The Material Basis of Modern Technologies. A Case Study on Rare Metals

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Abstract: Scientific progress in many technologies exploits new materials. The unique properties of a wide range of Rare Metals (RMs) make them key inputs to achieve the functionality of emerging technologies. The speed of technological progress can therefore be influenced by the availability of necessary RM materials. This paper discusses these relations and provides a first exploratory empirical analysis of the link between critical raw materials and frontier technological innovation. By text mining 5,146,615 USPTO patents during the period 1976–2015, we explore the dependence of new inventions of 13 key RMs, finding that the latter play an increasingly important role as the material basis of modern technologies: in the four decades observed, more than 1/10 patents rely on at least one RM. This dependence increases significantly over time and is particularly high for emerging technologies such as semiconductors, nanotechnology, and green energy. Further, we adopt a panel of 5644 technology subgroup-RM pairs to explore the impact of variations in RM supply. The results show that, controlling for science & technology push and demand-pull factors, innovation in RM-based technologies is positively associated with its supply conditions, contributing to the understanding of the shifts of critical materials' use in frontier technologies.

Keywords: Critical raw materials, Rare metals, Technological dynamics, Patent text mining, Instrumental variables estimation
JEL classification: O30; O31; O33; Q31

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1. Introduction

Through the Stone Age to that of Bronze, Iron, and up to the modern times, technological progress has always been accompanied by tremendous shifts in the utilization of material resources. Especially after the emergence of Material Science in the 20th century, the development of modern technologies in a variety of fields has shown growing dependence on advancements in material usage, unveiling new properties of existing materials but also making their use more diversified in achieving specialized functionalities and meeting specific market demands. Indeed, material changes and evolving technologies have long been recognized as one key dimension in technological paradigm shifts (Dosi, 1982; 1988).

We are currently entering the so-called "Age of Rare Metals" (RMs) (Abraham, 2015) – that is, a special group of raw materials are becoming increasingly prominent in high-tech industries and are often regarded as "technology metals" with great criticality at the innovation frontier (Graedel et al., 2015; European Commission, 2020). Differently from major and base metals (e.g., copper, iron, and aluminium), RMs can be considered as industrial "vitamins" or "spices" – only used in very small quantities, but providing unique and essential chemical, electrical or mechanical properties, and leading to extensive applications in a variety of high-tech products, such as semiconductors, catalysts, engines, turbines, batteries, as well as medical equipment and weapons (e.g. Gunn, 2014; Abraham, 2015; Watari et al., 2020).

While the importance of RMs for technological innovation is steadily expanding, they also face significant supply risks (e.g., National Research Council, 2008; Humphries, 2010; European Commission, 2012; Hayes & McCullough, 2018). These are related to depletion due to mineral scarcity, geographical concentration of deposits, political instability of producing countries, geopolitical risks in global RM trade as well as low recycling rates (Radetzki, 2008; Narine, 2012; Lederer & McCullough, 2018). Taken together, such supply conditions may constrain industrial development and influence the trajectory of modern technologies. For example, the solar energy industry and the corresponding technologies are seriously affected by fluctuations in the supply of gallium (Ga) and indium (In) (Gunn, 2014). On the other hand, RM extraction may give rise to serious negative externalities in the supply locations: this is the case, for instance, of tantalum and cobalt, labelled "conflict minerals" as specifically associated with armed conflict, human rights abuses and corruption. Despite such criticalities in frontier technologies, neither innovation studies nor economics research have so far paid enough attention to the topic.

The case of RMs provides a relevant context to analyse the material shifts in frontier technologies, and the interplay between changing material supply conditions, technological progress and market demands. Specifically, in what follows we attempt to address two crucial research questions:

1. To what extent do different areas of modern technologies use various RMs?

2. Are RM supply conditions associated with the innovation output of RM-based technology areas?

Conceptually, we draw upon Dosi's classical technology paradigm framework (1982, 1988) to explore technological reliance or dependence on RMs or, in other words, to investigate the use of RMs as a prerequisite for the commercialization of technology. This dependence is jointly influenced by basic discoveries in Material Science on RMs' properties, market needs demanding RMs' functionalities, as well as the fragile supply conditions of RMs. Empirically, we first examine the technological use of RMs by identifying RM-related keywords in the USPTO patent text. We observe a high dependence: namely, 10.87% of 5,146,615 patents granted over the period 1976-2015 mention at least one RM. Subsequently, we estimate a panel model of 5,644 technology subgroup-RM pairs to explore the relationship between RM supply variation – measured by the annual global metal production – and the innovation output of technological areas using RMs, also controlling for science & technology push and demand-pull factors. A major challenge in estimating our regression model stands in the endogeneity of the relationship under analysis, whereby technology developments may reversely influence metal production decisions; in addition, they can be simultaneously influenced by unobservable factors, such as policy changes. To alleviate this potential issue, we develop an instrumental variable (IV) that captures the exogenous variation of RM supply by considering the metal companionability and co-production relationship between RMs and their geological hosts, i.e. the base metals (Nassar et al., 2015; Sprecher et al., 2017). Our IV results point to a positive association between RM supply and technology trajectories, which is highly robust to the use of alternative IVs, regression models, samples and identification methods of RM-based technologies. These findings bring support to the idea that changes in the supply of critical raw materials may directly influence the dynamics of frontier technological innovation and paradigm shifts.

Our paper contributes to the literature in two main respects. First, we extend the debate on technological evolution to a scarcely explored aspect, that is, the shift of critical materials' use, suggesting that changes in their supply conditions could be a driving force of technology dynamics. Innovation processes lead to production paradigm shifts and new combinations of production factors (Schumpeter, 1949). Seminal contributions in economics have argued that technological innovation solves or improves issues related to resource scarcity, enabling society to overcome resource supply constraints and achieve sustainable development (e.g., Solow, 1974; Stiglitz, 1974; Rosenberg, 1976; Acemoglu et al., 2012). However, such a "technology optimism" overlooks the endogeneity of technological change: innovation itself may be reversely influenced by material and resource supply conditions. It is less clear whether and how material and resources' availability in turn affects technology dynamics, especially when we consider some critical raw materials with relatively low recycling and substitution rates like RMs (Graedel, 2015). In this paper we argue that, because of their unique properties, the supply condition of RMs may become the potential factor influencing the innovation dynamics of frontier technologies, contributing to our understanding of the trade-off between economic and technological dimensions in paradigm shifts (Dosi, 1988).

Second, this paper contributes to current literature on resource criticality, which has mainly focused on material flow analysis and supply chain management (e.g., Kim & Davis, 2016; Sauer & Seuring, 2017); criticality assessment (e.g., Hayes & McCullough, 2018); international regulations, as well as the corresponding behaviours and responsibilities of firms (e.g., Diemel & Cuvelier, 2015; Hofmann et al., 2018). Although regarded as "technology metals", RMs have rarely been systematically studied from a broad technological perspective. It is widely recognized in the literature that modern technology is strongly dependent on such critical raw materials, and possible supply risks may cause shocks to technological change, particularly in high-tech industries (Eggert, 2010). However, it is still unknown how intense and varied this dependence is: following Diemer et al. (2022), this paper attempts to quantitatively measure technological reliance on RMs through patent text mining.

The paper is organized as follows: Sections 2 reviews the relevant literature and establishes the theoretical foundations of our analysis; Sections 3 explains the selection and data sources for both RMs and technologies, as well as the text mining methods, whilst Section 4 calculates the technological dependence on RMs; Sections 5 and 6 estimate the relationship between RM supply and innovation dynamics and test the robustness of the findings; Section 7 concludes, providing further research directions.

2. Literature review

2.1 Technological paradigm and material inputs

The literature on the driving forces of technological dynamics is rich and longstanding. In his seminal papers, Dosi (1982, 1988) introduced the concept of technological paradigm as a widespread cluster of innovations which represents a response to a related set of technological problems, based on a common set of scientific principles and on similar organisational methods. This perspective includes three core aspects, that is: "1. The needs that are meant to be fulfilled; 2. The scientific principles utilized for the task and 3. The material technology to be used"

(Dosi, 1988, p.1127). Most subsequent research has focused on the first two elements, giving rise to the 'demand pull versus science & technology push' debate on the sources of technological change (e.g., Mowery & Rosenberg, 1979). In this line of research, science & technology push and demand pull interactively shape frontier innovation, with scientific knowledge providing the trajectories of the innovative effort and demand working as a crucial force in directing the trajectory towards the right economic targets (e.g., Dosi, 1982; Kline & Rosenberg, 1986).

The third aspect of the above definition, implying a physical foundation of technology and the changing patterns of material use, has been mostly neglected by social scientists' attention. Yet, an explicit consideration of critical materials and the related properties they possess is essential for fully capturing technology dynamics, as such materials may be key for problem solving within a certain technology paradigm (Dosi, 1988). Furthermore, a fundamental feature of the evolution of modern technologies pertains to the shift in materials' use – whereby radical technology and paradigm changes are always closely related to changing materials, with the appearance of new critical elements, as well as new processes and uses for existing ones and disappearance of those outdated and harmful (Cameron & Metcalfe, 1987; Tilton, 1991).

In this context, as critical raw materials, RMs provide a good case for analysing the mechanism of material use shifts in frontier technologies. Recent academic research emphasises a growing technological dependence on RMs, which work as essential components to achieve the functionality of technologies especially relevant for the two on-going main technological transitions (Grandell et al., 2016). In fact, almost all core green technologies, including solar electricity, wind power, fuel cells, hydrogen production and storage, electric cars and energy-efficient lighting are heavily dependent on different RMs (Grandell et al., 2016; Valero et al., 2018). Likewise, alongside the advent of industry 4.0, revolutionary technology breakthroughs in digitalisation and artificial intelligence have significantly increased the complexity and sophistication of electronic equipment, raising the demand for various RMs as essential inputs. For instance, the elements used in computing devices grew from 11 in the 1980s to 15 in the 1990s to 60 in the 2010s (Zepf & Achzet, 2015), including RMs such as lithium (Li) and cobalt (Co) in batteries, gallium (Ga) and germanium (Ge) in integrated circuits, tantalum (Ta) in capacitors, molybdenum (Mo) in transistors as well as indium (In) in displays (e.g., Eggert, 2010; Gunn, 2014).

Frontier technologies have thus experienced significant changes in their reliance on RMs, which occur through the competition and substitution process between two technology trajectories, the RM-based trajectory and that non-RM-based. Drawing upon the technology paradigm framework by Dosi (1982; 1988), we explore the relevance of RMs for both the demand and the supply sides of innovation. The changing dependence on RMs can be understood as a process fundamentally driven by the progress in basic science which discovers RM properties, is enabled by the market demand for functionality improvements based on such properties, and is also influenced by the dynamics of RM supply.

2.2 Science and technology push and RMs

From the science & technology-push perspective, scientific discoveries and technological breakthroughs set new innovation paradigms by defining entirely new modes of problem solving, and shaping the technological dynamics by changing the direction of R&D investments. Science and technology are becoming increasingly interdependent and inseparable in the modern society. One key scientific development in the 20th century was the emergence of Material Science in the 1960s as an amalgam of physics, chemistry and metallurgy, advancing the understanding of components, structure, properties, application and performance of a variety of materials. Over the last decades, many technological innovations have taken advantage of the progress in Material Science (Dosi & Nelson, 2010): technology paradigm shifts have increasingly been connected to discoveries on material properties and changes in material use.

Recent scientific progress has deepened the understanding of intrinsic properties of RMs – the unique electrical, thermal, chemical, and optical features gradually emerging, and expanding the boundaries within which they can be applied in frontier innovation. Many radical technological changes and paradigm shifts were triggered by key "Science Events" of breakthrough discoveries on specific RMs (Thirtle & Ruttan, 1987). For example, the material scientists Herb Maruska, in the 1970s, and Nobel Prize Isamu Akasaki, in the 1990s, discovered the properties of Gallium which resulted in the invention of blue and white LED. Such a discovery laid the foundation for a new paradigm in the lighting technologies, replacing the old one based on incandescent lamps; subsequent inventions have witnessed a significant material use shift from Tungsten to Gallium[1]. Another renowned example is the utilization of Uranium, whose discovery dates back to 1789, but whose properties remained unknown until 1938, when experiments by the chemist Otto Hahn led to the discovery of nuclear fission: this resulted in the application of Uranium in nuclear weapons in 1945 and the ensuing nuclear energy technologies. At the same time, continuous scientific advancement on input materials led also to incremental changes within the same technology paradigm (Rosenberg, 1976, 1982) and to the emergence of new technological trajectories. An example can be seen in the progress of studies on photovoltaic materials, leading to different generations of solar energy technologies. This process was accompanied by dramatic material shifts from mono-crystalline silicon cells

1. See also Figure 2 in this paper.

to multi-crystalline ones, moving then to the 2nd generation, with film cells using Cadmium, Telluride, Selenium, and later Gallium and Indium. These examples suggest that, due to scientific progress, the range of useful RM materials for the global economy and society has gradually expanded, allowing new uses and leading to a higher dependence of frontier technologies on RMs. In addition, scientific progress not only influences the demand for RMs, but a deeper understanding of their properties may also improve the efficiency of metal production and increase the supply, which in turn reinforces technological paradigms centred on RMs.

