Department of
Geography and
Environment

Papers in Economic Geography and Spatial Economics

Technology, resources and geography in a paradigm shift: the case of Critical & Conflict Materials in ICTs

Andreas Diemer, Simona Iammarino, Richard Perkins and Axel Gros

Paper No. 29
Geography and Environment Discussion Paper Series

September 2021

Technology, resources and geography in a paradigm shift: the case of Critical & Conflict Materials in ICTs

Andreas Diemer[a,b], Simona Iammarino [b], Richard Perkins [b] & Axel Gros [b]

[a] Swedish Institute for Social Research (SOFI)
[b] Department of Geography & Environment, London School of Economics and Political Science

Abstract

The mining of several critical raw materials – including the so-called 'conflict minerals' associated with armed conflict and human rights abuses – and their combination, refining and use in many new advanced electronic products, are providing an important material infrastructure to current technological progress. Relying on text analysis of USPTO patent data between 1976 and 2017, our explorative study provides a methodological and empirical starting point for exploring the technological and geographical linkages between technological paradigms and selected critical and conflict materials (CCMs). Our descriptive analysis finds evidence of a clear association between ICT technologies and CCM intensity over time, and of a striking resource-technology divide in global ICT value chains between value creating and value extracting activities across Global North and Global South and their regions. The paper intends to emphasize the need for a more critical, spatially sensitive approach to studying resource-based technological change to expose the uneven development consequences created, sustained, or mitigated by technological progress.

Keywords: critical and conflict materials, paradigm shift, technological demand, geography of technology, geography of resource supply.

JEL codes: O30, Q34, Q55, R11

Acknowledgment

The authors gratefully acknowledge financial support from STICERD, LSE, 2019-2020, and the URF of the Department of Geography & Environment, LSE. We are indebted to the comments on a preliminary version from the participants in the RSA Conference in Santiago de Compostela, June 2019; the Special Session "The dark side of innovation in times of shifting technological paradigm" at the 5th Geography of Innovation Conference, University of Stavanger - RUNIN, January 2020; the PhD course on the Dark Side of Innovation, TIK Centre, University of Oslo, September 2020. The authors are solely responsible for any errors contained in the paper.

1. Introduction

In the current world economic scene, two major developments appear to be strengthening the strategic interdependence between advanced manufacturing and mining industries. The first is an evolving global division of labour and capital involving the geographic expansion and 'unbundling' of global production networks and value chains (GPNs/GVCs) across space (Baldwin, 2013). The second is an ongoing paradigm shift centred on the transition from analogue to digital, and innovations in information and communication technologies (ICTs), to an emerging, albeit uncertain, technological paradigm predicated on, amongst others, artificial intelligence, automation, big data, cloud computing and electric vehicles (Sukhodolov, 2019; Brixner et al., 2020). The mining of several critical raw materials, including so-called 'conflict minerals' – i.e. those specifically associated with armed conflict, human rights abuses and corruption – and their combination, refining and ultimate use in many new advanced electronic and electrical products, are providing a critical material infrastructure for these shifts. This has far-reaching implications for regions, countries, governments, firms, and resource-dependent value chains.

Existing research into critical and conflict materials (CCMs) has largely focused on the (negative) impacts of mineral extraction in source countries, the functional and geographic relationship between minerals production and consumption, and security of supply. Yet missing from the literature is work which takes a more dynamic perspective by examining how technological innovation is shaping the demand for these important inputs, and how the spatial dimensions of this relationship have evolved in terms of the specific geography of technological innovation and the sourcing of CCMs. This is an important gap and starting to address it would shed light on the wider impact of technological progress on economic, social and political developments across geographic space.

This paper is exploratory in nature and aims to open-up a promising research agenda. It focusses on the relationship between technological change and selected CCMs used, for example, in the production of lithium-ion batteries, crucial for manufacturing of smart phones, computers, electric cars, etc.. We explore this relationship through two main perspectives: innovation and its geographies. On the one hand, we are interested in studying whether and to what extent the ICT-based paradigm has driven technological demand for CCMs in new inventions; if ICT has relied on other technological fields that use CCMs intensely; and how these relationships have changed over time. Adopting then a geographical lens, we consider the ownership of innovations, mostly by firms, proxying the geography of CCM technological demand, and comparing it with that of CCM supply sources.

The paper uses a novel method to trace the CCM content of technological innovations, relying on textual data of patent filings. Our descriptive analysis points to a striking resource-technology divide in global ICT value chains between value-creating and -extracting activities across Global North and Global South and their regions. The paper thus suggests the need for a more critical, spatially sensitive approach to studying resource-based technological change; one which exposes the geographically uneven development consequences created, sustained, or mitigated by technological progress (Coenen and Morgan, 2020; Phelps et al., 2018).

