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

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Abstract:

The unique properties of a wide range of Rare Metals (RMs) are crucial to achieve the functionality of modern technologies. By text mining 5,146,615 USPTO patents during the period 1976-2015, this paper systematically studies the technological dependence of new inventions on 13 key RMs, with the aim of exploring the link between critical raw materials and frontier technological innovation. We find that RMs play an increasing role as the material basis for modern technologies: the dependence varies significantly across technological areas and metal types, and it is particularly high for some emerging technologies such as semiconductors, nanotechnology, and green energy technologies. Further, we use a panel of technology-RM pairs over four decades to assess the impact of RM supply on innovation dynamics. The results show that increases in the supply of an RM significantly improve the patent output of technology areas based on it, contributing to the understanding of how innovation dynamics are shaped by the availability of natural resources with technological criticality.

Keywords: Critical raw materials, Rare metals, Technological dynamics, Patent text mining, Instrumental variables estimation

JEL classification: O30; O31; O33; Q31

1. Introduction

Natural resources are the material basis for industry development and economic growth. As a special group of critical raw materials, rare metals (RMs), also known as minor metals, are becoming more and more prominent in high-tech industries, and are regarded as "technology metals" with great criticality at the innovation frontier (Abraham, 2015; Graedel et al., 2015; European Commission, 2020). Different from major and base metals (e.g., copper, iron, and aluminium), RMs are like the "vitamins" or "spices" for the industry – 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 risks may constrain industrial development and the advancement of modern technologies. For example, the solar energy industry and the technologies related to it 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 and the potential impacts of RMs on frontier technologies, neither innovation studies nor economics research have paid enough attention to RMs.

Against this backdrop, in what follows we systematically analyse the extent to which modern technologies depend on various RMs and attempt to explore a crucial but unanswered question: as critical raw materials of emerging industries and technologies, do changes in RMs' supply influence the innovation dynamics by affecting the patent output of RM-based technology areas?

We first explore the technological dependence on RMs by identifying the RM keywords in the USPTO patent text and observe a high dependency — 10.87% of 5,146,615 patents granted over the period 1976-2015 depends on at least one RM in our sample. Subsequently, we estimate a panel model of 5,644 technology subgroup-RM pairs to assess the impact of RM supply, measured by the annual global metal production, on the innovation performance of RM-based technology areas, measured by patent numbers. A major challenge is the problem of endogeneity, whereby technology developments may reversely affect metal production decisions, or they are simultaneously influenced by unobservable factors, like policy changes and scientific discoveries. We address this issue by developing 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). We find a positive impact of RM supply on innovation — when the production of an RM increases by 1% relative to the level in 1975, on average patent outputs in technology subgroups based on this RM increase by 0.026%. The positive impact is highly robust using alternative IVs, regression models, samples, thresholds, and definitions of RM-based technology areas. These findings support the idea that RM supply influences the dynamics of frontier technological innovation.

Our paper contributes to the literature in various respects. First, we enhance the understanding of the driving forces of innovation and the endogenous technological development under the influence of changing supply conditions of critical natural resources. As a "creative destruction" process, innovation leads to production paradigm shifts and new combination modes of production factors (Schumpeter, 1942, p.81-86). Mainstream economics argues that technological innovation solves or ameliorates the resource scarcity, enabling society to overcome natural 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 resource supply conditions. It is less clear whether and how natural resources' availability in turn affects technology dynamics, especially, when we consider some critical raw materials with relatively low recycling rate and substitution possibilities, like the RMs (Graedel, 2015). In this paper we argue that because of their unique technological characteristics, the rarity and supply risks of RMs may become the potential constrains for the advancement of frontier technologies.

Second, this paper also contributes to the resource criticality studies by broadening the understanding of the rare metals. Existing literature on RMs mainly focuses 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 (Diemel & Cuvelier, 2015; Hofmann et al., 2018). Although regarded as "technology metals", RMs have rarely been systematically studied from an actual technological perspective. It is widely recognized in the literature that modern technology is strongly dependent on critical raw material and RMs, 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 dependency is: following Diemer et al. (2021), this paper makes an attempt to quantitatively and comprehensively measure RM technological dependence through patent text mining.

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

2.Literature review

2.1 Technology dynamics and natural resource availability

Different streams of literature have analysed the interdependency between technological dynamics, natural resource availability and economic growth. In the neo-classical growth theories, technology determines the relationship between natural resources and economic growth. Solow (1974), Dasgupta & Heal (1974) as well as Stiglitz (1974) use one-sector optimal growth models with non-renewable resources as input to explain the compatibility between natural resource constraints and economic development. They come to the conclusion that with exogenous technologies as the fundamental driving force, positive long-run growth can be achieved in the presence of non-renewable natural resources. Technological progress and capital accumulation can substitute resources and compensate for the negative effects of resource scarcity. However, this exogenous perspective does not consider that natural resources may in turn influence technological progress (Barbier, 1999). The relationship between natural resource availability and technology development is then endogenized by resource and ecological economists in the framework of the New Growth Theory. For example, Barbier (1999) modifies the Romer-Stiglitz model by allowing resource scarcity as a constraint condition for innovation and shows that it may offset the long-run rate of innovation. Bretschger (1999; 2005) uses a multi-sector setting, and assuming non-renewable resources as the essential inputs in the research sector he finds that resource supply conditions lead to structural changes across sectors and have a deep influence on both technology trajectory and economic development.

Under other endogenous views, the “induced innovation hypothesis” argues that technological progress is significantly determined by the dynamics of the supply of production factors (Hicks, 1932; Schmookler, 1962; Jaffe et al., 2004; Chakraborty & Chatterjee, 2017).

Specific factor supply conditions determine the optimal combination of resources, which changes as technology progresses by adjusting the meta-production functions to the dynamics of resource availability (Dosi, 1988). To test this important hypothesis, early empirical studies show that land supply conditions and its substitution with labour determine the trajectories of agricultural technologies (e.g. Hayami & Ruttan, 1970; Kawagoe et al., 1986; Olmstead & Rhode, 1993). More recent works focus on the relationship between conventional energy supply and development of alternative energy technologies (e.g. Newell et al., 1999; Cheon & Urpelainen, 2012; Aghion et al., 2016). In his pioneering article, Popp (2002) shows that anticipated energy prices encourage new patents for a wide range of green and energy-efficient technologies. This inducement effect is further strengthened by properly designed energy policies and environmental standards (e.g. Popp, 2001; 2002; Johnstone et al., 2010; Lindman & Söderholm, 2016; Böhringer et al., 2017), under the assumption of substitutable inputs, Acemoglu et al. (2012) find that environmental policies can direct innovation towards green technologies and lead to long-term sustainable growth.

In summary, existing economics and innovation research provides important explanations for the co-evolution between natural resource supply and technological progress. Nonetheless, many theoretical models are based on strong substitution assumptions between capital and resources (e.g. Solow, 1974) or between different resource inputs (e.g. Acemoglu et al., 2012). Accordingly, empirical studies mainly analyse how the shortage of general inputs (e.g. conventional energies, land) can stimulate new technologies that use relatively abundant resources as a substitute for the scarce ones. This perspective fails to fully consider resource heterogeneity: differently from general inputs, some natural resources, such as critical raw materials, are technologically crucial and therefore the high substitution assumption is unrealistic (Graedel et al., 2015). They work as essential inputs and directly enter core R&D processes, limiting constant innovation rates in the long run. To our knowledge, very little research has analysed the relationship between the supply of such critical resources and technological change.

In this context, this article focuses on the impact of critical raw materials on innovation, bearing in mind that inducement effects may be favoured by the abundance of general inputs like energy and basic materials, major shocks in prices/supplies and scarcities of critical and crucial inputs (Dosi, 1988). As a special group of natural resource, RMs represent a highly relevant case of critical raw materials that are rare, non-renewable and currently irreplaceable. Here we argue that their supply not only indirectly “induces” innovation but may also work as the critical material basis that directly “determines” technological frontier dynamics.