2.3 Market and demand pull for RM-based technologies

Besides scientific discoveries, research has also maintained that the demand for technology plays an important role in the establishment and selection of technology paradigms (e.g., Di Stefano et al., 2012). Not only do market signals work as selective devices, but they can also direct innovative activities and technical changes within a large set of possibilities allowed by science (Rosenberg, 1973; Dosi, 1978). Various economic factors are important in shaping the direction of the RM-based innovative processes.

Consumers’ demand for product improvements is a fundamental driver of innovation, encouraging inventors to seek alternative technological trajectories with functional improvements, including searching for advanced materials. The selection among trajectories happens through market competition between products using different technologies. The adoption of RM-based technologies generates substantial improvements in the performance of existing products, also leading to the creation of entirely new goods, which can better fulfil customers’ needs. New products using RM-based technologies have the potential to gain larger market shares than old ones, gradually bringing up new dominant designs. Changes in the sales of different products are followed by changes in technological patenting in the same direction (Schmookler, 1962). For example, in the last decades, significant material changes in permanent magnet technologies have been driven by the increasing demands for stronger magnetic properties by wind turbines and machineries. Such demand pressures led to shifts from steel-based magnets to those based on Rare Earth elements, such as Samarium-Cobalt (Sm-Co) and Neodymium (Nd-Fe-B) magnets. Once the technology trajectory is established, RMs become critical materials hardly replaceable in the short and medium run (Ayres & Peiro, 2013; Abraham, 2015). Engineering and natural science research indicate that for many RMs “no suitable substitutes can be found no matter what price is offered without performance and function being seriously compromised” (Graedel et al., 2015, p. 6299). R&D aimed at identifying possible substitutes often requires very long cycles and high costs, thus making alternatives for many RMs rarely available (European Commission, 2012, 2020). As such, the resource scarcity characterising RMs as well as their technological uniqueness make their supply increasingly central to understand the contemporary trajectories of frontier technology development.

2.4 Supply conditions of RMs

The development of technological trajectories confronts the “trade-offs between technological and economic dimensions” (Dosi, 1988, p. 1128). In the case here, on the one hand innovators are eager to exploit the useful technological properties of RMs in their inventions, on the other they face the fact that the RMs, as the name suggests, are scarce and the supply chain is impacted by potential critical obstacles. These supply risks come from different stages of the value chain, from upstream mineral mining to metal production (smelting, refining and heat processing) and then to global trade. For some RMs, the ore extraction is concentrated in a small number of locations subject to weak institutional and political environments, which make the critical ore supply vulnerable to conflicts and wars, social and political instability, human rights’ violations and natural disasters (e.g., Berman et al., 2017; Giuliani, 2018; Diemer et al., 2022). In addition, the smelting and refining of many RMs has gradually shifted to multinational companies from emerging countries (especially China), leading to more uncertainties from trade conflicts and geopolitical crises (e.g., Narine, 2012; Mancheri, 2015; Fiaschi et al., 2017; Lederer & McCullough, 2018). The high demand and criticality of RMs in high-tech industries further increase the risk of extreme price spikes or even material unavailability (Moss & Tzimas, 2013).

The induced innovation hypothesis argues that technological progress is significantly influenced by the supply dynamics of input factors (Hicks, 1932; Schmookler, 1962; Chakraborty & Chatterjee, 2017). Existing studies mainly focus on how the shortage of general inputs and relative prices (e.g., conventional energy sources, land, labour) stimulate advanced technologies that use relatively abundant resources as a substitute. For example, research shows how land supply conditions determine the trajectories of agricultural technologies (e.g., Hayami & Ruttan, 1970; Kawagoe et al., 1986; Olmstead & Rhode, 1993), and the inducement effect of conventional energy price on alternative energy technologies (e.g., Newell et al., 1999; Cheon & Urpelainen, 2012; Aghion et al., 2016).

This perspective, however, fails to fully consider resource heterogeneity: differently from general inputs, critical raw materials are technologically crucial, working as essential inputs and directly entering core technologies and functions (Graedel et al., 2015). They are also closely related to the scientific principles of the technological paradigm of reference, for instance, the “photoelectric effect” depending on semiconductor materials in the solar energy technologies. General inputs are unlikely to achieve the same functions and customer utility:

nevertheless, to our knowledge, very little research has investigated the relationship between the supply of critical resources and technological change.

In this context, RM supply conditions may influence researchers' incentives of investing in RM-based technologies. It is well-known that innovation is a risk-taking investment where invention efforts are allocated depending on the expected market returns. Fluctuations in the supply chain affects RM availability in downstream industries. Sufficient supply increases the production scale and market size of products intensive in RM-based technologies, therefore rising the probability of their application and commercialization and accelerating the advantages of RM-based technologies over others (Cameron & Metcalfe, 1987; Acemoglu, 2002). On the other hand, the scarcity of certain critical materials makes it less rewarding to invest in related technologies if the costs of alleviating scarcity are too high (Smulders, 2005). For the case of RMs, it is difficult to find viable alternatives to achieve the same functionality. As a result, insufficient production or disruption in an RM supply may directly render the downstream application and manufacturing more costly and reduce the returns of R&D in RM-based technologies.

Based on the above background, in the following sections, we analyse the trends of RM use in frontier technologies and employ econometric models to first explore the relationship between RM supply dynamics and RM-based patenting.

3.Data and methodology

3.1 Selection of RMs and global production trends

There is no universal list for Rare/Minor metals: definition and criteria vary from study to study (Ayres & Peiro, 2013). As described by the Minor Metal Trade Association[2], RMs encompass a vast array of metals which are: 1. reserved and produced in significantly smaller quantities than base metals, and almost do not exist alone in the earth but are obtained largely or entirely as a by-product of host metals from geologic ores; 2. not traded on formal exchanges, like the London Metal Exchange; 3. important for emerging industries as "technology metals" and "critical raw materials" (European Commission, 2012). In this paper, we select the most concerned RMs by referring to the resource criticality literature, as listed in Table 1. It is important to note that we did not include two groups of RMs which are also widely discussed in public debates. The first is precious metals, such as gold, silver and platinum which are also relatively rare and technologically important. However, their supply and demand conditions are

2. https://mmta.co.uk/glossary-of-minor-metal-terms/

very different from those of RMs, because of the financial and trade conditions in specialized precious metal markets, and because they are also used as currency or jewelleries rather than only as industrial materials, making it difficult to measure the actual availability by metal production. Second, we did not include rare earth metals[3]: although also crucially important and widely investigated by the literature (e.g., Humphries, 2010), information on their production is not available for individual elements.

INSERT TABLE 1 HERE

We obtained global production data of the selected 13 rare metals for the years 1975-2015 from the United States Geological Survey database of historical statistics for mineral and material commodities. Figure 1 shows the annual production of RMs during the whole period. In general, the production of most RMs has risen with fluctuations and, especially after 2000, the upward trends accelerate. At the same time, the production trends of different metals show significant variation: cadmium, tantalum, and selenium fluctuate greatly, while cobalt, lithium, vanadium, indium, and bismuth are relatively stable. We also observe that some macro events have common impacts on the production of all metals. For example, around 2010, almost all metals (although with different intensity) show some decline of production following the great financial crisis in 2008. We further compare production changes relative to 1975 across metals[4]. It emerges that RMs experienced different trends over the four decades: gallium and indium have the fastest growth, by 40 and 20 times respectively, lithium and cobalt have also increased by 5 times, while the growth of cadmium, germanium and tellurium remains limited.

INSERT FIGURE 1 HERE

3.2 Patent data and technology dynamics

We use patents granted by the US Patent and Trademark Office (USPTO) over the period 1976-2015 to measure the global dynamics of RM-based technologies. Patent statistics are a reasonable measurement for innovation output and technological structure (e.g., Pavitt, 1985; Griliches, 1990; Castellacci & Natera, 2013; Consoli et al., 2016, 2021).

There are in total about 5,300,000 granted patents in the USPTO during the observed

3. Rare earth elements are a group of 17 elements: La, Ce, Pr, Nd, Pm, Sm, Eu, Gd, Tb, Dy, Ho, Er, Tm, Yb, Lu, plus Sc and Y.

4. See Figure A1 in the online Appendix.

period [5] . We use two technological classifications. First, the Cooperative Patent Classification (CPC) system is used in the econometrics analysis. CPC is a more detailed and advanced version of the International Patent Classification (IPC) and has been officially used by both USPTO and European Patent Office (EPO) for classifications at five technological digits, which ensure consistency over time[6]. Following Consoli et al., (2021), we extract the CPC class for each patent from the 'cpc_current' table in the "Patents View" database. Second, the WIPO technology classification is then employed to analyse the dependence of different technology areas on RMs. This taxonomy, initially developed by Schmoch (2008), assigns all patents to 35 technology fields which are further aggregated into five main technology sectors – Chemistry, Electrical engineering, Instruments, Mechanical engineering, and Others. This is a useful classification in cross-sector comparison because of the balanced patent size, full coverage of all technology areas, within-sector homogeneity and cross-sector differences, and has been widely used in patent analyses (e.g., d'Agostino et al., 2013; Balland et al., 2019).

3.3 Identification of RM-based technologies

The identification of RMs in the patent databases is carried out by text-mining, searching within the patent description for the name/keyword of the relevant metals in the section "Detailed description text". This text-mining method has been used to identify specific characteristics of technologies, such as dependence on rare earth elements (Fifarek et al., 2008), and on conflict minerals (Diemer et al., 2022).[7] The detailed description text is the information disclosed by the inventors in the patent application: it includes information on the function and application of the invention, the detailed technical process and the materials used to achieve its function [8] . We note that mentioning a material could have different motivations: new technologies may result directly from basic and applied research on a specific material, or innovations may be in applied technologies for which that material is an essential component (Fifarek et al., 2008); patents can mention materials also in relation to obtaining, saving, substituting or recycling them (Diemer et al., 2022).

5. Patent data source: https://patentsview.org/

6. Technological classification standards have been evolving over time due to emergence of new areas and disappearance of old ones, making cross-time comparison impossible. The use of CPC avoids this issue because all historical patents are reclassified retrospectively by USPTO according to the current CPC classification.

7. More advanced methods of analysis have recently been developed on the basis of patent text-mining: for example, Biggi et al. (2022) identify patents related to target chemical compounds and calculate the patent toxicity according to the chemical structure of ingredients.

8. The text-mining analyses on RM-based patents may vary with the specific section of the patent text. The advantage of this description text is that it discloses all technological processes through which we can capture all materials used in the invention. The disadvantage is that it may be too detailed and the mentioned RMs may not be used as major components; thus, the patent may not be really "RM-based". On the contrary, the "claim text" includes the core innovative aspects of a patent for which the inventors want legal protection. Therefore, we provide a comparison and discussion on two patent samples identified by descriptions and patent claims respectively, shown in Figure A5 in the online Appendix.

In this paper, we focus on the technologies "based on" RM or employing them as inputs. To do so, we exclude two groups of technologies: (1) those potentially related to mining technologies (41,239 patents in the class E21), and (2) metallurgy technologies (67,328 patents in classes C21-C30), which include those for producing, refining, smelting as well as recovering and recycling metals and metalloids. Our final sample for the analysis includes 5,146,615 patents[9]. If the patent mentions an RM keyword in the detailed description text, we consider the innovation as resulting from the properties of the specified RM and the patent as RM-based. However, this method has other potential limitations. For example, it fails to identify the degree of dependence on individual RM: for two patents, which both mention an RM, one may use it as a necessity, while for the other RM may not play a major role. Nevertheless, in this paper we are concerned mainly about the relative proportion of RM-based patents in different aggregated technology groups and their temporal trends, rather than individual patents. We assume that if a technology field has a higher proportion of RM-based patents, then it has a higher dependence upon RM materials.

One may wonder whether this method really captures materials' use in innovation. In Figure 2 we provide an example of lighting technology which, as stated in section 2.2 above, has experienced a significant paradigm shift in the last four decades, from Tungsten-based incandescent to Gallium-based LED. Applying the aforesaid method, we observe that the patent share using Gallium increased rapidly from 5% to 26% while that of Tungsten gradually decreased and was surpassed by the former in 2010. Such an example provides support to the methods we use to identify the materials shifts in frontier technologies.