The paper is divided into 6 sections. Section 2 provides the literature background, and the relevance of an economic geography of innovation perspective. Section 3 describes data and the general empirical strategy, including the definition of both ICTs and CCMs. Section 4 presents the analysis from the technological innovation side, whilst Section 5 considers the main features of the geography of CCM-related technological demand at national and subnational levels, comparing it with CCM supply. Section 6 concludes, and highlights future research directions.

2. Literature Background

Our starting point is the claim that recent trajectories of technological change are giving rise to increased demand for a set of critical raw materials. Several different terms have been used to capture these dynamics. For example, Ali et al. (2019) invoke the idea of "technology minerals", while Linton (2017) introduces the concept of "Emerging Technology Supply Chains" (ETSC).

Within this broad frame of growing relevance of certain natural resources, the existing literature addresses several themes. One is the link between the extraction, control and export of a subset of critical resources – 'conflict minerals' in particular – and instability, conflict and the violation of human rights (e.g. Berman et al., 2017; Church and Crawford, 2020). Relatedly, the literature explores various public and private regulatory initiatives aimed at managing or regulating conflict minerals in supply chains (e.g. Kim and Davis, 2016; Young et al., 2019). Another prominent theme is security of supply (e.g. Stoop et al., 2019; Ziemann et al., 2012). A feature of many (but not all) technology minerals/materials is that geological deposits, production, and refining capacity are concentrated in a relatively small number of countries and subnational regions. Many are also commercially non-substitutable in the short-term. These observations have led to growing interest in "material criticality" (Roelich et al., 2014), concerned with the strategic importance of certain raw elements in the production of modern technologies (Kiggins, 2015). A further focus is material flow analysis (MFA) which seeks to map-out the stocks and flows of critical raw materials across time and space throughout their lifecycle (Hao et al., 2017; Sun et al., 2019).

Our exploratory study departs significantly from the above work. Most fundamentally, rather than production or consumption, it is centrally concerned with the dynamics of innovation in technological paradigms implicated in CCMs and the associated geographies. Existing studies on resource-based technology have not ignored invention outright. However, to the extent that they have investigated inventive activity, the focus has tended to be on innovation within specific technological areas (e.g. batteries) (Feng and Magee, 2020). Moreover, with few exceptions, the relationship with CCMs has largely been neglected.

Recent work in the innovation and technological change literature has called scholarly attention to the "dark side of innovation" and its harmful consequences, unevenly distributed through the networks and value chains in the global division of labour (e.g. Phelps et al., 2018; Biggi and Giuliani, 2021). Such inequality has spatial footprints at various geographic scales. It is therefore crucial to advance research at the intersection of technological change and regional studies to better understand the role of innovation in the production of unfolding patterns of inequality (Coenen and Morgan, 2020; Giuliani, 2018). This imperative is especially prescient within the context of CCMs given their association with negative social, environmental, and economic impacts in sub-national regions and countries where they are extracted.

Against this backdrop, our approach seeks to place CCM-based innovation in the ICT paradigm centre-stage and provide a preliminary geographical view on the resource-technology relationship. By using patents, one of the most widely accepted measures of the level of inventive activity (Jaffe and Rassenfosse, 2017), we can explore the relationship between technological paradigm shifts, innovative activity, and changing patterns of resource demand. The concept of technological paradigms directs attention to how historically dominant technological domains are underpinned by shared understandings of technological problems, search heuristics, and bodies of knowledge (Dosi, 1988; Mun et al., 2019). Technological paradigms are characteristically associated with clusters of pervasive and interrelated innovations. To the extent that the production of these constituent technologies may depend on selected material inputs, technological paradigms might be expected to have distinctive resource signatures. This in turn suggests a linkage between innovation and raw materials/minerals, with the invention of new resource-dependent technologies (directly and indirectly) giving rise to resource demand. Indeed, technological paradigms may be associated with a degree of technological-cum-resource “lock-in” (Unruh, 2000), in that innovative efforts may build on past technological knowledge which itself is predicated on certain resource inputs. It is possible, of course, that this relationship in technological trajectories may weaken over time as, for example, firms and inventors seek to reduce their dependence on certain inputs through materials substitution. Patents allow us to systematically investigate these dynamics: first, by examining whether innovative activity in broad technological domains (here ICTs) is associated with specific materials/minerals (notably CCMs); and second, by exploring the cumulative nature of resource-dependent technological trajectories.