2.2 Rare metals: technological criticality and supply risks

With the advancement of science, the unique electrical, thermal, chemical, and optical properties of RMs have become evident, paving the way for new cutting-edge technologies. As a result, the range of useful and available chemical elements for human societies has gradually expanded. For example, the elements used in computers grew from 11 in the 1980s to 15 in the 1990s, and to 60 in the 2010s (Zepf & Achzet, 2015). Furthermore, the adoption of RM-based technologies generates substantial improvements in the performance of existing products, leading also to the creation of entirely new goods.

Academic research emphasises the high reliance of two major technology paradigm shifts on RMs. First, the transition to clean and green energy technologies strongly depends on RMs (Grandell et al., 2016). 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). Second, alongside the advent of industry 4.0, revolutionary technology breakthroughs in information, communication, and artificial intelligence have significantly increased the complexity and sophistication of electronic equipment, raising the demand for various RMs as essential inputs in advanced electronic components. These include 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 the displays (Eggert, 2010; Gunn, 2014).

Unlike other natural resources, RMs work as critical materials and the technological use is hardly replaced due to their unique properties (Ayres & Peiro, 2013; Abraham, 2015). Engineering and natural science research indicates 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). The 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). Moreover, the potential substitutes of a certain RM are often other RMs which also face supply constraints. For example, this is the case of the replacement of cobalt (Co) with rare earth element neodymium (Nd) in permanent magnets (Ku, 2018). Consequently, studies highlight that the future advancement of many high-tech products will be constrained by the supply shortage of RMs. For instance, the drastic increase in critical RM prices may be an obstacle to the diffusion of green energy products. This may negatively affect the development and adoption of clean energy technologies (Leader et al., 2019).

Relatedly, RM markets are impacted by potential crises in the supply chain. 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). These supply risks come from different stages of the RM 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 environments, which make the critical ore supply vulnerable to wars, social and political instability, human rights violation and natural disasters (e.g. Berman et al., 2017; Giuliani, 2018; Diemer et al., 2021). In addition, the smelting and refining of many RMs has gradually shifted to multinationals from emerging countries (especially, China), which is accompanied by more uncertainties from trade conflicts and geopolitical events (Narine, 2012; Mancheri, 2015; Fiaschi et al., 2017; Lederer & McCullough, 2018).

In this context, the RM supply may influence researchers' innovation output. 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 (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 their viable alternatives to achieve the same functionality. As a result, insufficient production or disruption in an RM supply may directly make the downstream application and manufacturing more costly and reduce the returns of R&D in RM-intensive technologies, constraining the innovation output in such technological areas. Based on the above background, our main research hypothesis is:

Hypothesis: Rare Metal supply, in terms of global production, shapes the technological frontier dynamics by impacting the innovation output of RM-based technology areas.

3.Data and methodology

3.1 Selection of RMs and global production trends

There is no universal list for Rare metals /Minor metals, the definition and criteria vary from study to study (Ayres & Peiro, 2013). As described by the Minor Metal Trade Association[1], RMs encompass a vast array of metals which: 1. are 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. are not traded on formal

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

exchanges, like London Metal Exchange, 3. are 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. The first is precious metals, such as gold, silver and platinum which are also rare and technologically important, but they are more intensively used as currency or jewelleries rather than for industrial use. Moreover, we did not include rare earth metals[2]: 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 the global production data of these 13 rare metals during 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 1975-2015. In general, the production of most metals has risen with fluctuations, especially after 2000, the upward trends accelerate. At the same time, the production trends of different metals show significant differences. That of cadmium, tantalum, and selenium fluctuates greatly, while for cobalt, lithium, vanadium, indium, and bismuth the trend is 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 show different degrees of production decline connected to the financial crisis. We further compare production changes relative to 1975 across metals[3]. It is observed that RMs experienced different trends over four decades: gallium and indium have the fastest growth, by 40 and 20 times respectively, lithium and cobalt have also increased for five 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

2. 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.
3. Details are shown in Figure A1 in the online appendix.

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 covered period[4]. In this research, we use two technological classifications. First, the Cooperative Patent Classification (CPC) system is used as the regression unit in the econometrics analysis. CPC is a more detailed and advanced version of IPC and has been officially used by both USPTO and EPO for classifications at five technological levels, which ensure consistency over time[5]. Following Consoli et al., (2021), we extract CPC class for each patent from 'cpc_current' table in the "PatentsView" database. Second, the WIPO technology classification is used to analyse the dependence on RM among different technology areas. This taxonomy was initially developed by Schmoch (2008), it 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 of the relevant metal elements in the section of "Detailed description text". This text-mining method has been used to identify specific characteristics of technologies, such as dependency on rare earth elements (Fifarek et al., 2008), conflict minerals (Diemer et al., 2021), as well as toxic substance (Biggi & Giuliani et al, 2022). 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. We note that mentioning a material could have different motivations, as due to technologies produced directly from basic and applied research for that material, or to innovations in applied technologies for which that material is an essential component (Fifarek et al., 2008); moreover, it may also relate to obtaining, saving, or recycling that material (Diemer et al., 2021).

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

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

5. 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.

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.[6] If the patent inventor 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 some other potential limitations. For example, it fails to identify the degree of dependency 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 area has a higher proportion of RM-based patents, then this area has a higher dependency upon RM materials.

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 found 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 dependency 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 2 shows that the number of RM-based patents has risen 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 in total patents increased, from the initial 9% to 14% in 2015. This indicates that RMs are becoming increasingly important in modern technologies.

INSERT FIGURE 2 HERE

Next, trends are observed also for the 5 WIPO sectors (Figure 3). In terms of absolute RM patent numbers on the left, 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

6. For a detailed description see Figures A2 and A3 in the online appendix.

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 3 HERE

In terms of shares, that in Chemistry is significantly higher than in any other sectors, and the gap further widened over time, increasing to 32% in 2015. In comparison, the share of Electrical engineering remained relatively constant over time and was surpassed by Instrument technologies in 1992. Mechanical engineering and Other technologies had shares lower than the average and gradually increased over the period. We also compare the technological dependence on different RMs over time[7]: the number of patents using lithium remained the highest, meanwhile indium patents 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 varied with time.

4.2 RM dependence by technology field

We then consider the RM dependency of specialized technologies by zooming into the 35 WIPO fields and six green energy technologies (Figure 4).

INSERT FIGURE 4 HERE

Fields in the Chemistry sector has high share of RM-based patents, in which Micro-structure and nano-technology shows the highest dependence (37% of patents are related to at least one RM). Similarly, three fields: Material, metallurgy; Organic fine chemistry and Macromolecular chemistry, polymers also show a strong dependence. All fields above are closely related to material science (Schmoch, 2008), indicating that there are diversified technologies about inventing, producing new materials which use RMs as components looking for property improvements. It is important to note that these technologies are usually general-purpose technologies (GPTs), work as the basis for others, such as nano-technologies for semiconductors (Moser & Nicholas, 2004; Petralia, 2020).

For the Electrical engineering sector, unsurprisingly, the field of Semiconductors has the highest dependence on RMs, which is one of the core technologies in the hardware infrastructure for ICT (Schmoch, 2008). The second by importance is Electrical machinery,

7. Details are shown in Figure A4 in the online appendix.

apparatus, energy. Other fields in this sector, such as Computer technology, are mainly about software technologies, thus depend much less on RMs. For other sectors, Optics (22%), Analysis of biological materials (14%) and Medical technology (10%) show high dependence. For Green energy technologies, it can be observed that several fields show very high dependence on the RMs, such as, Fuel cells, where 34% patents use at least one RMs as input, particularly lithium and cobalt. In addition, patents in Bio-fuels, Solar energy and Nuclear energy also have a high degree of dependence, consistently with the literature of green and renewable energy technologies (e.g. Valero et al., 2018; Dominish et al., 2019; European Commission, 2020).