INSERT FIGURE 2 HERE
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4. Technological dependence on RMs

In this section we focus on the technological dependence on RMs by describing the general trends of RM-based patents and their distribution across technologies and RMs.

4.1 General trends

Through keyword identification, we find that 559,328 patents (10.87%) mention at least one RM keywords. Therefore, more than one tenth of modern technologies are somehow dependent on the selected 13 RMs, indicating their high importance in innovation. The technological

9. For a detailed description see Figures A2 and A3 in the online Appendix.

dependence on RMs is measured in both absolute and relative terms: 1. the total number of RM-based patents (with at least one RM keyword); 2. the share of RM-based patents in the total patent number. Figure 3 shows that the number of RM-based patents rose by nearly 7 times over the 40 years: from 6,000 new RM patents in 1976 to more than 40,000 in 2015. At the same time, despite two slight drops from 1976 to 1987 and 1993 to 1998, the share of RM-based patents on the total increased from 9% to 14%. This indicates the progressively more important role that RMs play in modern technologies.

INSERT FIGURE 3 HERE

Trends are observed also for the 5 WIPO sectors (Figure 4). On the left chart, in terms of absolute RM patent numbers the Chemistry sector started at a high level and had the most RM-based patents for nearly 25 years, maintaining relatively stable growth until 2005, which since then accelerated. For the Electronic engineering sector, we observe a sharp increase since 1997: in 2004 it surpassed Chemistry. The number of RM-based patents in Instruments also showed a stable increase, whilst that in Mechanical engineering was modest.

INSERT FIGURE 4 HERE

In terms of shares, Chemistry is significantly higher than other sectors, and the gap further widened over time, rising to 32% in 2015. In comparison, the share of Electrical engineering remained relatively constant over time and was overtaken by Instrument technologies in 1992. Mechanical engineering and Other technologies had lower shares, slightly increasing since the 1990s. We also compare the technological dependence on different RMs over time[10]: the number of patents using lithium remained the highest, followed by indium and cobalt patents which also experienced the fastest growth. Patents based on gallium, germanium, and tantalum also increased significantly. This indicates that the technological dependence is dynamic and the relative importance of different RMs varies over time.

4.2 RM dependence by technology field

We then consider the RM dependence of specialized technologies by zooming into the 35 WIPO fields (Figure 5).

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10. See Figure A4 in the online Appendix.

INSERT FIGURE 5 HERE

Technological fields in the Chemistry sector show high shares of RM-based patents: Micro-structure and nano-technology shows the highest dependence (i.e. 37% of patents are related to at least one RM). Other three fields – Material, metallurgy[11]; Organic fine chemistry; and, Macromolecular chemistry, polymers – also show a strong dependence: these four fields are all closely related to Material Science (Schmoch, 2008), indicating that different technologies which imply inventing and producing new materials use RMs as main components and search for property improvements. It is important to note that these technologies are usually general-purpose technologies (GPTs) and work as the basis for others, such as nano-technologies for semiconductors (Moser & Nicholas, 2004; Petralia, 2020).

For the Electrical engineering technological sector, unsurprisingly, the highest RM-dependence is recorded by the field of Semiconductors, which is one of the core technologies in the hardware infrastructure for ICT (Schmoch, 2008). The second by importance is Electrical machinery, apparatus, energy. Other fields in the sector, such as Computer technology, are mainly about software technologies, thus depend much less on RMs. In the Instruments sector, Optics, Analysis of biological materials, and Medical technology show relatively high RM-dependence, whilst fields in Mechanical engineering and Other technologies are far less dependent on RMs. Regarding Green energy technologies, several fields show very high reliance on the selected RMs: Fuel cells, where 34% patents use at least one RMs as input, particularly lithium and cobalt; Bio-fuels, Solar energy and Nuclear energy also show a strong dependence, consistently with the literature on green and renewable energy technologies (e.g., Valero et al., 2018; Dominish et al., 2019; European Commission, 2020).

To sum up, the descriptive analysis illustrates a strong reliance of modern technologies on RMs which varies across technologies, levels of analysis as well as RM types. RMs have become critical inputs in more and more patents, and have diversified applications in a number of GPTs, especially material technologies and many emerging technologies. At the same time, each technology field depends on specific RMs, reflecting specialized technical requirements and specific properties of RMs.

5. The impact of RM supply on technology dynamics

11. As mentioned earlier, we excluded metallurgy patents. Hence, this field only includes material technologies.

In this section, we use econometrics models to further explore whether dynamics in the metal supply influence the innovation output of RM-based technologies, controlling for science discoveries and demand.

5.1 Sample, RM-based technology areas

The CPC technology system has 5 levels of classification, namely: section, class, subclass, group and subgroup. We use the finest subgroup level to capture the relationship between RM and specialized technologies. Our dataset is structured in the format of technology-RM pairs. We focus on RM-based technology areas, $Tech_i - RM_j$, which are defined as all subgroups in which more than 10% of patents use a certain RM_j during the research period. All pairs exceeding this threshold enter the main sample[12]. This pair structure allows us to explain the technology dynamics by the joint effects of both dimensions. For each $Tech_i$, there may be one or several pairs, depending on how many RMs it depends upon. In order to ensure that subgroups in our sample are comparable, we exclude the extremely small ones whose total number of patents is less than 100 during the four decades. The final sample consists of 5,644 $Tech_i - RM_j$ pairs in which 2,534 subgroups were granted 611,249 patents (accounting for 11.88% of all USPTO granted patents) during 1976-2015 (details of the sample are shown in Tables A1 and A2 in the online Appendix).

5.2 Model specification

The model is set according to our conceptual framework and also by referring to studies on the induced innovation hypothesis, as mentioned in Section 2 (e.g., Popp, 2002). New patents in RM-based technology areas are explained by science & technology push, demand pull and also supply dynamics of RM materials. The dependent variable is the patent output of RM-based technological subgroups, measured by the share of patent numbers in each subgroup over the total USPTO patents in each year. Independent variables include the lagged production of the corresponding RMs as well as other control variables.

$$\frac{Patent\ Number\ of\ Subgroup_{i,j,t}}{Total\ Patent\ Number_t} = \beta_1\ RM\ production_{j,t-k} + \beta_2\ Science\ papers\ on\ RM_{j,t-k} + \beta_3\ Forward\ citation_{\ i,t-k} + \beta_4\ Knowledge\ stock_{\ i,t-k} + \beta_5\ RM\ price_{j,t-k} + Tech - RM\ FE + Year\ FE + \varepsilon_{i,j,t}$$

where i indexes 2,534 technology subgroups, j stands for the 13 RMs and t denotes the years 1976-2015. Our dependent variable is normalized by z-score. The model uses the application date rather than the granting date of patents as measure of innovation in order to

12. Results remain consistent when we change this threshold to 20% and 30%.

document it as early as possible (Popp, 2003; Böhringer et al., 2017). $RM\ production_{j,t-\mathrm{k}}$ measures the production of RM j in k years after t, k= 3 and 5 to consider the lagging effect of patent application. Along with production amount, we control the yearly prices for each metal[13], $RM\ price_{j,t-k}$: when production is constant, price dynamics reflects changes in the demand side. These two variables are measured by ratios relative to the initial level in 1975, because different metals are produced in very different amounts and units and have large price difference, making the comparison on absolute values meaningless. In addition to this model setting, we also check the robustness of our results by considering a fixed effect Poisson model in which the dependent variable is the absolute number of patents in each subgroup.

The effect of science & technology push is measured by the variable $Science\ papers\ on\ RM_{j,t-k}$ – the number of academic publications on each RMs, divided by the total scientific publication to control for the changing tendency of publication across years. Existing studies found that a science or technology breakthrough is followed by a sharp increase in scholarly publications on the topic (Winnink & Tijssen, 2015). So, we assume that an increasing share of papers on an RM means that there is more scientific research and deeper understanding of RM properties and applications. We only focus on the journals in the SCI Index which covers science and engineering areas. A paper is regarded as studying an RM if the RM keyword appears in the title: data is collected from Web of Science.

The demand pull for RM-based technologies is further measured by forward patent citation information. Previous studies found that the number of citations a patent received is closely related to its economic value and commercialization chances (Harhoff et al., 1999; Hall et al., 2005; Gambardella et al., 2008). If a technology is cited by many following inventions, this implies that it has a higher demand. Using a time window of 3 years, the mean forward citation numbers are calculated to measure whether the technological subgroup faces higher demand.

We also control for $Knowledge\ stock_{i,t-\mathrm{k}}$ which is the number of patents accumulated until the previous year in technology subgroup i: this variable represents the cumulative and path-dependent nature of technology development, a higher value reflecting deeper knowledge in the specialized technology area i. It is calculated as follows:

$$Knowledge\ stock_{i,t-k} = \sum_{s=0}^{P} e^{-\gamma_1 s} \cdot \left(1 - e^{-\gamma_2 (s+1)}\right) \cdot Patents\ _{i,t-s}$$

Referring to Popp (2001), this formula measures the pre-existing state of knowledge at each time t for technology subgroup i. Since innovation decays in value with time, γ_1 is the

13 . Price data is from: https://www.usgs.gov/centers/national-minerals-information-center/historical-statistics-mineral-and-material-commodities

depreciation rate of past technologies and γ_2 is the diffusion rate of existing patents, under the assumption that it takes time for technological knowledge to diffuse among innovators. Following (Kim et al., 2017), we use the mean values as estimated by Popp (2001) with $\gamma1 = 0.44$ and $\gamma2 = 2.97$. The two variables $Knowledge\ stock_{i,t-k}$ and $Forward\ citation_{i,t-k}$, measuring the weighted patent numbers, are both log transformed after adding 1.

Main descriptive statistics and correlation matrix for the independent variables are reported in Table A3 in the online Appendix. We include Tech-RM fixed effect in the model to control for constant unobservable factors for each pair. The propensity to patent innovation varies across technology areas: in some, such as Chemistry and Electronic engineering, it is higher than that in others, where secrecy is more important to protect innovation. Tech-RM fixed effect also helps to account for RM-specific unobserved heterogeneity. The year fixed effect is used to control for macrolevel economic development and technological trends.

5.3 Endogeneity and identification strategy

The empirical setting proposed above may be threatened by potential endogeneity issues. First, reverse causality can be a concern if technology dynamics influence the production of RMs. In fact, when more patents using an RM occur, the expected and actual demand for the metal will increase, stimulating metal producers to increase production capacity. Second, an omitted variable bias may also affect our estimates: besides demand and science, some other factors may influence RM production and technology dynamics. For example, government policies pay special attention to the shortage of certain RMs and try to stabilize their supply (European Commission, 2012); at the same time, policies may support certain industries or technologies which are impacted by potential RM shortages.

To mitigate these endogeneity concerns, we develop a new instrumental variable strategy by using the metal co-production relationships to identify exogenous shocks to RM production. Unlike major metals, RMs are typically found in relatively low concentrations in the mineral, and they are only, or largely, constituents in deposits of more abundant base metals (copper, iron, aluminium, etc.). As a result, RMs seldom form viable deposits on their own, and instead are mined and produced as companion metal or by-products and recovered from the different forms of waste, scraps, slags or gas of the base metals in the processing, smelting, refining stages (e.g., Eggert, 2010; Harper et al., 2015; Nassar et al., 2015;), as shown in Figure 6. Therefore, RM supply is strongly influenced by the demand for base metals: a major demand reduction for a base metal causes significant supply constraints for its companion RMs (Graedel, 2015; Sprecher et al., 2017).

INSERT FIGURE 6 HERE

We argue that the influence of the base metal production on RM production is exogenous for two reasons. First, this influence is unidirectional, the production of RM does not reversely influence base metal production because the latter accounts for the major revenue of mining and is mainly driven by macroeconomic factors such as, for instance, urbanization speed in China and India. On the other hand, even if the prices for by-product metals are high, a small market scale means the commercial incentive is limited (Moss et al., 2013). Therefore, mining and producing decisions are mainly determined by the exogenous shocks on base metals, and RMs do not typically experience supply expansions in a short timespan (Sprecher et al., 2017). A production increase for base metals results in supply increases and price drops for the by-product and co-product RMs (e.g. Campbell, 1985; Hagelüken, 2011; Moss et al., 2013). Second, the production of base metals does not impact the dependent variable – i.e., patents in RM-based technology areas – because base metals are more widely used as basic materials in much larger amounts in a variety of industrial sectors, such as construction materials and metal containers, and have very different properties and functions than RMs. This assumption is further verified in the robustness test.