Another strength of such an approach is that it can provide geographically informed insights into debates about value capture within the context of natural resources (Atienza et al., 2020; Bridge, 2008). More specifically, moving beyond a focus on production and consumption, we can examine the spatial and organisational value-added of resource-dependent technological innovation within the context of CCMs. Theoretical inspiration is taken from debates about the geography of value creation in resource-dependent GVCs (Breul and Revilla Diez, 2019, Lebdioui et al., 2020; Murphy and Schindler, 2009). A central idea of the GVC concept is that the production of a final product is the result of multiple, spatially dispersed activities co-ordinated by lead, often multinational, firms. Activities associated with the invention and control of new technological knowledge are widely seen as offering greater opportunities for economic value creation.

A recurrent theme in economic geography is that these high value-added economic activities are spatially concentrated. New technologies, especially more complex ones, are thus developed and owned by actors in a relatively small number of territories and subnational regions (Iammarino and McCann, 2013). Such locales, characterised by clusters of inter-related firms, high-skilled workers, and system resources, occupy an important position within GVCs. Applied to CCM-related technologies, these insights would suggest that patenting is likely to be concentrated in those locations with institutional and technological capabilities in related domains (e.g. chemicals, electronics, and information technology), and with the ability to cash in on the presence of global ‘gatekeepers’ (Feldman et al., 2020; Lema et al., 2021; Martin and Trippl, 2017). Organizationally, we might expect the ownership of patents to be dominated by multinational enterprises (MNEs), especially larger ones with well-established pipelines for global knowledge sourcing (Berman et al., 2020). Such firms, themselves mostly headquartered in power- and knowledge-intensive urban centres and regional clusters, are those governing their global-scale supplier networks. GVC governance is the “authority and power relationships that determine how financial, material and human resources are allocated and flow within a chain” (Gereffi and Korzeniewicz, 1994, 97; see also Giuliani, 2018).

The above insights call into question whether many countries and regions where CCMs are extracted are well-placed to capture greater economic value through the production and control of new technologies. Reinforcing these doubts is a body of earlier work on the hypothesised “resource curse” identifying several factors – boom-and-bust commodity prices, appreciating real exchange rates and over-specialisation – which may impede technological upgrading in resource-rich economies (Hayter and Patchell, 2016; Sachs and Warner, 2001). Similarly, other studies have emphasised how MNE-controlled GVCs in the extractive sector may develop only weak backward and forward linkages with local economies (Bridge, 2008; Emel et al., 2011; Scholvin, 2020). In doing so, they limit the opportunities for technological learning and the localised ownership of new technologies, such that extractive regions may remain little more than “places of extraction” (Atienza et al., 2020). More positively, recent contributions have highlighted the possibilities for domestic firms to engage in innovative activities in areas such as extractive and processing equipment (Pietrobelli et al., 2018; Figueiredo and Piana, 2016). Yet, against a backdrop where innovation and control in knowledge-intensive domains is spatially and organizationally concentrated, the prospects for the spaces of CCM extraction also to become dominant in the generation of complex technologies which use these inputs seem distant.

This does not mean that we should not expect a shifting geography in CCM-related innovation over time. The rise of East Asia, and China in particular, has been a major development in a shifting geographical division of labour in the world economy. An important feature of this temporal dynamic has been growing involvement in technologies known to be associated with CCMs, such as semi-conductors and batteries. Moreover, economies such as China, South Korea and Taiwan have not only developed manufacturing capabilities, but also accumulated significant innovative capabilities which has allowed domestic firms to capture greater economic rents in GVCs (Lee and Gereffi, 2021). What this suggests is that, over recent decades, technology-related demand for CCMs may increasingly be traced to geographies and firms in East Asian countries and subnational regions.

We intervene in these debates by providing preliminary, explorative insights into two sets of questions: 1. Innovation, and the demand for CCMs: To what extent is the ICT paradigm CCM-intensive? Does it rely on other technologies that use intensely CCM? Has this reliance changed over time? 2. The geography of CCM demand and supply: What is the organisational, national, and subnational geography of CCM-related technologies? How does it compare with CCM supply?

3. Data, Text Analysis and Definitions

3.1 Measuring CCM-Technology Links

We rely on text analysis to construct the main measures of interest. The data source is PatentsView, a platform providing structured information about the universe of all patents granted by the United States Patents and Trademark Office (USPTO) between 1976 and 2017. We obtain the descriptive text of all patents issued over this period, which are examined to see if they contain keywords which comprise selected CCMs (as defined below). The absolute and relative frequencies of keyword appearance for each International Patent Classification (IPC) technology classes are obtained. For each class, these measures consider whether patent texts mention each of the CCM keywords at least once. More formally, we define the following general measure of relative frequency for keyword k and technology i:

$$f_i^k = \frac{\sum_{p \in i} \mathbf{1}_p\left(k \in T_p\right)}{\sum_p \mathbf{1}_p(p \in i)}$$

Where the numerator is the count of patents p belonging to technology i that mention keyword k at least once in their associated text corpus T_p (i.e. the absolute frequency), and the denominator is the total number of patents issued in technology i. We never count multiple appearances of the same keyword in the same patent, only considering whether a keyword appears *at least once*.[1] We also use patent data to acquire three further sources of information: (1) the timing of technological developments; (2) the identity of the assignees (i.e. firms or other organisations owning the patents); and (3) their geographical location.