To sum up, the analysis illustrates a high dependence of technologies on RMs which varies across technologies, levels of analysis as well as RM types. RMs are becoming critical inputs in more and more patents, and having 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

The analysis above illustrates that certain technology areas are highly dependent on specific RMs. In this section, we focus on those "RM-based technology areas", using econometrics models to further explore whether changes in the metal supply, in terms of production, influence the innovative output in those areas, thus testing our main research hypothesis.

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[8]. 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 on. 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

8. Samples with different definitions of RM-based technology areas were also used, discussed in Robustness tests (3).

11.88% of all USPTO granted patents) during 1976-2015 (details of the sample are shown by Tables A1, A2 in the online appendix).

5.2 Model specification

The model is set by referring to studies on the induced innovation hypothesis, discussed in Section 2 (e.g. Popp, 2002). The dependent variable is the patent output of RM-based subgroups, measured by the share of patent grant number of each subgroup over the total USPTO granted patents in each year. Independent variables include the lagged production of corresponding RM as well as other control variables.

$$\frac{Patent\ Number\ of\ Subgroup_{i,j,t}}{Total\ Patent\ Number_t} = \beta_1\ RM\ production_{j,t-1} + \sum_{k=2}^{5} \beta_k\ Z_{i,j,t-1} + RM\ FE + \ Year\ FE + \ Tech\ FE + \varepsilon_{i,j,t}$$

where i indexes 2,534 technology subgroups[9], j stands for the 13 rare metals and t denotes the years 1976-2015. Our dependent variable is normalized by z-score. By using this share as the dependent variable, we consider the impact of macroeconomic and exogenous changes, such as changes in patent laws or government policy, leading to changes in both total and RM-based areas. The model uses the application date rather than the grant date of patents as measure of innovation in order to document it as early as possible (Popp, 2003; Böhringer et al., 2017). $RM\ production_{j,t-1}$ measures the production of RM j in year t, in terms of ratios relative to the initial level in 1975. 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.

Besides RM production, we control for several other factors that are likely to affect the innovation output of RM-based technologies, denoted by $Z_{i,j,t-1}$. First, we control for $Knowledge\ stock_{i,t-1}$ which is the knowledge accumulated until the previous year in technology subgroup *i*: this variable represents the cumulative and path-dependent nature of technology development, and it is calculated as follows:

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

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 depreciation rate of past technologies and γ_2 is the diffusion rate of existing patents with the assumption that it takes time for technological knowledge to diffuse among innovators.

9. In which, 1,312 subgroups are based on only one RM, and the rest 1,222 are based on multiple RMs and appear more than one time in the sample. An alternative sample of technology subgroups with the most important RM (with highest share of patents based on this RM) showed similar results, which are available upon request.

Following (Kim et al., 2017), we use the mean values as estimated by Popp (2001) with γ1 = 0.44 and γ2 = 2.97.

Second, technological change is not only influenced by technologies in the same area but also by spillovers from related technological areas (Grupp, 1996). Technological relatedness stimulates knowledge recombination and leads to more innovation output (e.g. Boschma & Frenken, 2012). Assuming that technologies in the same group have larger relatedness with each other, we include a control named $Technology\ in\ same\ Group_{i,t-1}$ which denote the number of patents in the same technology group but not in subgroup i. Furthermore, the development of RM-based technologies may also be influenced by other technology subgroups which depend on the same RMs. To control for this cross-technology effect we also include the variable $RM\ Demand\_other\ areas_{i,j,t-1}$ which measures the number of patents using the same RM j in other technology subgroups except i. A higher value implies that technology subgroup i may face more competition for the same metal. We also control for the degree of dependence of technologies on the corresponding RMs by the variable $RM\ dependence\ intensity_{i,j,t-1}$. A summary and correlation matrix for the independent variables is reported in Table A3 in the online appendix.

We include several fixed effects in the model to control for constant unobservable factors. The propensity to patent innovation varies across technology areas: in some, such as Chemistry and Electronic engineering, it is higher than in others, where secrecy is more important to protect innovation. Therefore, technology subgroup fixed effects are included. Year fixed effects are added to control for macrolevel economic and technological trends (Griliches, 1990). Finally, RM fixed effects are also included to account for RM-specific unobserved heterogeneity.

5.3 Endogeneity and identification strategy

The empirical setting proposed above may be subject to endogeneity problems. First, reverse causality can be a concern if technology dynamics influence the production of RMs. When a key technological breakthrough using an RM occurs, the expected and actual demand for the metal will increase, stimulating metal producers to increase production capacity.

The omitted variable bias represents another issue: some factors may influence RM production and technology dynamics at the same time. For example, some basic discoveries in natural or engineering sciences may enhance the understanding of the properties of certain RMs. This may simultaneously improve the metal production efficiency and inspire innovators about new ways of RM application. Moreover, 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 the potential RM shortages. All these factors potentially bias the estimated effect.

To solve 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 of 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 5. 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 5 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 account for the major revenue of mining and their production 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 the 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[10]. We start with the simple model in column 1, which solely includes the variable of interest, RM production, with RM fixed effects as well as technology fixed effects to capture the unobserved heterogeneity at these fine-grained levels. In columns 2 we include the full battery of covariates discussed above. 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, $RM\ production_{j,t-1}$ is always positive at the 1% significance level, indicating that the supply of an RM indeed increases the innovation output of the technology subgroups which are based on it. The coefficient on RM production in the specification of column 4 indicates that a one-unit increase (100% increase relative to 1975[11]) in the production of a certain RM on average leads to a rise in the share of patents in RM-based subgroups by 0.0139 standard deviation, which corresponds to 2.56% increase of the patent output. By comparing the results between the OLS and IV regressions, we notice that the coefficients on $RM\ production_{j,t-1}$ are all 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 importance. In general, these findings support our research hypothesis that increasing the supply of RMs does provide incentives to innovation in the relevant technology areas and encourage new patents. On the contrary, a decreasing supply or supply disruption of RMs may constrain the generation

10. The first stage estimation results are shown in Table A8 in the online appendix.

11. Until 2015, the production of the 13 RMs, on average, increased by 647.15% relative to the initial values in 1975.

of new technologies in areas based on these materials. Hence, these results provide a first suggestion that the supply of RMs shape frontier technological developments of the contemporary society.

As far as the control variables are concerned, the effect of $Knowledge\ stock_{i,t-1}$ on patents is significant and positive, indicating that past knowledge accumulation leads to more innovation output. In line with other studies (e.g. Kim et al., 2017), innovation in RM-based areas is also path-dependent and builds on the existing knowledge stock of its own technology subgroup. Similarly, the coefficient on $Technology\ in\ same\ \ Group\ _{i,t-1}$ is also positive and significant in all models, indicating a positive correlation between RM-based technologies with innovation activities in other technology subgroups of the same group. This may be due to positive spillover effects from related technologies, or to technologies in the same group being influenced simultaneously by similar market demands and policies. Moreover, $RM\ Demand\_other\ areas\ _{i,j,t-1}$ is significantly negative. This may indicate that the increasing demand for a certain RM in other areas is negatively correlated with the innovation output in the observed RM-based technology subgroup. The literature argues that there is competition for sourcing RMs across different industrial sectors: for example, solar energy competes with electronics for gallium and indium materials (Leader et al., 2019). Our results show that this competition also seem to occur in upstream R&D activities.

INSERT TABLE 3 HERE
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6. Robustness checks

In this section we further test the robustness of our results by: (1) checking the validity of the IV, (2) using different thresholds, grouping and definitions for RM-based technologies and (3) using alternative regression methods.

(1) Further validations of the instrumental variable

First, 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, there is the possibility 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 patents which mentioned both RMs and their main base metals. By doing so, we rule out the probability that RMs and base metals are not only related on the supply (production) side but also on the technological demand side. The regression result is shown in column 1 of Table A4. After excluding those patents, the estimated effect remains significantly positive.