The type of base metal and the degree of metal companionability vary greatly among RMs, are shown in Table 2. For almost all RMs in our sample, more than 50% of the production is from a single base metal. Some RMs are entirely co-produced with one base metal, for example cadmium from zinc, zirconium from titanium, and gallium from aluminium. Others have more than one base metal as source, like cobalt and tantalum.

INSERT TABLE 2 HERE

Therefore, we use the production of the base metal (if one RM have multiple base metals, we use the primary one with the highest companionability degree) as an instrumental variable to predict the exogenous shocks to the RM production. Similar to the RMs production variable, our instrument is also standardised relative to the production in 1975.

5.4 Regression results

Table 3 shows the OLS regression results and the second stage results of the IV estimation[14]. We start with the simple model in column 1, which solely includes RM production, with Tech-

14. The first stage estimation results are shown in Table A8 in the online Appendix.

RM pair fixed effects to capture the unobserved heterogeneity at these fine-grained levels. In column 2 we include the full battery of covariates discussed above, whilst in columns 3 and 4, we implement our IV strategy for the same specifications of column 1 and 2. In all models, the variable of interest, $RM\ production_{j,t-3}$ is always positive at the 1% significance level, indicating that the supply of an RM is positively correlated to the patent output of RM-based technology subgroups. The coefficient of RM production in the specification of column 4 indicates that a one-unit increase (100% increase relative to 1975[15]) in the production of a certain RM on average leads to a rise in the share of patents in each RM-based technological subgroup by 0.0373 standard deviation, which corresponds to an increase of 7.11% ($\frac{\beta_1 \times Std}{Mean} = \frac{0.0373*0.00007836}{0.00004114}$) in the share of this subgroup in all granted patents. By comparing the results between the OLS and IV regressions, we notice that the coefficients on $RM\ production_{j,t-3}$ are always larger in the IV models. This indicates that the simple OLS estimation underestimates the effect of RM supply. There are many factors, such as for instance public policies and trade regulation shocks, exerting opposite influences on RM supply and RM-based innovation. For example, national and international governments, including the US, Japan and the EU Commission, provide supports for sectors under the threats of critical raw material scarcities. Moreover, as the major RM supplier, China has imposed export restrictions on some RMs with increasing technological criticality. In general, these findings are in line with our expectation that increasing the supply of RMs does provide incentives to innovation in the relevant technological areas and encourage new patents. On the contrary, a decreasing supply or supply disruption of RMs may constrain the generation of new technologies in areas based on these materials[16].

The validity of the IV rests on the assumption that the base metal production is related to the RM production, but uncorrelated with innovation in RM-based technology areas. However, the possibility exists that the base metals are also used in those technologies, which may invalidate the IV and bias the estimation results. To address this potential problem, by using the same text mining method, we identify keywords of base metals in the patent descriptions and exclude all $Tech_i - RM_j$ in which any patent in $Tech_i$ mentioned the main base metals of $RM\ j$. By doing so, we rule out the possibility that RMs and base metals are not only related on the supply (production) side but also on the technological demand side. The regression results are shown in column 5 of Table 3. After excluding those patents, the estimated effect remains significantly positive.

15. Until 2015, the production of the 13 RMs, on average, increased by 647.15% relative to the initial values in 1975.
16. The results for the T-5 period are shown in Table A4 in the online Appendix, in which we observe similar results.

In general, these findings support our expectation that increasing supply of RMs does provide incentives to innovation in the subgroups based on them and encourages more R&D activities. On the contrary, a decreasing production or supply disruption of RMs may constrain the generation of new technologies based on these materials. Hence, these results provide a first suggestion that the supply of RMs influences frontier technological dynamics.

As far as the other variables are concerned, we find strong evidence for demand pull: patent output in subgroup i is positively related to the average forward citation numbers. Moreover, the effect of $Knowledge\ stock_{i,t-\mathrm{k}}$ on patents is significant and positive, indicating that past knowledge accumulation in a technology area leads to more dependence on it in the future. In line with other studies (e.g. Kim et al., 2017), innovation is path-dependent and builds on the existing knowledge stock of its own technology subgroup. The science & technology push argument is only partially supported – the variable scientific papers on the corresponding RM is only significantly positive in the OLS model but loses significance in the IV estimation.

INSERT TABLE 3 HERE
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6. Robustness checks

We further test the robustness of our results by: (1) checking the validity of the IV, (2) using different identification of RM-based technologies, and (3) applying alternative regression methods. All robustness tests reported are for T-3 period, results for T-5 are available upon requests.

(1) Further validations of the instrumental variable

First, the IV in the main model captures the production of the primary base metal of the RMs without considering differences in the companionability across RMs and corresponding base metals (BMs) and changes with time. First, RMs with a high companionability may be more impacted by changes in the base metal production. To consider this heterogeneity, we re-construct our IV by weighting the base metal production by the degree of companionability (the percentage of an RM produced from co-production process with a base metal) between RMs and base metals. Another regression was then run on the Tech-RM pairs for which the companionability degree between RM and BM is higher than 80%. Next, we introduce the cross term of BM production with the two-dimensional dummies of 13 RMs and time (decades) in order to further control the fact that the relationship between base and rare metal production may change with both metal type and time. Next, we pay attention to the influence of the energy transition, which has a strong dependence on some RMs and BMs: in such case, both BM and

RM production are influenced by the green energy transition, which may invalidate our assumptions. We thus exclude all RMs who are intensively used as energy transition metals (Molybdenum, Lithium, Cobalt), and RMs whose base metals are energy transition metals (Selenium, Tellurium, Indium, Cadmium, Germanium) (IEA, 2021)[17]. All results are shown in Table A5 in the online Appendix: the coefficients of interest and other variables remain similar and highly significant, further validating our IV estimation approach.

(2) Using the claim text of patents to identify RMs

In the above regressions, we use the "full description text" to identify the RM-based patents. As an alternative, we use the "claim text" which includes the core innovative aspects of a patent for which the inventors want legal protection. The results based on claim text are shown in Table A6 in the Appendix: RM production is still significantly positive in both OLS and IV estimations.

(3) Changing regression methods

We further check the robustness of our findings by adopting a Poisson model as an alternative regression method. In this setting, the dependent variable is now the absolute number of patents in subgroup *i*, based on *RM j*. We also take the first difference for both dependent and independent variables. The results are shown in Appendix, Table A7. Overall, the variable of interest, RM production, remains significant and positive, thus further corroborating our findings.

The robustness checks above suggest that our main findings are stable with alternative samples and methods, no matter how we change the IV, or use alternative patent texts for identification, or regression models. We interpret this evidence as suggestive that the effect of RM supply on innovation dynamics is robust.

7. Conclusion and discussion

Technological innovation co-evolves with the availability and supply of natural resources and materials. On the one hand, frontier technologies are experiencing tremendous shifts, changing types, modes, and efficiency in the utilisation of different inputs. Economists believe that technological innovation makes it possible to replace rare and expensive resources with relatively abundant and cheap ones, which helps overcoming natural resource constraints and achieving sustainable development (Rosenberg, 1976). For example, for energy resources, new technologies enabled us to shift from wood to coal, to petroleum to hydropower, and then to

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solar, nuclear, and other unconventional energy sources. On the other hand, technological progress also makes the materials in use become more diversified and advanced to achieve some specific functionalities. As a result, modern society is more and more dependent on some important non-renewable resources like critical raw materials, which have become essentials in technological progress and economic growth (Groth & Schou, 2002). In this way, natural resource and material supply in turn influences the trajectory of frontier technology dynamics.

By using 13 widely concerned RMs, this paper contributes to the understanding of the material shifts of modern technologies, with particular focus on the deep interdependence between material supply and technology progress. RMs are regarded as “technology metals” with great criticality to high-tech manufacturing and cutting-edge technological innovation, especially under the paradigm shifts of clean and green energy and AI revolution. The functionality and special properties of RMs cannot be easily replaced with substitutes (Ayres & Peiro, 2013; Graedel et al., 2015; Leader, 2019). The case of RMs suggests that, by controlling for the effects of science & technology push and demand pull, the availability of critical raw materials has a direct influence on the dynamics of frontier innovation — technological progress in the current society is still endogenously subject to the natural environment and the supply of resources and materials with technological criticality. Our research broadens the understanding of technological paradigm shifts by adding the perspective of “material shift”, which is fundamentally driven by the discoveries on materials in basic science, enabled by market demands for functionality improvement based on RM properties and also influenced by the RM supply dynamics.

Empirically, this paper contributes by providing a first exploration of the dependence of frontier technologies on RMs. We find that during the last four decades, 10.87% of patents granted by the USPTO use RMs as inputs, and that this dependence varies with technology area, scale of analysis as well as type of rare metals. Technology application of RMs has experienced scale and structural changes over time: the number of RM-based patents has increased by 7 times over the observed decades, and Electronic engineering surpassed Chemistry, becoming the technological sector most reliant on RMs. Our econometric exercise, which accounts for endogeneity, indicates that RMs supply is positively associated with the innovation output of RM-based technologies.

Our findings have policy relevance and implications for future research. The case of RMs may further encourage scholars and policymakers to devote attention to the entire global organisation and value chain networks within which innovation occurs, considering the distribution of benefits and costs across actors and geographies involved. Given the high dependence on critical natural resources, it is likely that a constantly increasing supply of RMs would be needed to ensure steady innovation rates. However, RM supplies are recognized to be subject to great societal and environmental risk and uncertainty (National Research Council, 2008; Humphries, 2010; Hayes & McCullough, 2018; European Commission, 2020). The extraction, exploitation and trade of many rare metals, such as cobalt and tantalum which are labelled among others as "conflict minerals", contribute to wars, conflicts and human right violations in developing countries and regions (Hofmann et al., 2018). Exploring the relationship between RM supply and technological dynamics provides a fuller grasp of the "dark side of innovation" and help resolve the apparent trade-off between technological change and global fairness and equity (Castellacci & Archibugi, 2008; Giuliani, 2018; Diemer et al., 2022).

Our research has limitations and further investigation is required. First, because of data availability, this paper only focuses on 13 critical RMs. Other RMs are also of significant technological importance, especially the widely concerned Rare Earth Elements (REE) (Hayes & McCullough, 2018). Different critical raw materials have distinct technological properties and applications and may experience different supply risks. Second, our empirical analysis mainly focuses on the influence of material supply by keeping other important elements – scientific discoveries and demand – as control variables. Further research should be done to test the whole Dosi's framework. For example, it would be very interesting to study the endogenous relationship between Material Science and downstream technology inventions, on the one hand, and science-pushed technology applications, on the other; application potentials may also encourage more research efforts. Third, in this paper RM supply and technological dynamics are measured at the global scale. However, their actual availability varies with geography, thus being influenced by multifaceted factors such as geological mineral distribution, local socio-economic and political conditions, national and international policies, trade agreements as well as global geopolitics events. For example, in 2010 under the embargo of China, Japan had little access to new REEs (Mancheri, 2015); and because of the Dodd Frank Act, business companies listed in the US stock market have additional limits in obtaining RMs included in the "conflict minerals" category from the Democratic Republic of Congo (Dalla & Perego, 2018). Future research should focus on finer geographic scales (Diemer et al., 2022) to explore whether and how differences in the availability of RMs shape the development trajectories of firms, regions and countries. From a methodological standpoint, we acknowledge the limitations of our instrumental variable approach, particularly as not all by-product RMs are extracted from base metal production leading to a "slack condition". Furthermore, our definition of RM-based technologies relies on a criterion where over 10% patents in a CPC subgroup utilizes an RM. Future research may consider different criteria for selecting technology areas or focus on case studies for specific ones.

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Table 1. Selected RMs and examples of related literature

Rare metals	Related Literature
Bismuth (Bi)	Hagelüken (2011); Moss et al. (2011);
Cadmium (Cd)	Moss et al. (2011); Valero et al. (2018)
Cobalt（Co）	Humphries (2010); Campbell (2020)
Gallium (Ga)	Ayres & Peiro (2013); Frenzel et al. (2017)
Germanium (Ge)	Harper et al. (2015); Frenzel et al. (2017)
Indium (In)	Elshkaki & Shen. (2019); Grandell et al. (2016); Frenzel et al. (2017)
Lithium (Li)	Liu et al. (2019); King & Boxall (2019)
Molybdenum (Mo)	Leader et al. (2019); Zhu et al. (2020)
Selenium (Se)	Grandell et al. (2016); Elshkaki & Shen (2019);
Tantalum (Ta)	Humphries (2010); Kim et al. (2019)
Tellurium (Te)	Watari et al. (2020); Valero et al. (2018)
Vanadium (V)	Moss et al. (2013); Gunn et al. (2014)
Zirconium (Zr)	Moss et al. (2011); Zhu et al. (2020)

Note: Two elements, selenium and tellurium are metalloids rather than metals. However, they have some similar characteristics and applications with metals, therefore they are analysed together with other metals in the literature (i.e. Elshkaki & Shen, 2019; Zhu et al., 2020; Watari et al., 2020).