[1] We also construct a similarly defined variable where for each patent we consider whether *any* of the keywords appears at least once. This differs from the sum of all relative frequencies for each keyword in a given technology because the same patent might be mentioning multiple keywords. In these instances, again, we only count that patent once.

Our method relies on the definition of keywords that accurately capture CCMs as described in the relevant literature. We examine six key CCMs, thus defining the keyword list as the set:

$$K = \{\text{tin}, \text{tungsten}, \text{tantalum}, \text{gold}, \text{cobalt}, \text{lithium}\}$$

The first four, also known as the "3TG", are increasingly used in electronic components such as semiconductors and electrical energy capacitors, and widely defined as conflict minerals. That is, they are minerals which "in politically unstable areas can be used to finance armed groups, fuel forced labour and other human rights abuses, and support corruption and money laundering" (European Commission, 2020). Cobalt and lithium are also featured because they are two critical materials with wide process and/or product applications (including batteries), and their demand is expected to increase significantly (e.g. to meet the needs of electric vehicles). Although not officially designated a conflict mineral, more than half the world's cobalt supply is extracted from the Democratic Republic of Congo (DRC), a country with a recent history of instability and conflict (e.g. Frankel 2016). Lithium is mostly extracted and produced in Australia, China, and the so-called Lithium-Triangle of South America (Chile, Argentina, and Bolivia).

The substantive significance of our six CCMs is therefore two-fold. First, they are identified in the literature as important material inputs to technologies which are part of ongoing technological paradigm shifts. Second, while the materials may be a valuable source of value-added, their extraction, refining and processing have historically been associated with negative social, economic, and environmental externalities in various supplying regions.

3.2 Validation of the Proposed Method

Recent years have witnessed the growing application of text analysis and mining to patents (Petralia et al., 2016). Such analysis is not without its shortcomings. Our keyword search is potentially susceptible to 'false positives'. These might arise if CCMs are mentioned in conjunction with negations (e.g. if the keyword denotes something being replaced as an input). Our method also relies on the assumption that keyword mentions and the intensity of CCM use are positively correlated.

To validate our approach, we investigate the degree to which global trends in keyword appearance predict global production of each CCM from 1976 to 2017, using data from the British Geological Survey.[2] We estimate the elasticity of mineral production to keyword occurrence by regressing the natural log of new production onto the natural log of relative frequency of keyword occurrence in the patents' text in that same year for each element (Figure 1). The histogram denotes the magnitude of these elasticities, along with 90% confidence intervals; the scatterplots below visualise this relationship. Our measure appears to fit the production data quite well with the exception of tungsten. While aggregated, we believe that these findings offer encouraging, albeit qualified, validation of our keyword-based approach.[3] Figure A.1 in the Appendix superimposes the relative frequency of at least one keyword mention onto commodity production, showing that the two measures closely track each other.

[Figure 1 about here]

3.3 Defining ICTs

[2] Available at: https://www2.bgs.ac.uk/mineralsuk/statistics/wms.cfc?method=searchWMS.

[3] In unreported analysis, we also considered a three-year lag between patenting and resource extraction, confirming this result.

Our analysis focusses on ICTs – further distinguishing AI within this wider group. To obtain ex ante definitions, we first match IPC subclasses to WIPO fields. The WIPO classification is purposely high-level and was developed to allow consistent cross-country comparison. We isolate fields that are unambiguously related to ICTs (see Appendix Table A.1), then isolating the IPC subclasses that Kim et al. (2018) identify as the top 20 ranking technologies in AI. After Tseng and Ting (2013), we also manually add three further classes (G06E, G06G, and G06J). Table A.2 in the Appendix reports our final classification of AI IPC subclasses falling within ICTs.