Second, the IV in the main model captures the production of the primary base metal of RMs without considering differences in the companionability across RMs and corresponding base metals. 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. The results are shown in column 2 of Table A4. The coefficient of interest remains positive and highly significant. These results further validate our IV estimation approach.

(2) Using alternative samples definitions and grouping of RM-based technology areas

The regression sample we use consists of Tech-RM pairs for which subgroups have at least 10% of patents based on a specific RM. There are two major issues with this definition. First, the 10% threshold is an arbitrary choice and changing the threshold may impact our findings. Second, our results may also be influenced by technology grouping levels. Hence, we address these two concerns by using alternative definitions of RM-based technology areas.

Thus, in addition to the initial value 10%, we used 4 alternative thresholds, from 20% to 50%. The results are shown in Table A5. $RM\ production_{j,t-1}$ remains positively significant using all four alternative thresholds and the coefficients are larger than in the 10% threshold sample. This result confirms that the findings above are robust to different thresholds of RM-based technology areas.

Furthermore, the regressions in Table 3 are based on the finest technology scale, that is subgroups at the 5-digit level of the CPC classification. We test whether our previous findings are robust to alternative definitions of technology levels. Using the same data structure, we consider group (4-digit) and subclass (3-digit) levels, as shown in Table A6. Because of the changes in the aggregation level, the number of observations significantly decreases. These results show that the relationship between patents and RM production remains statistically significant and positive irrespective of the level of detail adopted in defining technologies.

(3) Changing regression method

Finally, 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*. The results are shown in Table A7, where we estimate different specifications, also including the IV. Overall, RM production remains still significant and positive in all columns, thus further corroborating our hypothesis.

The robustness checks above suggest that our main finding is stable with alternative samples, no matter how we change the technology aggregation level, thresholds, and definition of “RM-based technology areas”, or also using alternative regression models. We interpret this evidence as very suggestive that the effect of RM supply on innovation output is highly robust.

7. Conclusion and discussion

Technological innovation co-evolves with the availability and supply of natural resources. On the one hand, frontier technologies are experiencing tremendous shifts, changing types, modes, and efficiency in the utilisation of natural resource. Economists believe technological innovation makes it possible to replace rare and expensive resources with relatively abundant and cheap resources, 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 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 supply in turn influences the trajectory of frontier technology dynamics.

Using 13 widely concerned RMs, this paper contributes to the understanding on this deep interdependence between resource 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 as well as ICT and AI revolutions. 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 the availability of critical raw materials has a direct impact on the frontier innovation dynamics — technological progress of the current society is still endogenously subject to the natural environment and the supply of resources with technological criticality.

Empirically, this paper contributes by providing the first systematic exploration of the dependency 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 areas, scale of analysis as well as type of rare metals. Moreover, technology application of RMs has experienced scale and structural changes over time: the number of RM-based patents has increased by 7 times over time, and Electronic engineering surpassed Chemistry and became the technology sector with most RM-based patens. Among all RMs, whilst lithium has shown the highest numbers of patents over the period, indium and gallium have experienced the biggest increase in technology applications, and at the same time their production growth has been the most significant. Our econometric exercise, which accounts for endogeneity, support the hypothesis that RMs supply has a significant causal impact on the innovation output of RM-based technology areas.

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 network and value chain system within which innovation occurs, considering the distribution of benefits and costs across the actors and the geographies involved. Given the high dependency 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 better understand 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., 2021).

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, this paper focuses on the impact on innovation activities. It is also important to further explore the impact on the downstream industries and products which depend on RMs. 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 REE materials (Mancheri, 2015); because of the Dodd Frank Act, business companies listed in the US stock market have additional limits in obtaining “conflict minerals” RMs such as cobalt and tantalum from the Democratic Republic of Congo (Dalla & Perego, 2018). Future research should focus on finer geographic scales (Diemer et al., 2021) to explore whether and how differences in the availability of RMs shape the development trajectories of firms, regions and countries.

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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%)

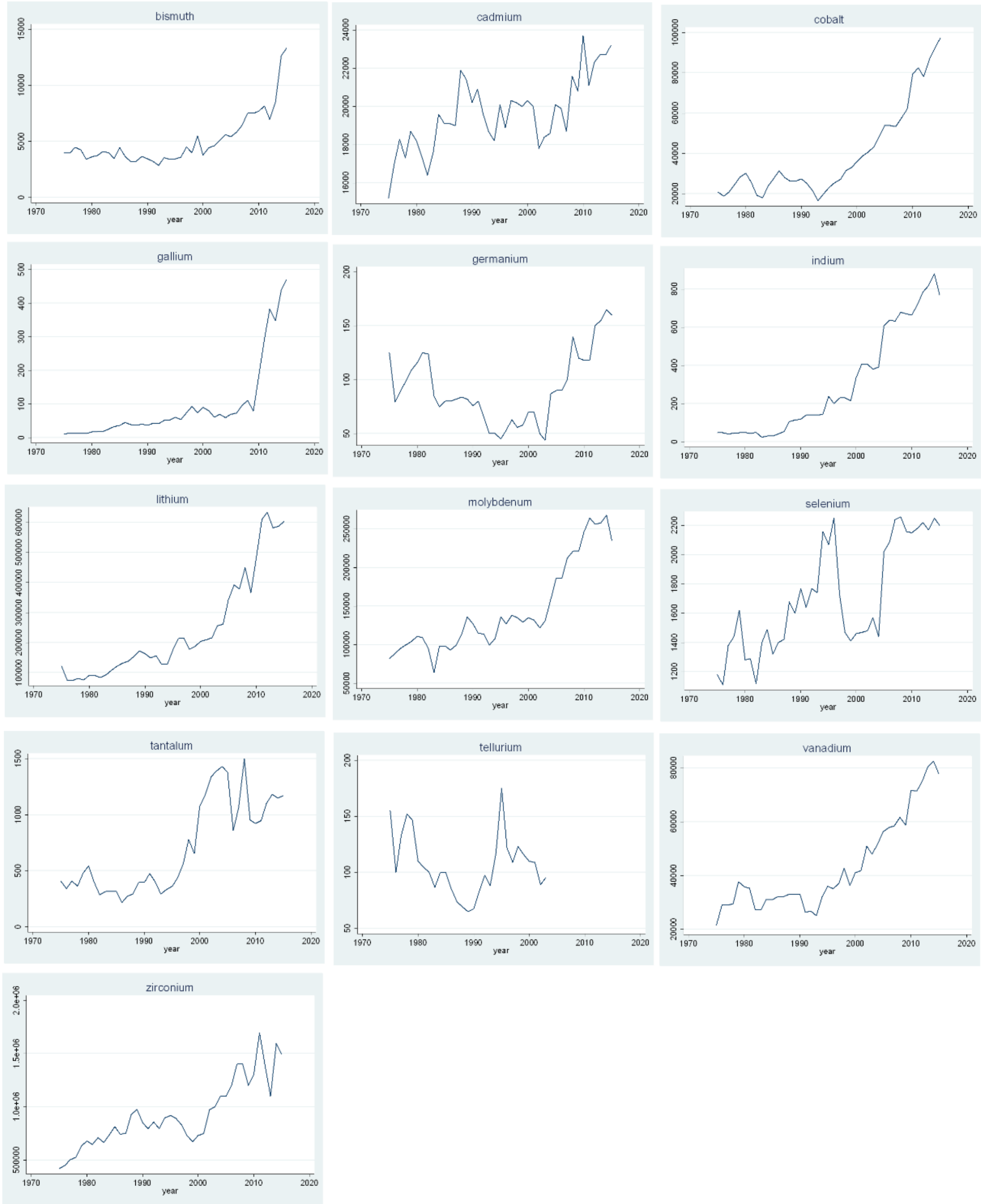
Information Sources: Nassar et al. (2015); Harper et al. (2015). Companionability degree measures what percentage of an RM is produced from the co-production process with a base metal.