Table 2. Metal companionability between base and rare metals

Rare metals	Base metals and companionability degree
Bismuth (Bi)	Lead (Pd) (54%)
Cadmium (Cd)	Zinc (Zn) (100%)
Cobalt（Co）	Nickel (Ni) (50%); Copper (Cu) (35%)
Gallium (Ga)	Aluminium (Al) (100%)
Germanium (Ge)	Zinc (Zn) (60%)
Indium (In)	Zinc (Zn) (80%)
Lithium (Li)	Potassium (K) (52%)
Molybdenum (Mo)	Copper (Cu) (46%)
Selenium (Se)	Copper (Cu) (90%)
Tantalum (Ta)	Tin (Sn) (15%); Niobium (Nb) (13%)
Tellurium (Te)	Copper (Cu) (90%)
Vanadium (V)	Iron (Fe) (62%)
Zirconium (Zr)	Titanium (Ti) (100%)

Information Sources: Nassar et al. (2015); Harper et al. (2015). Companionability degree measures what percentage of an RM is produced from the co-production process with a base metal.

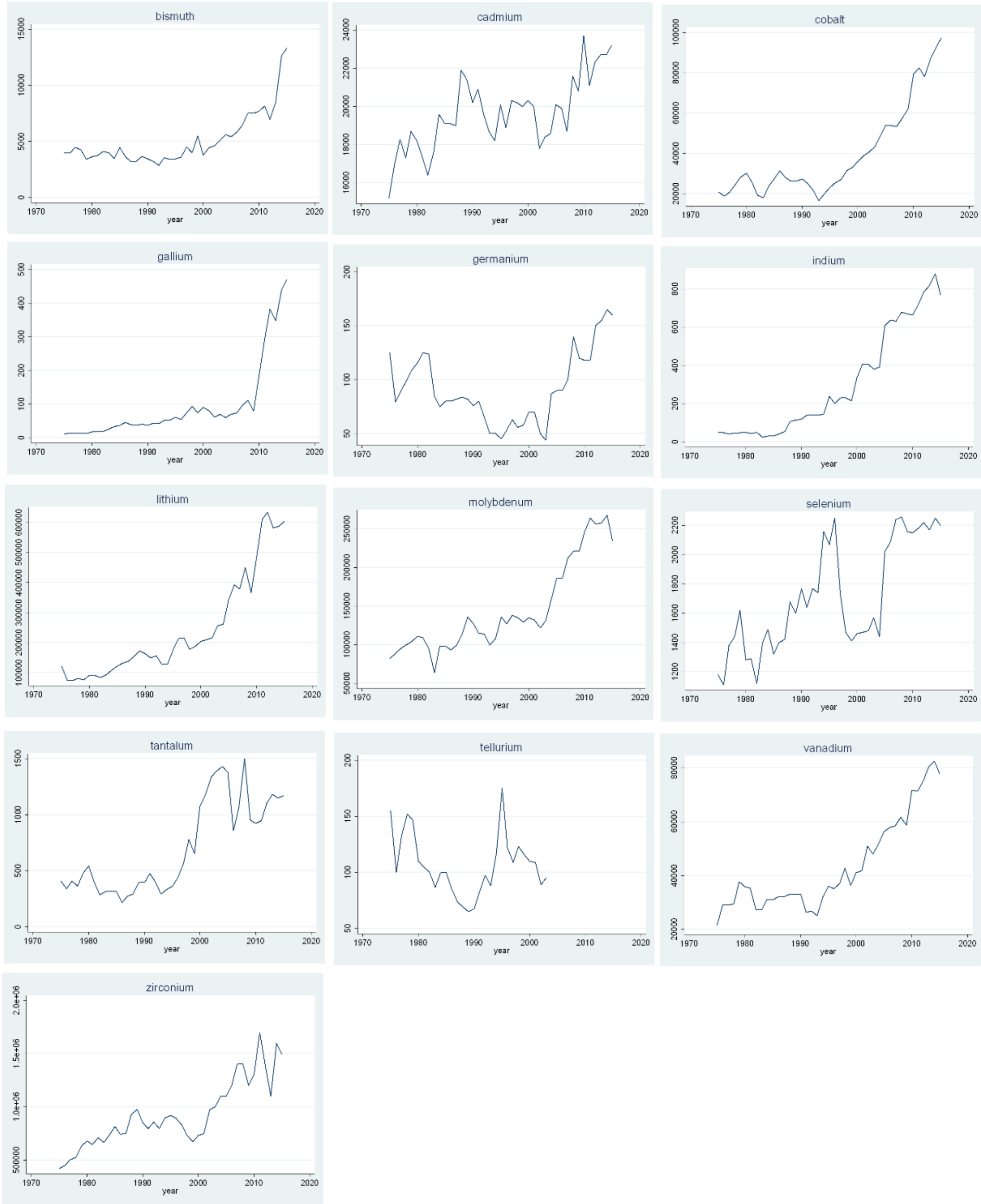
Table 3. Regression results for (T-3)

	OLS		IV		
VARIABLES	(1)	(2)	(3)	(4)	(5)
$RM\ production_{j,t-3}$	0.0271***	0.0120***	0.0647***	0.0373***	0.0211***
	(0.00286)	(0.00252)	(0.00865)	(0.00659)	(0.00752)
$Science\ papers\ on\ RM_{j,t-3}$		0.0803***		0.0314	-0.00529
		(0.0201)		(0.0247)	(0.0293)
$Forward\ citation\ difference\ _{i,j,t-3}$		0.0724***		0.0723***	0.0663***
		(0.00179)		(0.00180)	(0.00409)
$Knowledge\ stock\ _{i,j,t-3}$		0.377***		0.372***	0.174***
		(0.0143)		(0.0140)	(0.0139)
$RM\ price_{j,t-3}$		0.00410*		0.00716***	0.00713
		(0.00225)		(0.00242)	(0.00491)
Constant	-0.0934***	-1.038***			
	(0.00573)	(0.0477)			
Tech-RM Fixed effect	Yes	Yes	Yes	Yes	Yes
Observations	214,004	214,004	214,004	214,004	12,718
R-squared	0.023	0.186	0.011	0.182	0.244
Number of pairs	5,644	5,644	5,644	5,644	347

Note: *, **, *** indicate significance level at 10%, 5% and 1%, respectively. First stage results for columns 3, 4 and 5 are reported in Table A8 in the online Appendix. Robust standard errors are clustered at the Tech-RM level, shown in the parentheses.

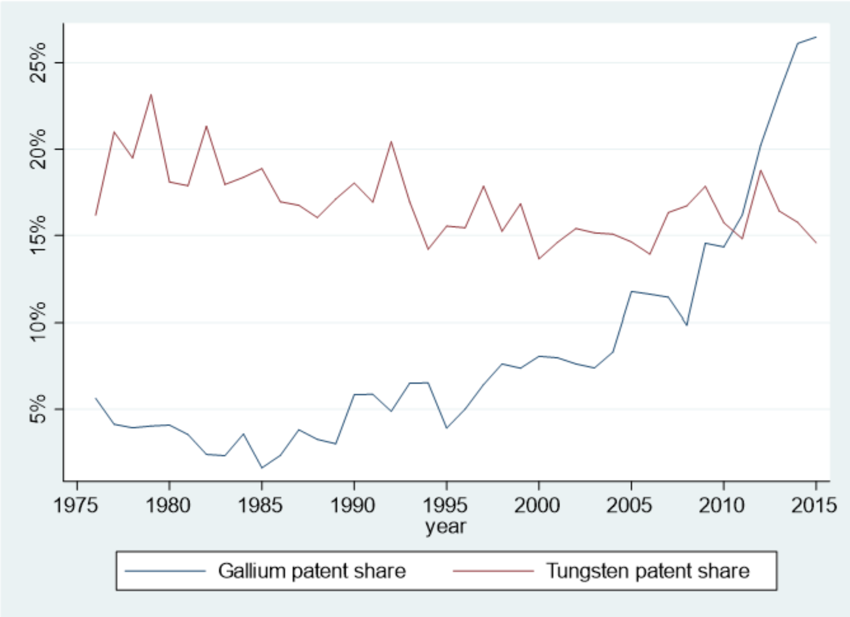
The sample of the column 5 excludes subgroups in which any patents use BM.

Figure 1. Global annual production of the 13 RMs, 1975-2015 (Unit, metric ton)



Data source: US Geological Survey

Figure 2. Example: material shift in lighting technologies, share of patents based on different RMs: Gallium vs Tungsten



Note: Lighting technologies include H01J: electric discharge tubes or discharge lamps; H01K: electric incandescent lamps; H01L33: Semiconductor devices with at least one potential-jump barrier or surface barrier specially adapted for light emission, including LED technologies.

Figure 3. General trends of technological dependence on RMs

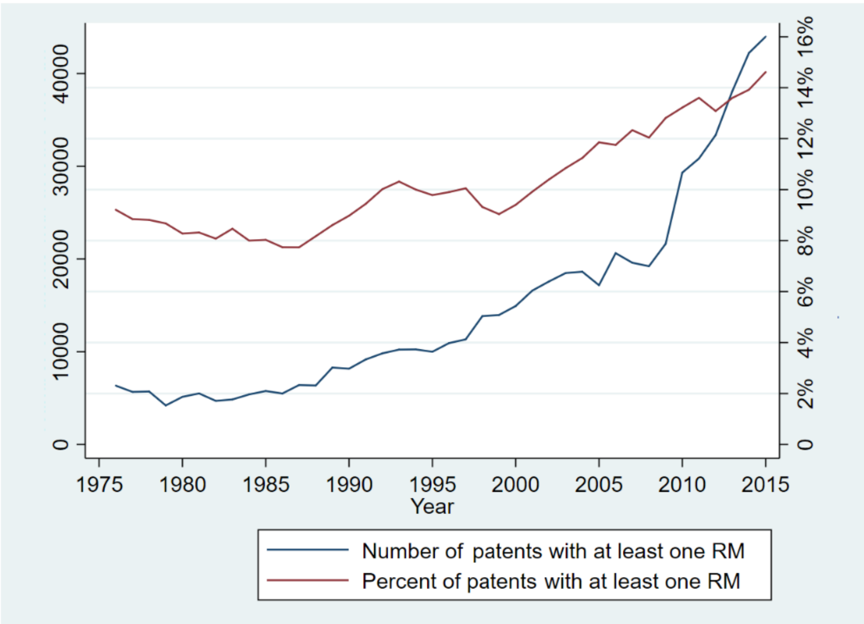


Figure 4. Trends in RM-dependence by WIPO technology sector, 1976-2015 (left: absolute nos.; right: % shares)

