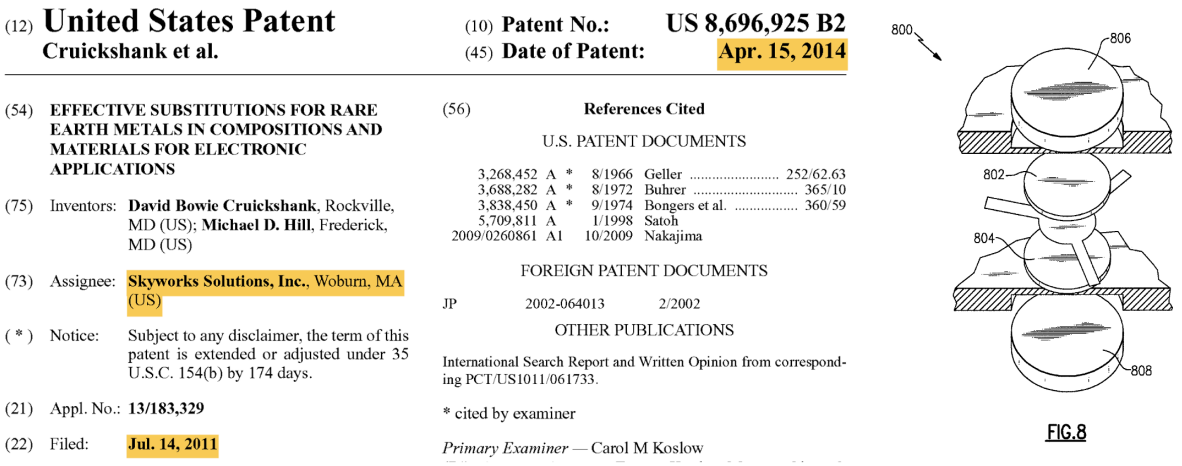
3
DETAILED DESCRIPTION OF THE INVENTION

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

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

Notes: The Figure shows excerpts of patent US8480815B2. In January 2011, the US firm GM Global Technology Operations filed a patent for a powder coating process that uses much less Dy and Tb as coating for REE magnet. 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: US8696925B2: Microwave Garnets Material Substitute



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

(10) **Patent No.: US 8,696,925 B2**
(45) **Date of Patent: Apr. 15, 2014**

(54) **EFFECTIVE SUBSTITUTIONS FOR RARE EARTH METALS IN COMPOSITIONS AND MATERIALS FOR ELECTRONIC APPLICATIONS**

(75) Inventors: **David Bowie Cruickshank**, Rockville, MD (US); **Michael D. Hill**, Frederick, MD (US)

(73) Assignee: **Skyworks Solutions, Inc.**, Woburn, MA (US)

(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 174 days.

(21) Appl. No.: **13/183,329**

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

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Primary Examiner — Carol M Koslow

FIG.8

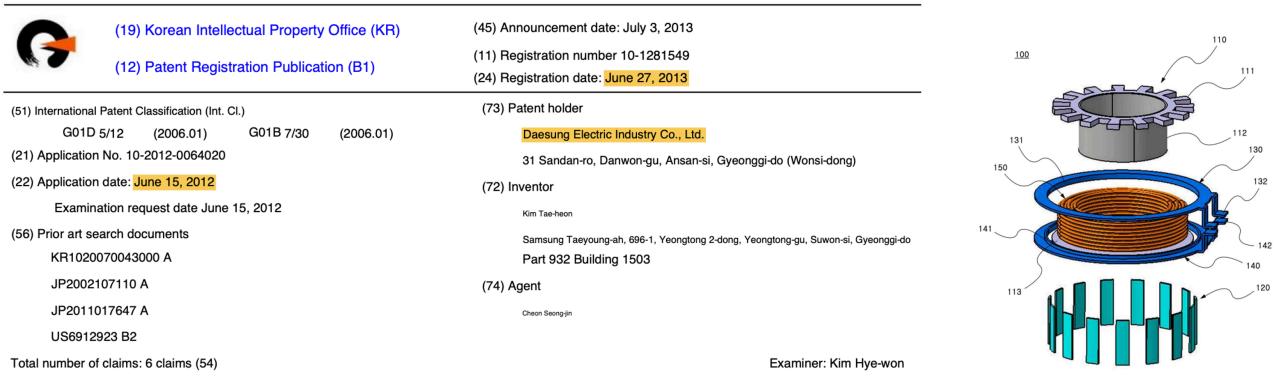
(57) **ABSTRACT**

Embodiments disclosed herein include methods of modifying synthetic garnets used in RF applications to reduce or eliminate Yttrium or other rare earth metals in the garnets without adversely affecting the magnetic properties of the material. Some embodiments include substituting Bismuth for some of the Yttrium on the dodecahedral sites and introducing one or more high valency ions to the octahedral and tetrahedral sites. Calcium may also be added to the dodecahedral sites for valency compensation induced by the high valency ions, which could effectively displace all or most of the Yttrium (Y) in microwave device garnets. The modified synthetic garnets with substituted Yttrium (Y) can be used in various microwave magnetic devices such as circulators, isolators and resonators.

frequency portions of the microwave region. Many microwave magnetic materials are derivatives of Yttrium Iron Garnet (YIG), a synthetic form of garnet widely used in various telecommunication devices largely because of its favorable magnetic properties such as narrow line absorption at its ferromagnetic resonance frequency. YIG is generally composed of Yttrium, Iron, Oxygen, and possibly doped with one or more other rare earth metals such as the Lanthanides or Scandium. However, the supply of rare earth elements such as Yttrium has recently become increasingly restricted, thus resulting in correspondingly steep increases in cost. As such, there is a need to find a cost-effective substitute for rare earth elements in synthetic garnet structures that does not compromise the magnetic properties of the material and can be used for microwave applications.

Notes: The Figure shows excerpts of patent US8696925B2. In July 2011, one month after REE prices peaked, Skyworks Solutions from the US filed a patent that substitutes the yttrium used in synthetic garnets, which are a component of electronic microwave devices. The patent document refers to the REE supply shock, mentioning that "the supply of rare earth elements such as yttrium has recently become increasingly restricted, thus resulting in correspondingly steep increases in cost." Yttrium is the least substitutable rare earth element after dysprosium and europium according to Graedel et al. (2015).

Figure A.7: KR101281549B1: Position Sensors Without REE



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Total number of claims: 6 claims (54)

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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.8: 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**

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

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(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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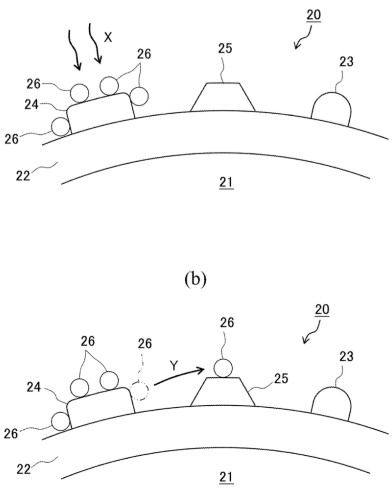
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FIG. 38



(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 rare earth element with the greatest price jump in 2010-2011. The patented composite oxide still needs to use REE 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."