Table 3. Regression results

	OLS estimation		IV estimation	
	(1)	(2)	(3)	(4)
$RM\ production_{j,t-1}$	0.0220***	0.0111***	0.0392***	0.0139***
	(0.000615)	(0.000537)	(0.00148)	(0.00102)
$Knowledge\ stock_{i,t-1}$		0.0319***		0.0319***
		(0.000111)		(0.000111)
$Technology\ in\ same\ Group_{i,t-1}$		0.000193***		0.000191***
		(3.27e-06)		(3.30e-06)
$RM\ Demand\_other\ areas\ _{i,j,t-1}$		-3.18e-05***		-3.47e-05***
		(1.94e-06)		(2.14e-06)
$RM\ dependence\ intensity_{i,j,t-1}$		-0.000201		-0.000199
		(0.0140)		(0.0140)
Constant	-0.0537***	-0.332***	-	-
	(0.00236)	(0.00626)		
Year Fixed effect	Yes	Yes	Yes	Yes
RM Fixed effect	Yes	Yes	Yes	Yes
Technology Fixed effect	Yes	Yes	Yes	Yes
Technology subgroup number	2534	2534	2534	2534
Technology-RM pairs	5644	5644	5644	5644
Observations	225,188	223,945	225,188	223,945
R-squared	0.384	0.578	-	-

Note: *, **, *** indicate significance level at 10%, 5% and 1%, respectively. First stage results for columns 3 and 4 are reported in Table A8 in the online appendix.

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



Data source: US Geological Survey

Figure 2. General trends of technological dependence on RMs

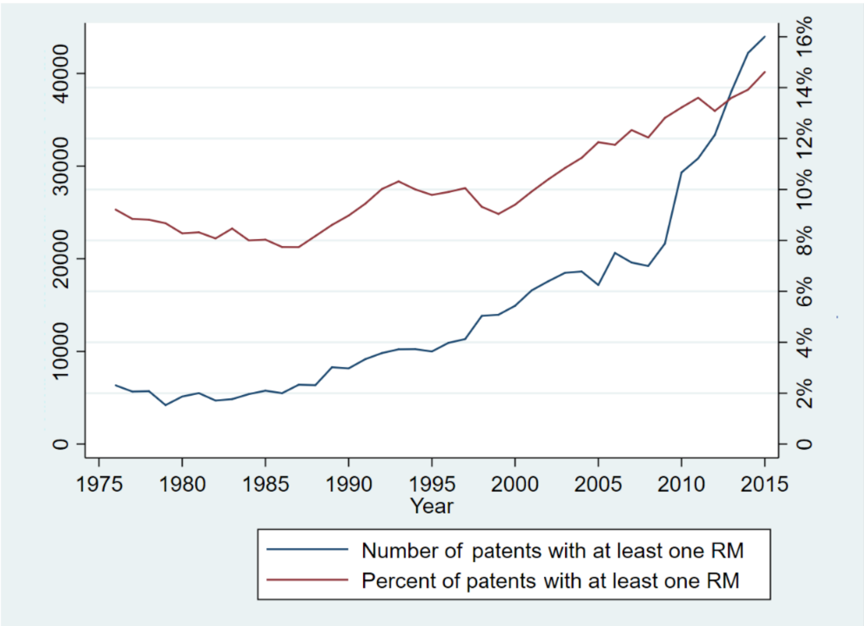


Figure 3. Trends in RM-dependence by WIPO technology sectors, 1976-2015 (left: absolute numbers; right: shares)