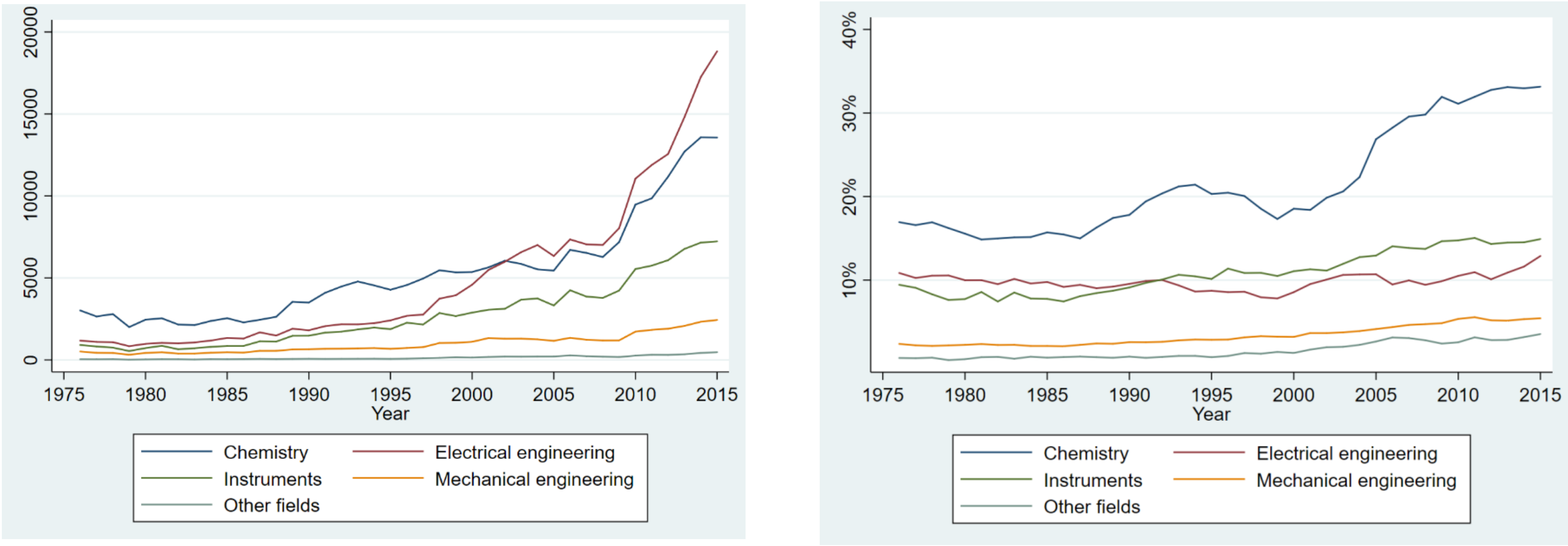


Figure 5. Share of RM-based patents by technology field, 1976-2015

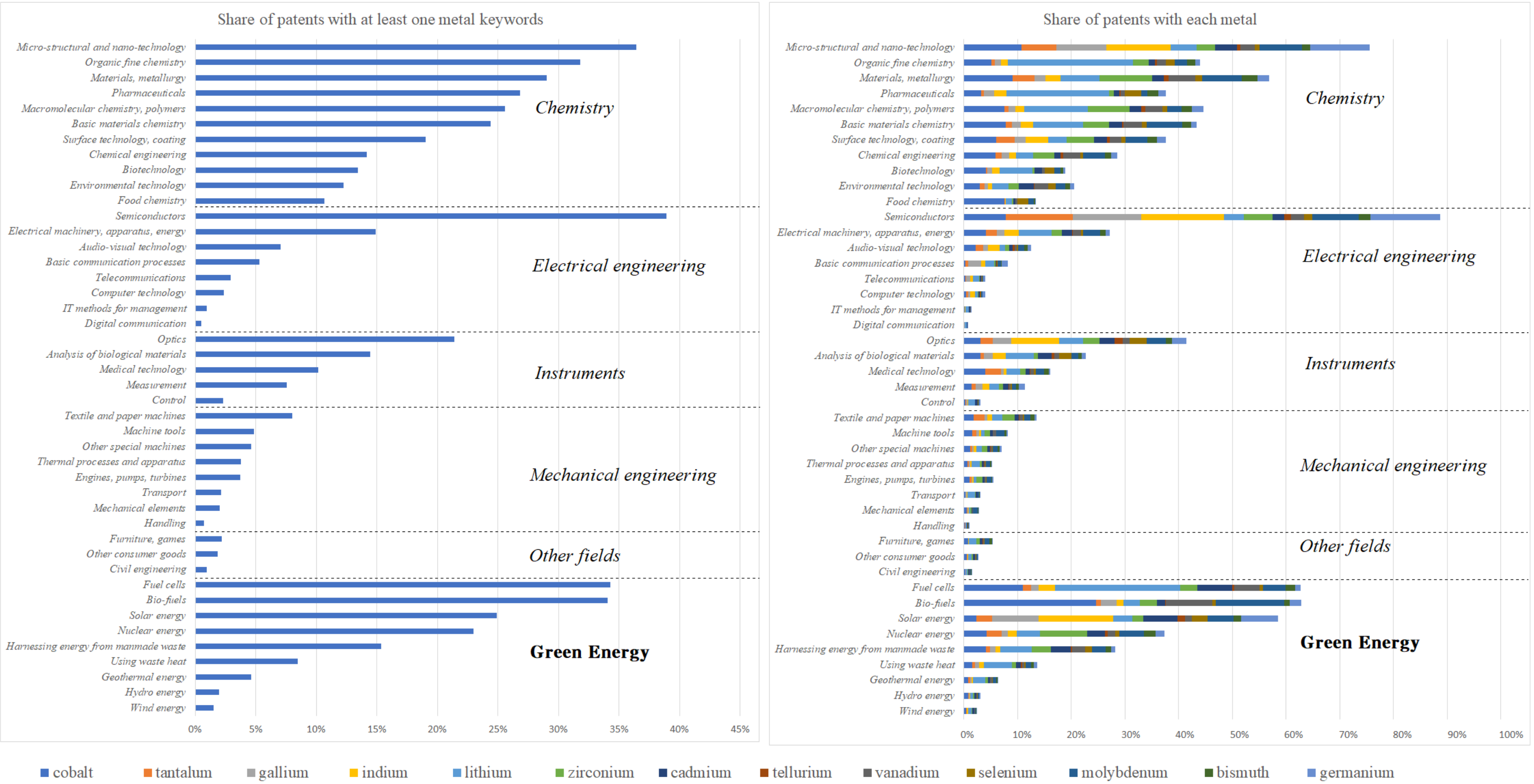
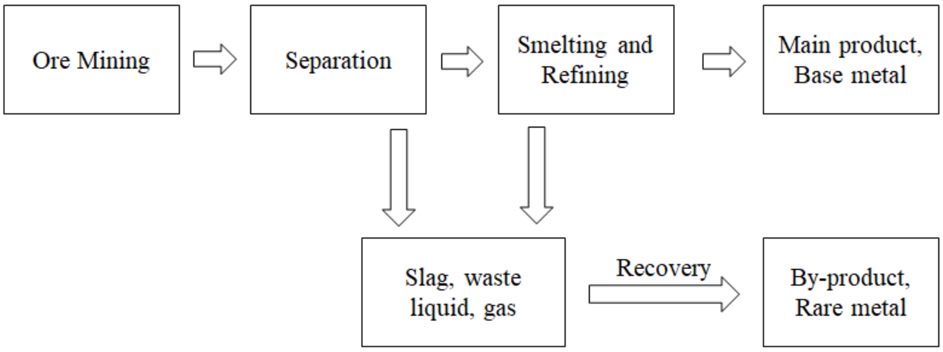


Figure 6. Co-production process of base metals (main product) and RMs (by-product)

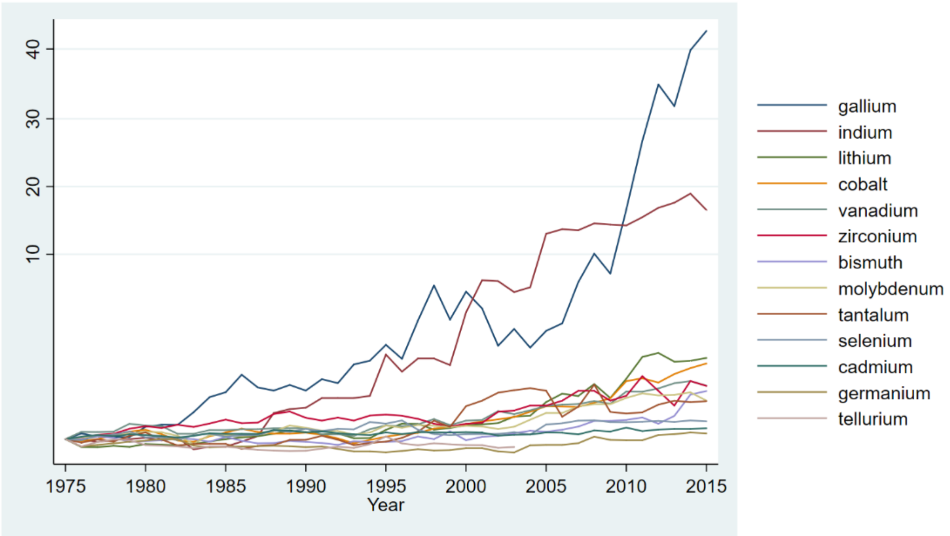


Information Sources: (Nassar et al., 2015; Harper et al., 2015)

Online Appendix. Supplementary materials

A.1 Description of RM global production

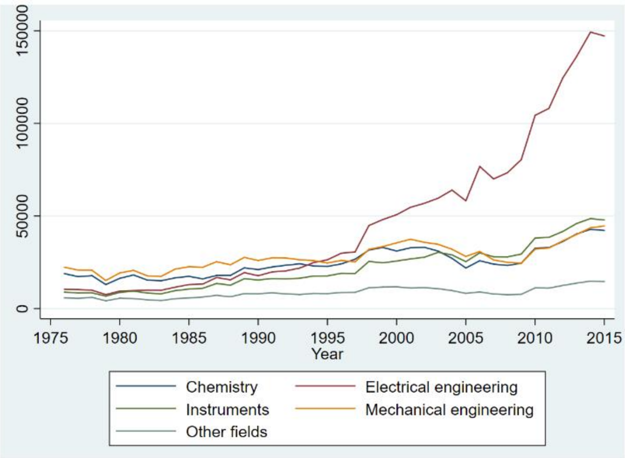
Figure A1. Production changes for the 13 RMs, 1975-2015, relative to 1975 (Y axis has unequal intervals)



Data source: US Geological Survey

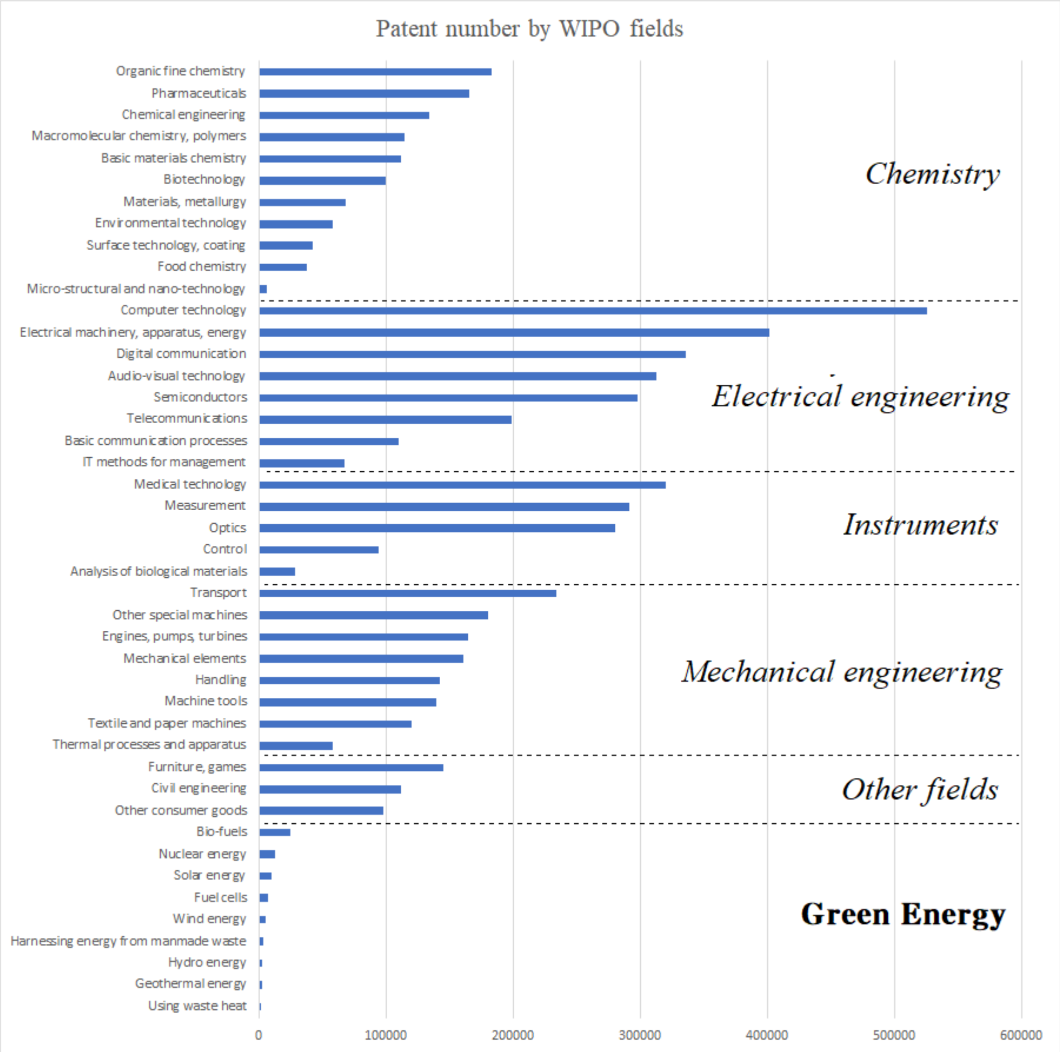
A.2 Patent Description

Figure A2. Patent trends, 1976-2015



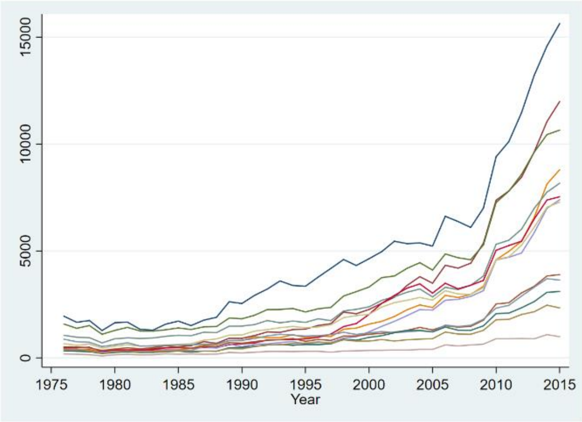
Total USPTO granted patents **Total USPTO patents by WIPO technology sector**