4. Explorative Analysis: Technology

4.1 CCM Keyword Contribution

Our main interest in this section is to explore whether and to what extent the ICT paradigm has driven the technological demand for CCMs over recent decades. Considering the relative frequency of CCMs keyword appearance over time by IPC section and subclass[4], by far the highest is found in Chemistry and metallurgy: this is unsurprising, given the direct relationship between this set of technologies and the chosen keywords.[5] Electricity also displays high relative frequencies: indeed, much of the patent growth in recent years, and especially since 1997, is driven by ICTs and electronics, mostly included in this section. For instance, the top 10 subclasses (4-digit, IPC4) in 2017 included battery technologies, capacitors and semiconductor technologies. In general, cobalt, gold, lithium, tantalum, tin, and tungsten are all relevant, albeit differently across technological groups. Lithium and gold, in particular, represent a large share for many technologies.[6]

We are interested in how relative frequencies of keyword-use differ depending on whether patents belong to ICTs and ICT-related AI applications, or other technological sectors. We test for statistically significant differences between ICTs and other types of technologies in terms of how intensely the selected keywords are mentioned in the patent text at least once. Figure 2 shows conditional means of relative frequency of keywords by three broad technology groups: ICTs excluding AI ("ICT"), AI technologies within the ICTs list ("AI"), and all other technologies. Conditional means are broken down by intervals of five years, to track how this relationship changed over time. Ninety percent confidence intervals are also constructed around each mean to allow comparison across groups and within each group over time.

[Figure 2 about here]

On average technologies related to ICT use keywords more intensely than any other technology: within any period, relative frequencies are at least twice as high in ICTs than other technologies. Yet, AI patents within ICTs show even lower frequencies than all other technologies. Also noteworthy is that, over time, all technology groups display growing intensities of keyword appearance. This is especially true for ICT: since 1975, the relative frequency for the use of at least one of the selected keywords grew by nearly 50%, settling at significantly higher levels at the end of the observed period.

We interpret these results as suggesting an association between changing technological paradigms and CCM-related innovation. This interpretation is further supported by the analysis revealing that ICTs are statistically significantly different from other technologies in the extent to which constituent

[4] Relevant graphs at IPC class/subclass levels are available from the authors.
[5] Thus, Section C (Chemistry and metallurgy) is later excluded due to the tendency of these technologies to prevail in terms of keywords for reasons unlikely related to the applications of interest here.
[6] For further detail see Figure A.2 in Appendix.

patents reference CCMs. Yet our findings for ICTs do not appear to be driven by AI technologies within the aggregate, which show only a weak relationship with CCMs.

4.2 Citation Analysis for ICTs

Beyond looking at the text of patents themselves, backward citations in ICTs/AI can be used to get a sense of how, over time, these technologies have relied on others that previously tended to use CCM keywords intensely. We produce a dataset of all citations between IPC subclasses based on the universe of citations made by all patents ever issued by the USPTO since 1976. We collapse citation counts by subclass pairs in each year, weighting citations by patents assigned to multiple subclasses equally. Larger subclasses (those with more patents) will tend to send more citations. We thus divide the number of citations made by each subclass by the total number of patents in that group (expressing the result in thousands). We refer to this as the (backward) citation rate c_{ij} for each citing IPC4 technology class i and cited class j. Since patent citations have increased over time, we demean each technology's citation rate by the average number of citations made across all classes in that same year (Hall et al., 2001). Next, we regress this demeaned citation rate onto the relative frequency of CCM keyword appearance in the cited class, interacted with a citing-technology period dummy capturing five-year interval groups from 1980 to 2015 (using a sample that runs until 2017). We additionally control for period trends and citing technology fixed effects to address systematic differences between IPC subclasses. More formally, we estimate the following empirical model:

$$\tilde{c}_{ij,t} = {f^k}_{j,t} \times \lambda_t + \lambda_t + \phi_i + \upsilon_{ij,t}$$

Where $\tilde{c}_{ij,t}$ is the demeaned citation rate, ${f^k}_{j,t}$ is the relative frequency of keyword k in cited technology j, λ_t is a citing technology period trend, and ϕ_i is a citing technology fixed effect. The term $\upsilon_{ij,t}$ is a residual error.[7] We can thus track these effects over time by looking at how they change across interacted coefficients. Figure 3 summarises the results with respect to the relative frequency of at least one keyword using a coefficient plot; the lines track the marginal effect for IPC subclasses falling within ICT/AI and other technologies respectively.[8]

[Figure 3 about here]

Throughout the period, the higher the relative frequency of CCM keyword appearance in a technology, the more likely this technology was to be cited by ICTs/AI patents. Consistent with Dosi's (1988) conception of technological paradigms, these findings are indicative of a path- and CCM-dependent technological trajectory within the domain of ICT/AI. This backward citation relationship weakened until the 1990s, strengthened until 2005, when it appeared to weaken again although remaining positive. In recent years, even though patents in ICT/AI have tended to name keywords more frequently in their own descriptive text (see section 4.1), it appears that they also have relied less on technologies that have named the CCM keywords intensely in the past. One probable interpretation of these dynamics is that they may reveal some degree of pressure – possibly following regulatory attempts by governments and international organisations in the early 2010s (e.g. the U.S. Dodd Frank Act in 2010, and the OECD Due Diligence Guidance in 2011) – to increase reporting in GVCs, encouraging companies to substitute away from technologies that use CCMs.