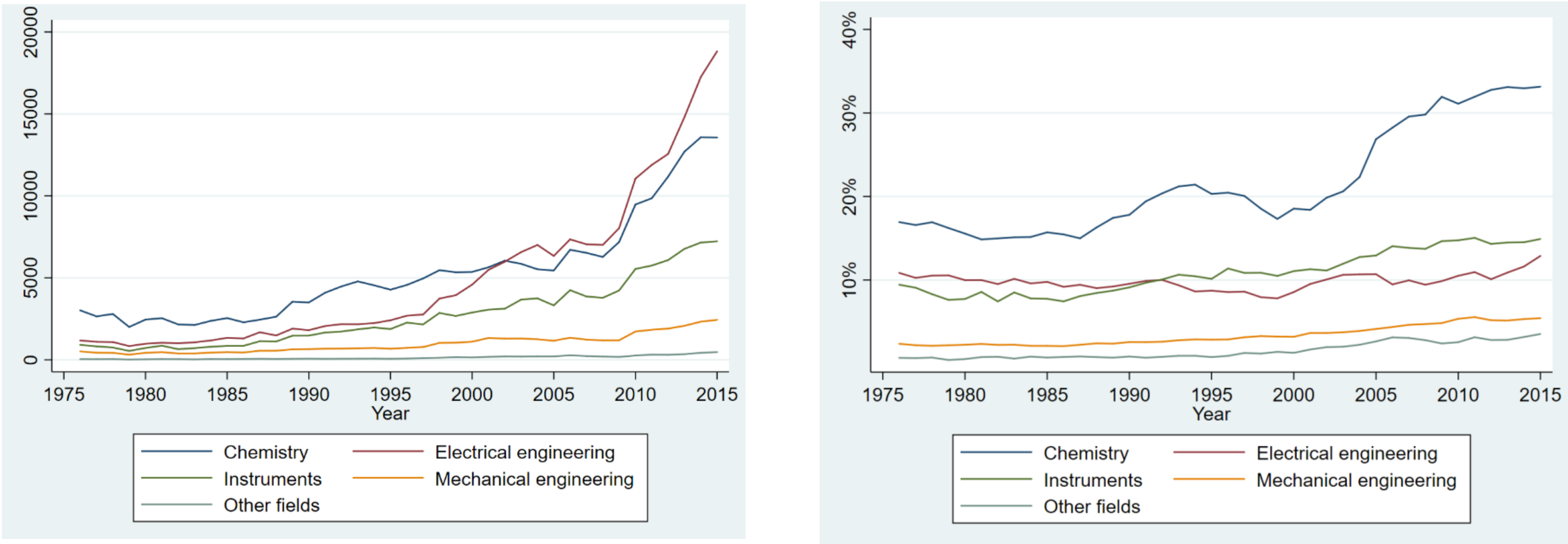


Figure 4. Share of RM-based patents by technology field, 1976-2015

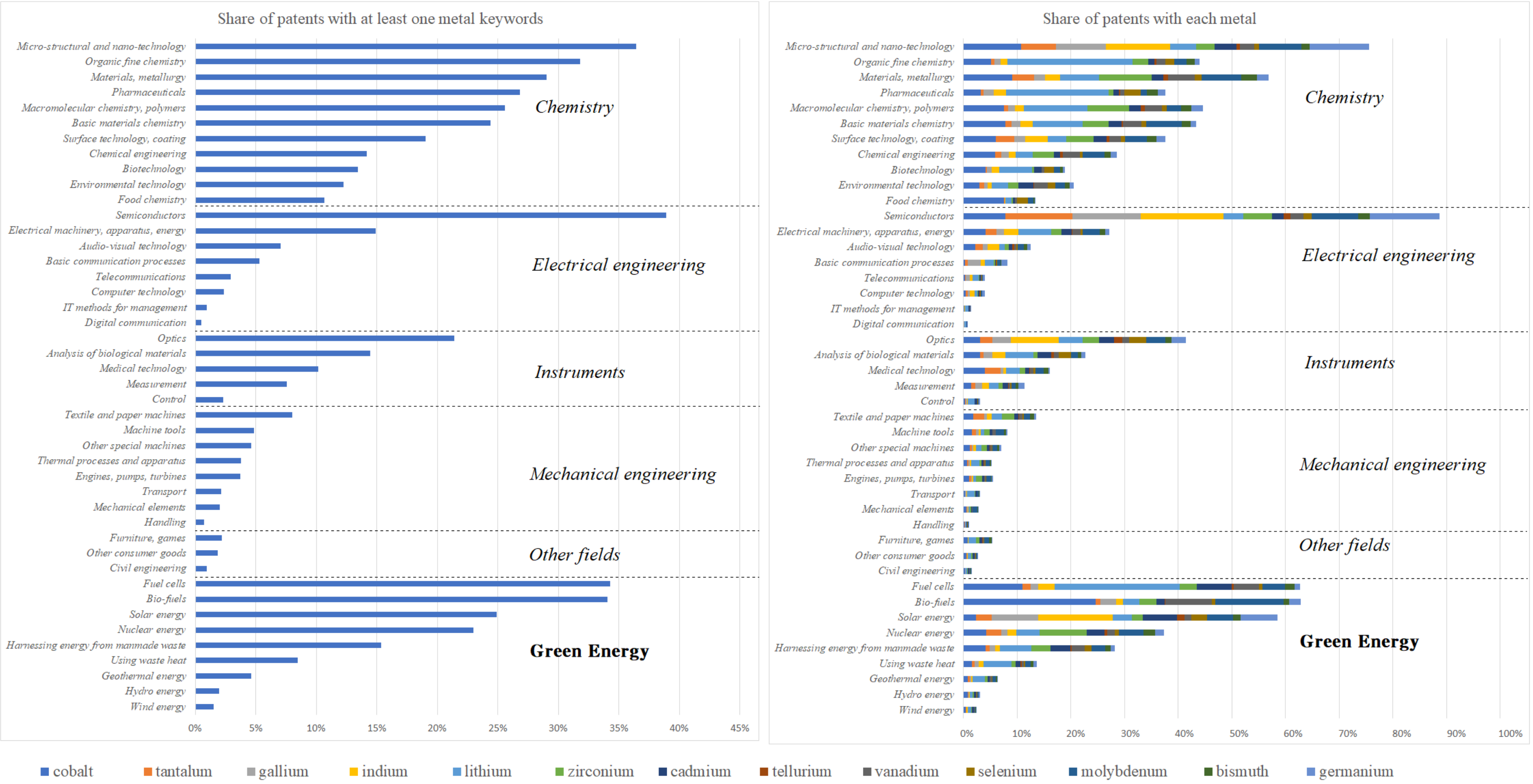
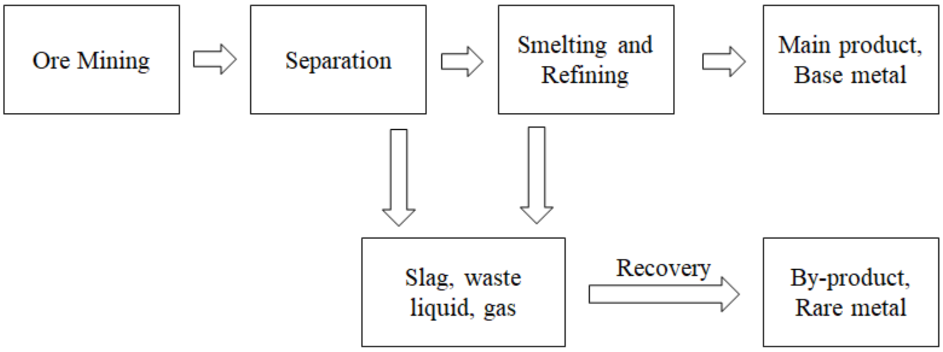


Figure 5. Co-production process of base metals (main product) and RMs (by-product)

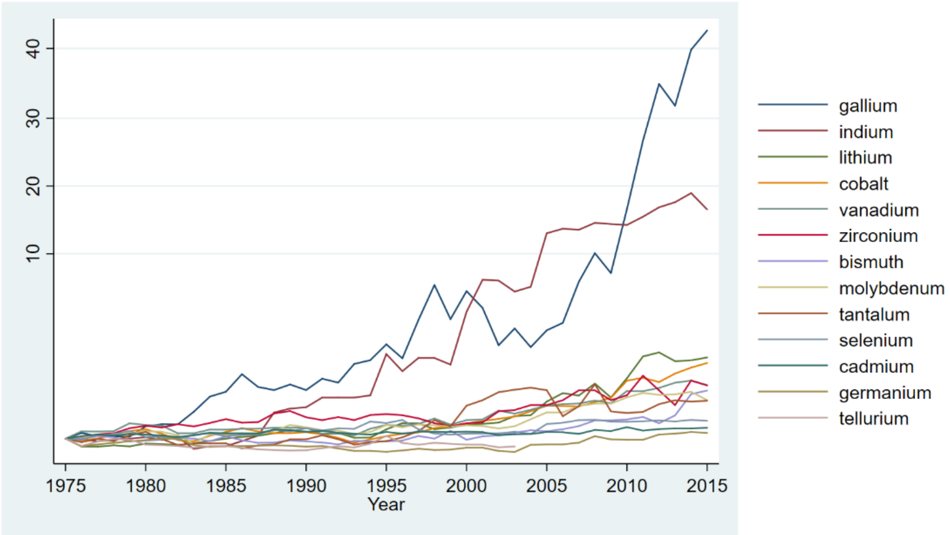


Information Sources: (Nassar et al., 2015; Harper et al., 2015)

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)