Figure A3. Total patent number by WIPO 35 technology fields and 5 sectors



Note: Green technologies are identified according to the WIPO Green Inventory list. (https://www.wipo.int/classifications/ipc/green-inventory/home)

Figure A4. Trends of technological dependence by RM, 1976-2015 (left: absolute patent nos.; right: ratios relative to 1976)



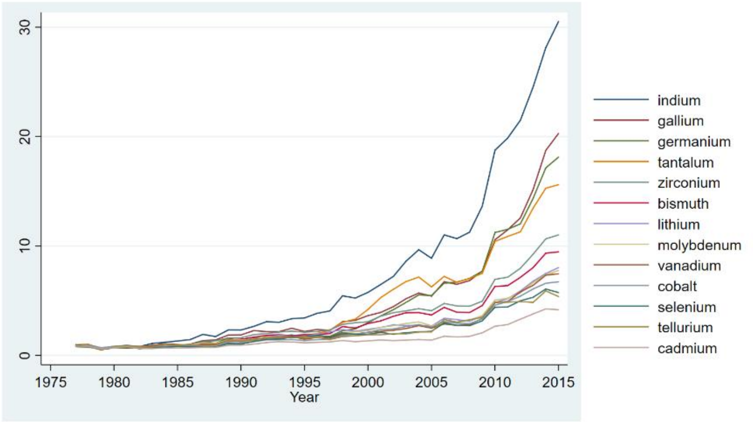
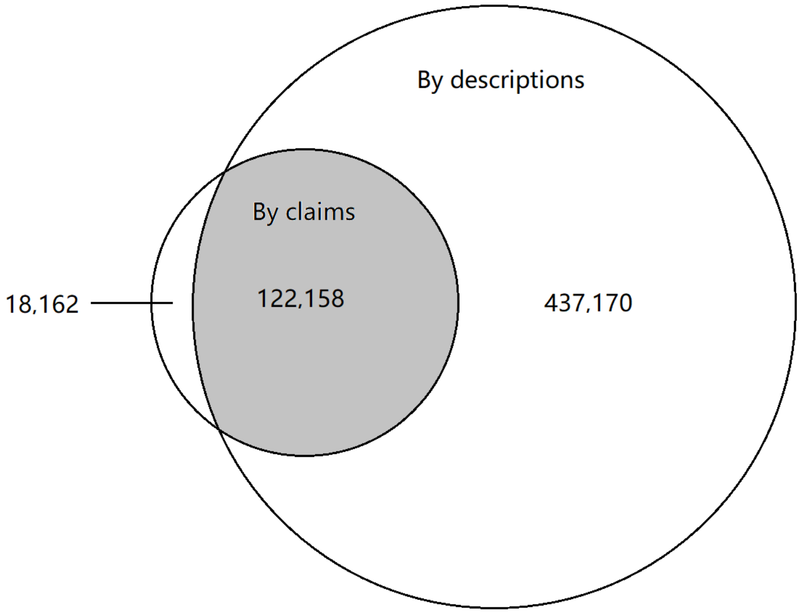


Figure A5. Number of RM-based patents identified using different parts of the patent text



As figure A5 shows, there are in total 577,490 RM-based patents that can be identified as such either by descriptions or claims. Of these, 437,143 (75.69%) can only be identified as RM-based by description, and 18,162 (3.14%) only by claim; the remaining 122,158 (21.15%) can be identified by both. This means that most RM-based patents identified as such by claim can also be identified by description; instead, for those identified on the basis of RM keywords found in the descriptions, only 22% are also identified in claims (in such cases, RMs are materials used in the technology but are not regarded as the major innovative content by the inventor). Therefore, using both parts of the patent text to identify RM keywords provides a balance between the "completeness" and "innovativeness" of patent information.

A.3 Sample description

Table A1. Distribution of Tech-RM pairs by technology sector and field

Sector	Field	Number of pairs
Chemistry	Organic fine chemistry	618
Chemistry	Basic materials chemistry	263
Chemistry	Macromolecular chemistry, polymers	216
Chemistry	Chemical engineering	157
Chemistry	Materials, metallurgy	117
Chemistry	Biotechnology	111
Chemistry	Environmental technology	49
Chemistry	Surface technology, coating	29
Chemistry	Micro-structural and nano-technology	26
Chemistry	Food chemistry	6
Electrical engineering	Semiconductors	1807
Electrical engineering	Electrical machinery, apparatus, energy	589
Electrical engineering	Audio-visual technology	173
Electrical engineering	Computer technology	78
Electrical engineering	Basic communication processes	21
Electrical engineering	Telecommunications	11
Electrical engineering	Digital communication	1
Instruments	Optics	751
Instruments	Medical technology	260
Instruments	Analysis of biological materials	65
Instruments	Measurement	55
Instruments	Control	5
Mechanical engineering	Textile and paper machines	75
Mechanical engineering	Machine tools	41
Mechanical engineering	Other special machines	30
Mechanical engineering	Transport	30
Mechanical engineering	Engines, pumps, turbines	22
Mechanical engineering	Thermal processes and apparatus	9
Mechanical engineering	Mechanical elements	8
Mechanical engineering	Handling	3
Other fields	Furniture, games	16
Other fields	Civil engineering	1
Other fields	Other consumer goods	1

Table A2. Distribution of Tech-RM pairs by metal

Metal	Number of pairs
lithium	1117
cobalt	764
indium	657
tantalum	546
molybdenum	522
gallium	451
zirconium	446
germanium	437
vanadium	206
cadmium	182
selenium	135
bismuth	129
tellurium	52
Sum	5,644

Table A3. Independent variables description and correlation matrix

	Mean	Std dev	Min	Max	1	2	3	4	5
1. $RM\ production_{j,t}$	2.83419	4.34898	.352	42.6363	1.0000				
2. $Science\ papers\ on\ RM_{j,t}$ (z-score)	0	1	-1.3069	2.6912	-0.2368	1.0000			
3. $Forward\ citation\ _{i,j,t}$ (log)	2.478011	1.908416	0	8.070594	0.0154	-0.1196	1.000		
4. $Knowledge\ stock\ _{i,t}$ (log)	1.699815	1.144589	0	7.069808	0.2777	-0.1982	0.456	1.0000	
5. $RM\ price_{j,t}$	2.382514	2.00034	.0488529	15.9375	-0.0187	-0.1373	0.025	0.2194	1.0000

Table A4. Regression results (T-5)

	OLS		IV		
VARIABLES	(1)	(2)	(3)	(4)	(5)
$RM\ production_{j,t-3}$	0.0368***	0.0169***	0.182***	0.136***	0.0591***
	(0.00411)	(0.00384)	(0.0222)	(0.0210)	(0.0226)
$Science\ papers\ on\ RM_{j,t-3}$		0.122***		-0.105**	-0.0379
		(0.0227)		(0.0473)	(0.0459)
$Forward\ citation\ _{i,j,t-3}$		0.0891***		0.0878***	0.0652***
		(0.00227)		(0.00233)	(0.00487)
$Knowledge\ stock\ _{i,j,t-3}$		0.240***		0.227***	0.0709***
		(0.0142)		(0.0141)	(0.0175)
$RM\ price_{j,t-3}$		0.00276		-0.000869	-0.00659
		(0.00221)		(0.00223)	(0.00446)
Constant	-0.107***	-0.694***			
	(0.00710)	(0.0526)			
Tech-RM Fixed effect	Yes	Yes	Yes	Yes	Yes
Year Fixed effect	Yes	Yes	Yes	Yes	Yes
Observations	202,820	202,820	202,820	202,820	12,128
R-squared	0.022	0.124	0.008	0.082	0.157
Number of pairs	5,644	5,644	5,644	5,644	347

Note: *, **, *** indicate significance level at 10%, 5% and 1%, respectively. First stage results for columns 3, 4 and 5 are reported in Table A8 in the online appendix. Robust standard errors are clustered at the Tech-RM level, shown in the parentheses.

The sample of the column 5 excludes subgroups in which any patent use the base metal.

A.4 Robustness test results

Table A5. Robustness tests on IV

VARIABLES	(1) Heterogeneous companionability	(2) Companionability higher than 80%	(3) First stage with cross term of BM and RM-decade dummies	(4) Excluding energy transition metals
$RM\ production_{j,t-3}$	0.0272***	0.0185*	0.0144***	0.0130**
	(0.00559)	(0.0104)	(0.00288)	(0.00536)
$Science\ papers\ on\ RM_{j,t-3}$	0.0554**	0.0131	0.0756***	0.0334
	(0.0236)	(0.0797)	(0.0200)	(0.0902)
$Forward\ citation\ _{i,j,t-3}$	0.0714***	0.0656***	0.0724***	0.0761***
	(0.00179)	(0.00291)	(0.00179)	(0.00309)
$Knowledge\ stock\ _{i,j,t-3}$	0.373***	0.367***	0.377***	0.377***
	(0.0141)	(0.0177)	(0.0143)	(0.0162)
$RM\ price_{j,t-3}$	0.00543**	-0.00745	0.00439*	-0.00387
	(0.00239)	(0.0105)	(0.00225)	(0.00508)
Year Fixed effect	Yes	Yes	Yes	Yes
Tech-RM Fixed effect	Yes	Yes	Yes	Yes
R-squared	0.182	0.212	0.186	0.208
Observations	208,360	72,606	214,004	67,564
Number of pairs	5,644	1,923	5,644	1,778

Note: *, **, *** indicate significance level at 10%, 5% and 1%, respectively. Robust standard errors are clustered at the Tech-RM level, shown in the parentheses. First stage results of column 1, 2 and 4 are reported in column 1-3 in Table A9. First stage results of column 3 are reported in Table A10.

Table A6. Identifying RM key words by claims

VARIABLES	(1) OLS	(2) IV
$RM\ production_{j,t-3}$	0.0129***	0.0205***
	(0.00292)	(0.00645)
$Science\ papers\ on\ RM_{j,t-3}$	0.0450	0.0299
	(0.0335)	(0.0343)
$Forward\ citation_{\ i,j,t-3}$	0.00658	0.00655
	(0.00477)	(0.00476)
$Knowledge\ stock_{\ i,j,t-3}$	0.192***	0.190***
	(0.0239)	(0.0244)
$RM\ price_{j,t-3}$	-0.0300***	-0.0294***
	(0.00960)	(0.00959)
Constant	-1.151***	
	(0.102)	
Tech-RM Fixed effect	Yes	Yes
Observations	26,660	26,660
R-squared	0.182	0.181
Number of pairs	703	703

Note: *, **, *** indicate significance level at 10%, 5% and 1%, respectively. First stage results of column 3 are in Table A11. Robust standard errors are clustered at the Tech-RM level, shown in the parentheses.

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Table A7. Robustness test by alternative regressions

	(1) Poisson IV	(2) First Difference IV
$RM\ production_{j,t-3}$	0.0435***	0.0188***
	(0.00866)	(0.00707)
$Science\ papers\ on\ RM_{j,t-3}$	0.190***	-0.0256**
	(0.0293)	(0.0119)
$Forward\ citation_{i,j,t-3}$	0.246***	0.00241***
	(0.00331)	(0.000555)
$Knowledge\ stock\ _{i,j,t-3}$	0.444***	0.00225
	(0.00801)	(0.00450)
$RM\ price_{j,t-3}$	0.00511**	0.00443***
	(0.00255)	(0.00107)
Constant	0.0937***	0.0109***
	(0.000829)	(0.000915)
Tech-RM Fixed effect	Yes	Yes
Year Fixed effect	Yes	Yes
Observations	197,540	208,360
R-squared		-0.000
Number of pairs	5,644	5,644

Note: *, **, *** indicate significance level at 10%, 5% and 1%, respectively. First stage results of column 3 are in Table A11. Robust standard errors are clustered at the Tech-RM level, shown in the parentheses.