[7] Interacting the relative frequency coefficient with period dummies allows us to 'break down' the effect of relative frequency of keyword use in the cited technology by each period.

[8] Analogous results for each CCM keyword are available upon request.

5. Explorative Analysis: Geography

5.1 Firms, world regions and countries

This section provides a preliminary answer to our second research question: what are the organisational, national, and subnational geographies of CCM-related ICT/AI technologies? And have they changed over time? We are not interested in studying where the innovative activity takes place, but rather mapping the geography of ownership of economic rights associated to patents and new technologies, which are more accurately captured through the assignee.[9]

Similar to section 4.1, we start by looking at which assignees own the patents that use the chosen keywords most intensely. Because our focus is on individual actors, counts of patents with at least one of the keywords of interest are used, rather than shares. This is for two reasons. Firstly, we are interested in the actors most active in patenting inventions that are CCM-related. Secondly, looking at shares on all patents would potentially bring a small assignee with very few patents that happen to mention one of the keywords on top of the list.

Among the top 50 assignees in ICT/AI we find many familiar electronics MNEs – primary located in Japan, closely followed by the US, and then South Korea – such as Samsung, IBM, Canon, Micron Technology, Sony, Intel, AMD, and Apple, together with a few chemical-pharmaceutical giants – e.g. Du Pont, Bristol-Myers Squibb, Pfizer – known historically for their wide technological diversification (Cantwell, 1995). Their dominance is consistent with theory and evidence framing large MNEs in a handful of advanced economies as major drivers of leading technology paradigms.

To quantitatively investigate differences in the relative frequency measure across groups of countries, Figure 4 provides conditional means of relative frequency of keyword use by three macro-regions of origin of patent assignees: the Americas, Asia, and Europe. We adopt the official definition provided by the UN, excluding Africa and Oceania from the analysis due to insufficient observations. Additionally, we break-down conditional means by intervals of five years, to track how this relationship changed over time. Similar to Figure 2 above, we also construct 90 percent confidence intervals around each mean, allowing comparison across groups and within each group over time.

[Figure 4 about here]

Starting from comparable levels of keyword-use intensity around mid-1970s, ICT/AI patents across the three regions started to diverge. By the 1990s, our measure suggests that technologies produced in the Americas would tend to rely more intensely on CCMs than those in Asia or Europe. However, while average relative frequency tended to drop in Europe over subsequent periods, that of ICT/AI technologies patented in Asia increased. In the 2010-2015 period, the reliance on CCMs of Asia's newly developed ICT/AI technologies was well above Europe, and just above the Americas (although the two averages cannot be distinguished at conventional levels of statistical significance). In 2015, the average relative frequency for Asian patents was higher than it had ever been since 1985, with point estimates even reaching an all-time high based for our sample period. This tentatively indicates that CCM demand associated with the ICT/AI paradigm has increasingly been driven by technological innovation controlled by MNEs and other actors in emerging Asia.

[9] We additionally checked the location of all inventors associated with patents in our sample from PatentsView, and assigned located patents on this basis by retaining the mode of all the locations of the patents' listed inventors. We then compared matching rates for country location based on assignees to that based on inventors. For over 90% of all patents in our sample, these locations coincided (results available from the authors).

Given the “conflict-related” nature of our selected materials, we deem it interesting to conduct a very preliminary geographical analysis of the empirical relationship between demand for CCMs and conflict/violence. We use yearly data on state and non-state armed conflicts, our relative frequency of keyword appearance measures, and global mineral production data. While largely exploratory[10], the analysis confirms a correlation between global technological demand for CCMs and armed conflict in conflict in the Middle East, Africa, and the Americas (notably Central and South America). By contrast, this statistical association is entirely absent in Europe and Asia (or North America). These very preliminary finding warrant further empirical investigation, possibly at a more fine-grained spatial level.

5.2 Subnational locations

Providing more detailed spatial profiles, Figure 5 focuses on the subnational location of assignees.[11] We retain only assignees that developed at least one patent in ICT/AI that mentioned at least one keyword of interest over the 2000-2017 period. These are mapped onto their reported location, dropping assignees with less than 10 patents. The size of point markers is proportional to the number of the assignees’ patents with at least one keyword. Country polygons are coloured in varying shades of blue depending on the counts of all assignees represented on the map, divided in six size-categories ranging from less than 10, up to over 1,000. Remarkably, despite the abundance of mines for these raw materials in Africa and South America, no locations in these continents innovate in the ICT/AI area that rely on them – highlighting a geographical disconnect between resource supply and the control of technological innovation. This provides evidence that the presence of critical raw materials has, by itself, not created a context for source countries to expand value capture in GVCs through inventive activity within high-technology areas.