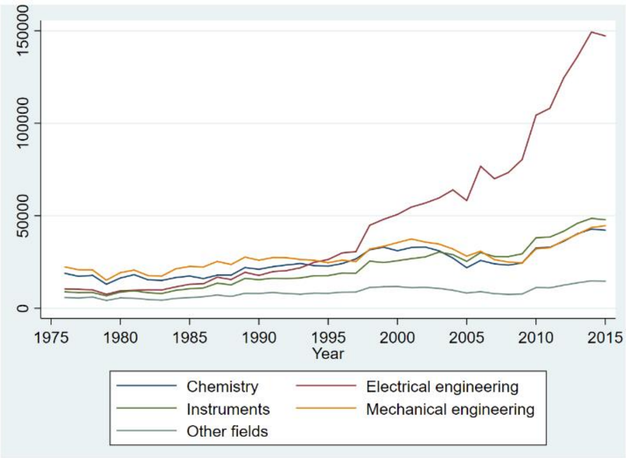


Data source: US Geological Survey

A.2 Patent Description

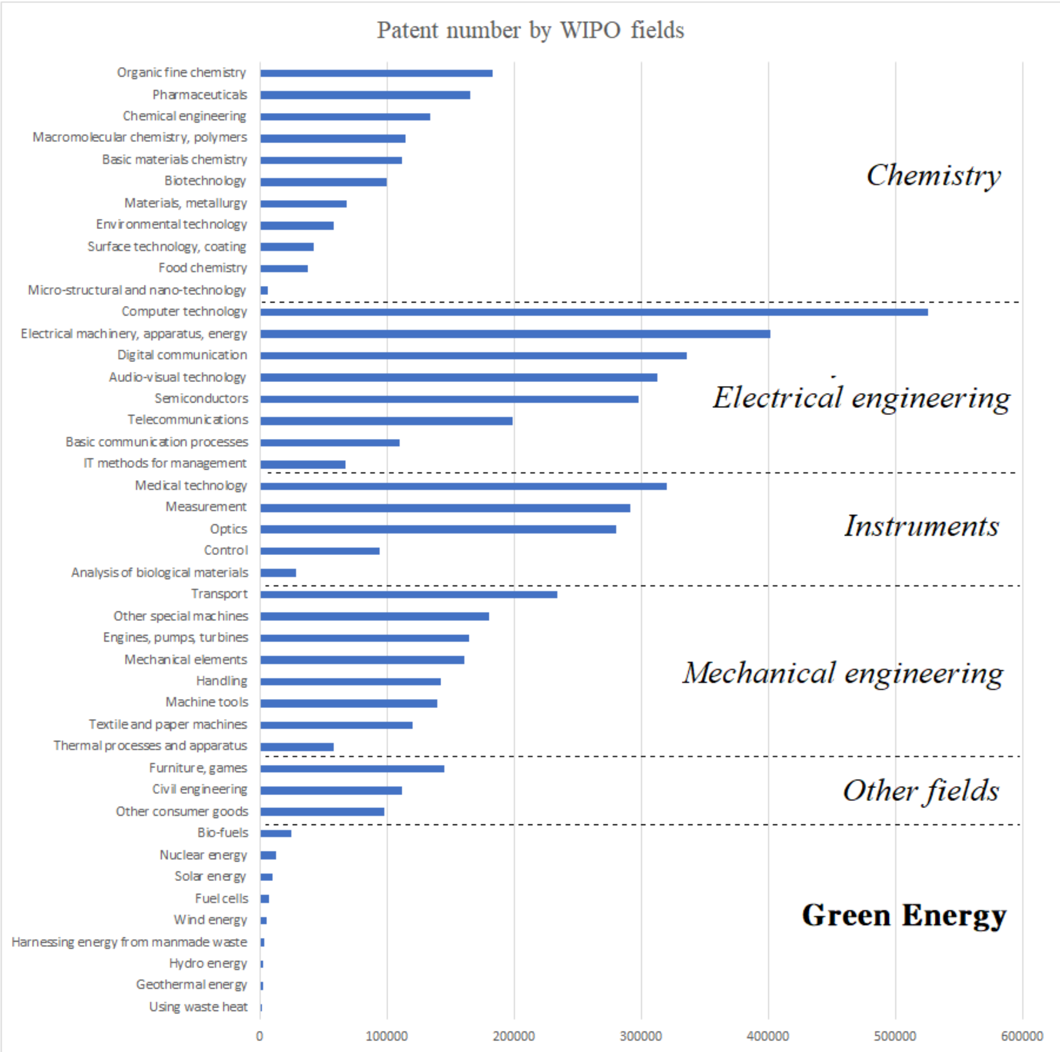
Figure A2. Patent trends, 1975-2015

Total USPTO granted patents



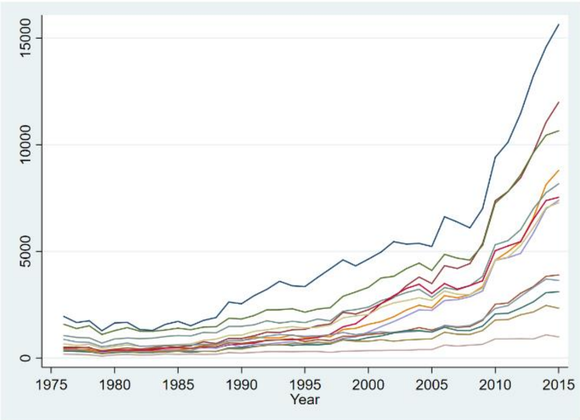
Total USPTO patents by WIPO technology sector

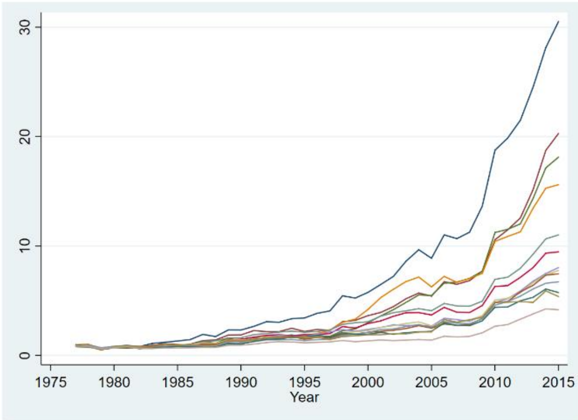
Figure A3. Total patent number by WIPO 35 technology fields and 5 sectors



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 numbers; right: ratios relative to 1976)





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	5644

Table A3. Independent variable description and correlation matrix

	Mean	Std dev	Min	Max	1	2	3	4	5
1. $RM\ production_{j,t-1}$	2.700	3.951	0.352	39.818	1				
2. $Knowledge\ stock_{i,t-1}$	9.544	18.291	0.000	1174.922	0.1862	1			
3. $Technology\ in\ same\ \ subgroup_{i,t-1}$	456.309	750.11	0.000	4445.000	0.2099	0.224	1		
4. $RM\ Demand\_other\ areas_{i,j,t-1}$	2620.281	2332.312	110.000	9817.000	0.276	0.2926	0.2883	1	
5. $RM\ dependence\ intensity_{i,j,t-1}$	0.223	0.143	0.100	0.981	0.0483	0.0148	0.0545	0.0849	1

A.4 Robustness test results

Table A4. Robustness test on IV

	(1) Excluding patents with base metal keywords	(2) Heterogeneous companionability
$RM\ production_{j,t-1}$	0.0189***	0.0122***
	(0.00105)	(0.000853)
$Knowledge\ stock_{i,t-1}$	0.0305***	0.0319***
	(0.000114)	(0.000112)
$Technology\ in\ same\ \ Group_{i,t-1}$	0.000201***	0.000191***
	(3.39e-06)	(3.35e-06)
$RM\ Demand\_other\ areass\ \ _{i,j,t-1}$	-5.07e-05***	-3.23e-05***
	(2.20e-06)	(2.10e-06)
$RM\ dependence\ intensity_{i,j,t-1}$	-0.150***	-0.000169
	(0.0143)	(0.0142)
RM Fixed effect	Yes	Yes
Year Fixed effect	Yes	Yes
Technology Fixed effect	Yes	Yes
Technology subgroups number	2534	2534
Technology-RM pairs	5644	5644
Observations	223,945	218,366
R-squared	-	-

Note: *, **, *** indicate significance level at 10%, 5% and 1%, respectively. First stage results are reported in Table A9.

Table A5. Changing thresholds for RM-based technologies (IV estimation)

Thresholds	20%	30%	40%	50%
$RM\ production_{j,t-1}$	0.0236***	0.0233***	0.0288***	0.0288***
	(0.00180)	(0.00232)	(0.00244)	(0.00342)
$Knowledge\ stock_{i,t-1}$	0.0349***	0.0333***	0.0317***	0.0365***
	(0.000174)	(0.000283)	(0.000325)	(0.000465)
$Technology\ in\ same\ \ Group_{i,t-1}$	0.000221***	0.000285***	0.000296***	0.000359***
	(5.85e-06)	(8.73e-06)	(1.16e-05)	(1.94e-05)
$RM\ Demand\_other\ areas\ \ _{i,j,t-1}$	-4.86e-05***	-4.88e-05***	-5.50e-05***	-5.44e-05***
	(3.73e-06)	(5.10e-06)	(6.44e-06)	(1.03e-05)
$RM\ dependence\ intensity_{i,j,t-1}$	0.00201	0.00518	0.0110	-0.000897
	(0.0273)	(0.0495)	(0.0949)	(0.192)
RM Fixed effect	Yes	Yes	Yes	Yes
Year Fixed effect	Yes	Yes	Yes	Yes
Technology Fixed effect	Yes	Yes	Yes	Yes
Technology subgroup number	1346	817	537	250
Technology-RM pairs	2224	1142	673	310
Observations	88,243	45,360	26,768	12,373
R-squared	-	-	-	-

Note: *, **, *** indicate significance level at 10%, 5% and 1%, respectively. First stage results are reported in Table A10.