A.5 First stage regression results

Table A8. First stage regression results of Table 3, Table A4 and Table A5

VARIABLES	(1) T+3	(2) T+3	(3) T+3 excluding BM key words	(4) T+5	(5) T+5	(6) T+5 excluding BM key words
$BM\ production_{j,t-\mathrm{k}}$	2.983***	3.082***	5.451***	1.365***	1.236***	2.453***
	(0.0900)	(0.0830)	(0.152)	(0.0434)	(0.0453)	(0.0967)
$Science\ papers\ on\ RM_{j,t-k}$		2.070***	-0.248		1.854***	0.449***
		(0.0574)	(0.291)		(0.0539)	(0.166)
$Forward\ citation\ _{i,j,t-k}$		0.000525	0.0196		0.00826**	0.0216*
		(0.00457)	(0.0175)		(0.00383)	(0.0122)
$Knowledge\ stock\ _{i,j,t-k}$		0.142***	0.269***		0.0865***	0.0349
		(0.0197)	(0.0882)		(0.0170)	(0.0679)
$RM\ price_{j,t-k}$		-0.132***	-0.229***		0.00819**	-0.0471**
		(0.00564)	(0.0222)		(0.00404)	(0.0199)
Constant	0.743***	1.499***	-0.278	2.603***	3.516***	2.025***
	(0.128)	(0.122)	(0.370)	(0.0641)	(0.0946)	(0.331)
Observations	214,004	214,004	12,718	202,820	202,820	12,128
R-squared	0.408	0.483	0.672	0.359	0.485	0.612
Number of pairid	5,644	5,644	347	5,644	5,644	347
Underidentification test (Kleibergen-Paap rk LM statistic):	527.420***	611.589***	150.003***	513.468***	429.763***	118.053***
Weak identification test (Kleibergen-Paap rk Wald F statistic):	1098.672	1379.718	1278.082	991.156	745.868	642.953
Stock-Yogo weak ID test critical values:						
10% maximal IV size	16.38	16.38	16.38	16.38	16.38	16.38
15% maximal IV size	8.96	8.96	8.96	8.96	8.96	8.96
20% maximal IV size	6.66	6.66	6.66	6.66	6.66	6.66
25% maximal IV size	5.53	5.53	5.53	5.53	5.53	5.53
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Tech-RM FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: *, **, *** indicate significance level at 10%, 5% and 1%, respectively. Robust standard errors are clustered at the Tech-RM level, shown in the parentheses.

The IV $Base\ metal\ production_{j,t-k}$ is significantly and positively correlated with the variable of interest $RM\ production_{j,t-\mathrm{k}}$, indicating that one unit increase in the production of primary base metal corresponds to a 3.082 unit increase in the by-product RM production, controlling for other variables and fixed effects. We now obtain the levels of RM production exogenously predicted by the instrument and examine their effects on innovation dynamics. Considering that our models account for clustered standard errors for Technology and RM pairs, the i.i.d assumption is not valid and we report the LM and Wald versions of the Kleibergen and Paap (2006) statistics. The results reject the under-identification null hypothesis, as shown by the p-values of LM statistics. Moreover, as the Kleibergen-Paap rk Wald F statistics is larger than all Stock-Yogo critical values, we can also reject the weak identification null hypothesis.

Table A9. First stage regression results for alternative IV

VARIABLES	(1) Heterogeneous companionability	(2) Companionability lower than 80%	(3) Excluding energy transition metals
$BM\ production_{j,t-\mathrm{k}}$	25.50***	4.386***	6.557***
	(0.475)	(0.122)	(0.0756)
$Science\ papers\ on\ RM_{j,t-k}$	1.895***	6.887***	3.402***
	(0.0609)	(0.135)	(0.182)
$Forward\ citation\ _{i,j,t-k}$	-0.00149	0.0352***	0.00342
	(0.00456)	(0.00953)	(0.00516)
$Knowledge\ stock\ _{i,j,t-k}$	0.138***	0.459***	0.228***
	(0.0194)	(0.0433)	(0.0185)
$RM\ price_{j,t-k}$	-0.127***	-0.702***	-0.513***
	(0.00537)	(0.0177)	(0.0118)
Constant	0.961***	11.18***	1.534***
	(0.106)	(0.478)	(0.222)
Observations	208,360	72,606	67,564
R-squared	0.520	0.695	0.732
Number of pairs	5,644	1,923	1,778
Underidentification test (Kleibergen-Paap rk LM statistic):	595.267***	411.498***	1166.334***
Weak identification test (Kleibergen-Paap rk Wald F statistic):	2885.850	1286.273	7533.44
Stock-Yogo weak ID test critical values:			
10% maximal IV size	16.38	16.38	16.38
15% maximal IV size	8.96	8.96	8.96
20% maximal IV size	6.66	6.66	6.66
25% maximal IV size	5.53	5.53	5.53
Year FE	Yes	Yes	Yes
Tech-RM FE	Yes	Yes	Yes

Note: *, **, *** indicate significance level at 10%, 5% and 1%, respectively. Robust standard errors are clustered at the Tech-RM level, shown in the parentheses.

Table A10. First stage with cross term Of BM and RM-decades dummies

VARIABLES	First stage with cross term Of BM and RM-decade dummies
BM×Dummy_bismuth_decade1	-4.091***
	(0.163)
BM×Dummy_bismuth_decade2	-5.221***
	(0.185)
BM×Dummy_bismuth_decade3	-13.43***
	(0.521)
BM×Dummy_bismuth_decade4	-0.182***
	(0.0670)
BM×Dummy_cadmium_decade1	-2.662***
	(0.0261)
BM×Dummy_cadmium_decade2	-2.543***
	(0.0339)
BM×Dummy_cadmium_decade3	-7.143***
	(0.217)
BM×Dummy_cadmium_decade4	0.456***
	(0.109)
BM×Dummy_cobalt_decade1	-3.980***
	(0.153)
BM×Dummy_cobalt_decade2	-3.335***
	(0.128)
BM×Dummy_cobalt_decade3	-6.756***
	(0.285)
BM×Dummy_cobalt_decade4	0.826***
	(0.0347)
BM×Dummy_gallium_decade1	11.31***
	(0.0213)
BM×Dummy_gallium_decade2	9.709***
	(0.0166)
BM×Dummy_gallium_decade3	4.622***
	(0.146)
BM×Dummy_gallium_decade4	9.256***
	(0.0654)
BM×Dummy_germanium_decade1	-1.816***
	(0.0228)
BM×Dummy_germanium_decade2	-2.227***
	(0.0330)
BM×Dummy_germanium_decade3	-6.984***
	(0.216)
BM×Dummy_germanium_decade4	0.736***
	(0.110)
BM×Dummy_indium_decade1	6.797***
	(0.0257)

BM×Dummy_indium_decade2	6.860***
	(0.0344)
BM×Dummy_indium_decade3	3.619***
	(0.216)
BM×Dummy_indium_decade4	11.83***
	(0.108)
BM×Dummy_lithium_decade1	-0.956***
	(0.0458)
BM×Dummy_lithium_decade2	-0.952***
	(0.0528)
BM×Dummy_lithium_decade3	-6.937***
	(0.315)
BM×Dummy_lithium_decade4	4.284***
	(0.134)
BM×Dummy_molybdenum_decade1	-0.922***
	(0.0541)
BM×Dummy_molybdenum_decade2	-0.897***
	(0.0414)
BM×Dummy_molybdenum_decade3	-4.314***
	(0.150)
BM×Dummy_molybdenum_decade4	1.719***
	(0.106)
BM×Dummy_selenium_decade1	-1.967***
	(0.0513)
BM×Dummy_selenium_decade2	-1.798***
	(0.0421)
BM×Dummy_selenium_decade3	-5.174***
	(0.148)
BM×Dummy_selenium_decade4	0.738***
	(0.107)
BM×Dummy_tantalum_decade1	1.875***
	(0.0526)
BM×Dummy_tantalum_decade2	1.353***
	(0.0489)
BM×Dummy_tantalum_decade3	-4.201***
	(0.245)
BM×Dummy_tantalum_decade4	5.457***
	(0.206)
BM×Dummy_tellurium_decade1	-0.615***
	(0.0750)
BM×Dummy_tellurium_decade2	-1.077***
	(0.0600)
BM×Dummy_tellurium_decade3	-4.573***
	(0.134)
BM×Dummy_tellurium_decade4	0
	(0)
BM×Dummy_vanadium_decade1	-1.041***
	(0.0431)

BM×Dummy_vanadium_decade2	-1.399***
	(0.0385)
BM×Dummy_vanadium_decade3	-7.074***
	(0.274)
BM×Dummy_vanadium_decade4	1.879***
	(0.0985)
BM×Dummy_zirconium_decade1	0.115***
	(0.0186)
BM×Dummy_zirconium_decade2	0.0367
	(0.0247)
BM×Dummy_zirconium_decade3	-4.135***
	(0.173)
BM×Dummy_zirconium_decade4	2.011***
	(0.0890)
$Science\ papers\ on\ RM_{j,t-3}$	0.352***
	(0.00987)
$Forward\ citation\ _{i,j,t-3}$	-0.00342**
	(0.00145)
$Knowledge\ stock\ _{i,j,t-3}$	-0.00474
	(0.00425)
$RM\ price_{j,t-3}$	0.0287***
	(0.00189)
Constant	-1.829***
	(0.170)
Observations	214,004
Number of pairs	5,644
R-squared	0.867
Underidentification test (Kleibergen-Paap rk LM statistic):	5521.551***
Weak identification test (Kleibergen-Paap rk Wald F statistic):	3.9e+07
Stock-Yogo weak ID test critical values:	
5% maximal IV relative bias	21.31
10% maximal IV relative bias	11.11
20% maximal IV relative bias	5.87
30% maximal IV relative bias	4.08
10% maximal IV size	136.30
15% maximal IV size	70.03
20% maximal IV size	47.65
25% maximal IV size	36.43
Year FE	Yes
RM-Tech FE	Yes

Note: *, **, *** indicate significance level at 10%, 5% and 1%, respectively. Robust standard errors are clustered at the Tech-RM level, shown in the parentheses.

Table A11. First stage regression results for alternative model settings and claim model

VARIABLES	(1) Poisson regression	(2) Claim model	VARIABLES	(3) First difference
$BM\ production_{j,t-3}$	3.082***	3.652***	$D.BM\ production_{j,t-3}$	1.890***
	(0.0830)	(0.235)		(0.0576)
$Science\ papers\ on\ RM_{j,t-3}$	2.070***	2.407***	$D.Science\ papers\ on\ RM_{j,t-3}$	0.404***
	(0.0574)	(0.148)		(0.00724)
$Forward\ citation\ _{i,j,t-3}$	0.000525	0.00326*	$D.Forward\ citation\ _{i,j,t-3}$	-0.00477***
	(0.00457)	(0.00174)		(0.000831)
$Knowledge\ stock\ _{i,j,t-3}$	0.142***	0.452***	$D.Knowledge\ stock\ _{i,j,t-3}$	-0.0584***
	(0.0197)	(0.0722)		(0.00844)
$RM\ price_{j,t-3}$	-0.132***	-0.238***	$D.RM\ price_{j,t-3}$	0.0416***
	(0.00564)	(0.0286)		(0.000845)
Constant	1.499***	-0.931**	Constant	0.123***
	(0.122)	(0.441)		(0.00172)
Observations	214,004	26,660	Observations	208,360
R-squared	0.483	703	R-squared	0.080
Number of pairs	5,644	0.503	Number of pairid	5,644
Underidentification test (Kleibergen-Paap rk LM statistic):	611.589***	91.750***	Underidentification test (Kleibergen-Paap rk LM statistic):	956.495***
Weak identification test (Kleibergen-Paap rk Wald F statistic):	1379.718	240.644	Weak identification test (Kleibergen-Paap rk Wald F statistic):	1077.271
Stock-Yogo weak ID test critical values:			Stock-Yogo weak ID test critical values:	
10% maximal IV size	16.38	16.38	10% maximal IV size	16.38
15% maximal IV size	8.96	8.96	15% maximal IV size	8.96
20% maximal IV size	6.66	6.66	20% maximal IV size	6.66
25% maximal IV size	5.53	5.53	25% maximal IV size	5.53
Year FE	Yes	Yes	Year FE	Yes
RM-Tech FE	Yes	Yes	RM-Tech FE	Yes

Note: *, **, *** indicate significance level at 10%, 5% and 1%, respectively. Robust standard errors are clustered at the Tech-RM level, shown in the parentheses.