[Figure 5 about here]

Using the ArcMap 10.3 software, Maps 1a, b and c display the specific geography of the world most productive assignees – i.e. those with more than 100 CCM-related patents in the case of the US and Europe, and 500 in the case of Asia. The top assignees in the US number 116 (out of a total of 2559), and are mostly concentrated in the Silicon Valley – e.g. Intel in Santa Clara, Apple in Cupertino, and the only non-business owner of CCM-related patents in the top-50, the Board of University of California; New York State – e.g. IBM in Armonk, General Electric in Schenectady, Xerox and Eastman Kodak in Rochester, Bristol-Myers Squibb and Pfizer in New York; and Texas – e.g. Hewlett Packard and Texas Instruments in Dallas.

There are 27 top assignees in Europe (out of 804 in total), located in Germany, France, Netherlands, Austria, and the UK. Prime locations are the renowned and most innovative manufacturing regions in Southwest Germany – e.g. Munich, which hosts the only German company in the top 50, Infineon Technologies, Stuttgart in Baden-Württemberg, and the area south of Frankfurt, in Hesse – and Berlin. In France, assignees with the highest patent intensity are mostly concentrated in Paris; on Map 1.b the pointer in Crolles (Grenoble) in the region of Rhône-Alpes flags the presence of ST Microelectronics France, the largest plant in the country. Very few other locations appear in the Map, showing the strong spatial agglomeration of top assignees of CCM-related ICT patents: Eindhoven, where Philips is headquartered, and Amsterdam in the Netherlands; the region of Carinthia (Villach), a semiconductors hub in Austria; and the UK cluster of Cambridge.

The top assignees in Asia total 51 (out of 1588): in this case the threshold was 500, confirming the large and rising Asian prominence in ICT/AI inventions relying on CCMs. Relevant MNEs are located

[10] See, in Appendix, ‘Technological demand for CCMs and conflict/violence: preliminary evidence’ and Table A.3.
[11] Cf. also Figure A.3 in Appendix.

mostly in Japan, in the Tokyo metropolitan region (e.g. SEL, Canon, Toshiba, Sony), followed by the large electronic clusters around Osaka (e.g. Sharp, Panasonic, Nitto Denko, Sanyo) and in the Nagano prefecture (e.g. Seiko). Top assignees in South Korea are strongly agglomerated in the metropolitan region of Seoul; other notable urban agglomerations for top assignees are Taipei, Singapore, and Beijing.

Several observations follow from the above. One is that the production and control of new technological knowledge related to CCMs in the ICT paradigm is, as expected, highly spatially concentrated in major urban areas and regional clusters within a relatively small number of countries in the Global North. Another is the dominant role of large MNEs – including many high-profile technology "giants". Such observations suggest that worldwide CCM-related demand is, directly or indirectly, related to the innovative activities of a relatively small number of leading corporates located in comparatively few sub-national locations with favourable urban and regional assets. This is highly consistent with the growing evidence on the regional inequality implications of globalization in the Global North (e.g. Crescenzi and Iammarino, 2017; Feldman et al., 2021).

[Maps 1a, 1b, 1c about here]

We then broadly compare the geography of CCM-related technologies' ownership with that of the mining sites for our six selected CCMs: data for the mining sites come from the Mineral Resources Data System (MRDS) and refer to the US Geological Survey 2017. Figure 6 (and Figure A.4 in the Appendix) shows the striking resource-technology divide: the concentration of mining sites is mainly found in specific regions of the Global South in Sub-Saharan Africa and South America, and in some developing countries in Central Asia, in contrast with assignees almost exclusively located in the Global North – and as we have seen above, highly concentrated in a few hot spots.[12]

[Figure 6 about here]

6. Conclusions and Next Steps

The relationship between technological innovation and natural resources has been a long-standing concern for scholars, though the predominant focus has been on the impact of technological advances on resource scarcity, efficiency, and price (e.g. Marañon and Kumral, 2019). The present paper moves the focus of the debate to CCMs, a set of resources where there has been very limited work from an economic geography perspective.