Table A6. Changing technology grouping levels (IV estimation)

Levels	(1) 4-digits CPC group level	(2) 3-digits CPC subclass level
$RM\ production_{j,t-1}$	0.00655***	0.0164***
	(0.00190)	(0.00477)
$Knowledge\ stock_{i,t-1}$	0.00189***	0.000248***
	(7.79e-06)	(2.63e-06)
$Related\ technologies\ _{i,t-1}$	3.69e-05***	-5.23e-06***
	(1.71e-06)	(1.61e-06)
$RM\ Demand\_other\ areas\ \ _{i,j,t-1}$	1.94e-06	-1.50e-05***
	(2.14e-06)	(5.67e-06)
$RM\ dependence\ intensity_{i,j,t-1}$	-0.000903	-0.00218
	(0.0227)	(0.107)
RM Fixed effect	Yes	Yes
Year Fixed effect	Yes	Yes
Technology Fixed effect	Yes	Yes
Technology subgroup number	603	63
Technology-RM pairs	1104	108
Observations	43,929	4,294
R-squared	-	-

Note: *, **, *** indicate significance level at 10%, 5% and 1%, respectively. First stage results are shown in Table A11.

In the group level model, the variable *Related technologies* is measured by the number of other patents in the same subclass. Similarly, for the subclass level model, it is measured at the class level.

Table A7. Robustness test by Poisson regression

	(1) Poisson	(2) Poisson	(3) Poisson IV
$RM\ production_{j,t-1}$	0.0309***	0.0268***	0.0520***
	(0.000339)	(0.000368)	(0.000728)
$Knowledge\ stock_{i,t-1}$		0.00399***	0.00354***
		(2.32e-05)	(2.43e-05)
$Technology\ in\ same\ \ Group_{i,t-1}$		0.000620***	0.000615***
		(2.44e-06)	(2.46e-06)
$RM\ Demand\_other\ areas\ \ _{i,j,t-1}$		-7.79e-05***	-8.88e-05***
		(1.38e-06)	(1.41e-06)
$RM\ dependence\ intensity_{i,j,t-1}$		-2.759	14.70
		(932,521)	(3.290e+06)
Year Fixed effect	Yes	Yes	Yes
Technology-RM pairs fixed effect	Yes	Yes	Yes
Technology subgroup number	2534	2534	2534
Technology-RM pairs	5,643	5,643	5,644
Observations	225,159	223,917	224,512
R-squared	0.384	0.578	-

Note: *, **, *** indicate significance level at 10%, 5% and 1%, respectively. First stage results of column 3 are the same as column 2 in Table A8.

A.5 First stage regression results

Table A8. First stage regression results of Table 3

	(1)	(2)
$Base\ metal\ production_{j,t-1}$	4.199***	5.283***
	(0.0195)	(0.0181)
$Knowledge\ stock_{i,t-1}$		0.00792***
		(0.000372)
$Technology\ in\ same\ \ Group_{i,t-1}$		0.000375***
		(1.10e-05)
$RM\ Demand\_other\ areas\ \ _{i,j,t-1}$		0.00153***
		(6.50e-06)
$RM\ dependence\ intensity_{i,j,t-1}$		0.00480
		(0.0470)
Constant	-3.314***	-9.143***
	(0.0284)	(0.0367)
RM Fixed effect	Yes	Yes
Year Fixed effect	Yes	Yes
Technology Fixed effect	Yes	Yes
Technology subgroup number	2,534	2,534
Weak identification: Cragg-Donald Wald F statistic	46554.11	85163.20
Observations	225,188	223,945
R-squared	0.608	0.689

Note: *, **, *** indicate significance level at 10%, 5% and 1%, respectively

The IV $Primary\ Base\ metal\ production_{j,t}$ is significantly and positively correlated with the variable of interest $RM\ production_{j,t-1}$, indicating that one unit increase in the production of primary base metal corresponds to a 5.283 unit increase in the by-product RM production, controlling for other variables and fixed effects. The results of Cragg-Donald Wald F statistic show that the IV passes the weak identification test. We now obtain the levels of RM production exogenously predicted by the instrument and examine their causal effects on innovation dynamics.

Table A9. First stage regression results of Table 4

	(1) Excluding patents with base metal keywords	(2) Heterogeneous companionability
$RM\ production_{j,t-1}$	5.283***	42.45***
	(0.0181)	(0.110)
$Knowledge\ stock_{i,t-1}$	0.00792***	0.00751***
	(0.000372)	(0.000341)
$Technology\ in\ same\ \ Group_{i,t-1}$	0.000375***	0.000339***
	(1.10e-05)	(1.01e-05)
$RM\ Demand\_other\ areas\ \ _{i,j,t-1}$	0.00153***	0.00154***
	(6.50e-06)	(5.92e-06)
$RM\ dependence\ intensity_{i,j,t-1}$	0.00480	0.00642
	(0.0470)	(0.0433)
Constant	-9.143***	-9.549***
	(0.0367)	(0.0308)
RM Fixed effect	Yes	Yes
Year Fixed effect	Yes	Yes
Technology Fixed effect	Yes	Yes
Technology subgroups number	2,534	2,534
Weak identification: Cragg-Donald Wald F statistic	85163.20	1.5e+05
Observations	223,945	218,366
R-squared	0.689	0.748

Note: *, **, *** indicate significance level at 10%, 5% and 1%, respectively

Table A10. First stage regression results of Table 5

Threshold	20%	30%	40%	50%
$Base\ metal\ production_{j,t-1}$	5.287***	5.716***	6.751***	7.574***
	(0.0291)	(0.0418)	(0.0546)	(0.0819)
$Knowledge\ stock_{i,t-1}$	0.00524***	0.0111***	0.00828***	0.00645***
	(0.000530)	(0.000887)	(0.00107)	(0.00147)
$Technology\ in\ same\ \ Group_{i,t-1}$	0.000674***	0.00105***	0.00127***	0.00156***
	(1.74e-05)	(2.59e-05)	(3.58e-05)	(5.68e-05)
$RM\ Demand\_other\ areas\ \ _{i,j,t-1}$	0.00163***	0.00179***	0.00201***	0.00223***
	(1.05e-05)	(1.55e-05)	(2.11e-05)	(3.26e-05)
$RM\ dependence\ intensity_{i,j,t-1}$	0.0106	0.00573	-0.0291	0.0329
	(0.0835)	(0.156)	(0.314)	(0.608)
Constant	-9.592***	-10.90***	-12.86***	-14.33***
	(0.0658)	(0.114)	(0.206)	(0.433)
RM Fixed effect	Yes	Yes	Yes	Yes
Year Fixed effect	Yes	Yes	Yes	Yes
Technology Fixed effect	Yes	Yes	Yes	Yes
Technology subgroup number	1346	817	537	250
Weak identification: Cragg-Donald Wald F statistic	32925.02	18666.79	15272.54	8551.50
Observations	88,243	45,360	26,768	12,373
R-squared	0.705	0.737	0.776	0.819

Note: *, **, *** indicate significance level at 10%, 5% and 1%, respectively

Table A11. First stage regression results of Table 6

Levels	4-digits CPC Group level	3-digits CPC Subclass level
$Base\ metal\ production_{j,t-1}$	3.244***	3.344***
	(0.0357)	(0.115)
$Knowledge\ stock_{i,t-1}$	0.000620***	0.000325***
	(4.46e-05)	(1.61e-05)
$Related\ technologies_{i,t-1}$	0.000144***	2.54e-05**
	(9.77e-06)	(1.15e-05)
$RM\ Demand\_other\ areas\ _{i,j,t-1}$	0.00101***	0.00113***
	(1.18e-05)	(4.07e-05)
$RM\ dependence\ intensity_{i,j,t-1}$	0.0330	0.216
	(0.132)	(0.773)
Constant	-5.520***	-6.206***
	(0.0787)	(0.279)
RM Fixed effect	Yes	Yes
Year Fixed effect	Yes	Yes
Technology Fixed effect	Yes	Yes
Technology subgroup number	603	63
Weak identification: Cragg-Donald Wald F statistic	8265.54	849.02
Observations	43,929	4,294
R-squared	0.637	0.651

Note: *, **, *** indicate significance level at 10%, 5% and 1%, respectively