Our explorative analysis makes several important contributions. First, we find evidence of a significant increase in overall innovative activity related to CCMs over our sample period. This rise tallies with data from other sources which documents rising production and consumption of CCMs over a similar time frame. Our goal in the present paper was not to establish a causal linkage between these concurrent trends. Yet it is plausible to suggest that innovation and increased demand for key CCMs are related. Second, we find that technological applications associated with the ICT paradigm have a particularly strong association with CCMs. Although only indicative, our descriptive exercise lends weight to the claim that specific technological paradigms have distinctive resource signatures, with potentially important implications for resource demand and associated geographies. Third, whilst past work within the frame of material flow analysis has usefully mapped out the sources, production and

[12] Our analysis restricts the sample to assignees with at least one patent mentioning one of the relevant keywords. As such, there may well be some firms patenting in regions in Africa or South America, just not in a way that falls within the scope of our analysis.

consumption of a number of CCMs (Ziemann et al., 2012; Sun et al., 2019), our analysis goes one step further by exposing a significant spatial disparity between the locations where large amounts of CCMs are extracted and those where the majority of CCM-based technological returns is appropriated. Some of the former are high-income (e.g. Australia) and middle-income (e.g. China) economies, but many are low-income ones (e.g. DRC). On the other hand, a relatively small number of metropolitan regions and clusters in the Global North – hosting the largest MNEs who also are the main nodes and act as flagships in the relevant GPNs and GVCs – appear to be dominating the high value-added parts of CCM-dependent value chains predicated on innovative activity. These combined findings further lay challenge to optimistic accounts about both the potential for places of the Global South to couple resource-based with knowledge-based development, and for peripheral regions of the Global North to reap the benefits of globalisation through cutting-edge investments in innovation.

It is important to caveat our findings. The fact that a patent contains a relevant keyword does not mean that the respective technology necessarily impacts physical demand for CCMs. Moreover, patent counts are only a rough approximation of the technology's actual CCM-intensity, or whether it increases or reduces resource inputs (e.g. though efficiency or substitution). What is more, USPTO data may provide a somewhat geographically biased picture of the true level of inventive activity across space, in that inventors from certain countries (e.g. US and Canada) are more likely to file for patents in the US than others (De Rassenfosse et al., 2013). That said, while some geographical bias is possible, it is unlikely that any other source of patenting data would offer a more comprehensive picture, particularly one that focuses on ICTs and that can be dated back to the 1970s. Finally, our aggregated approach – wherein we group different CCMs together – may also conceal important differences across individual materials, e.g. in the geographies of both technology demand and CCM extraction. We nevertheless believe that our novel patent-based approach usefully complements past work relying on trade statistics, input-output tables, and physical estimates of material inputs in production and consumption.

Future research lines are multiple, not least because ours is one of the first studies of its kind, investigating a topic with a wide range of academic and applied implications. One direction is to develop and refine the methods used in the present study; for example, deploying more advanced text mining *and* machine learning technique to identify and discriminate innovations which are resource demand-creating and -reducing. Undertaking more detailed work, which seeks to capture input-output relationships linking the supply and demand of specific CCMs along the entire GVC, would also be highly valuable in understanding uneven regional development. Taking account of both technology, product and organizational aspects, such studies would help to shed light on both value capture *and* value extraction within the context of CCMs, and the extent to which this is organizationally mapped onto the control of technological innovation. Another critically important issue is investigating the depth of causal connections between technological change, technological demand and negative territorial outcomes such as conflict and violence related to CCM extraction – with a particular need for work at sub-national scales. Research should also be undertaken into policy and other factors influencing CCM-related technological change. One line of enquiry would be to examine whether government-mandated supply chain due diligence/reporting requirements – at various scales of governance, e.g. local, national, and macro-regional – are effective in stimulating technological innovation and diffusion aimed at reducing dependence on regulated CCMs. Such studies could additionally seek to investigate the extent to which regulation (e.g. at the national or sub-national scale) only stimulates innovation locally, or whether innovators elsewhere are responsive to policy signals in other jurisdictions.

More generally, further exploration of the nexus between technological paradigms and their critical resource intensity through the lens of economic geography would substantially improve the current policy response. In particular, it could help inform and support a move from exclusively top-down fragmented regulatory frameworks to globally coordinated, multi-governance and place-sensitive ones (Coenen and Morgan, 2020; Giuliani, 2018; Phelps et al., 2018). Being able to disentangle the specific geography of resource-technology linkages and their consequences can also uncover policy and other opportunities for those places that – both in the Global North and in the Global South – currently struggle to reap the returns to technological progress within an evolving global division of labour.

References

Ali, S. H., Perrons, R. K., Toledano, P., & Maennling, N. (2019). A model for “smart” mineral enterprise development for spurring investment in climate change mitigation technology. *Energy Research & Social Science*, 58, 101282.

Atienza, M., Arias-Loyola, M. and Lufin, M. (2020). Building a case for regional local content policy: The hollowing out of mining regions in Chile, *Extractive Industries and Society*, 7(2), 292–301.

Baldwin, R. (2011). *Trade and industrialisation after globalisation’s 2nd unbundling: How building and joining a supply chain are different and why it matters.* NBER Working Paper No. 17716, December.

Berman, A., Marino, A. and Mudambi, R. (2020). The global connectivity of regional innovation systems in Italy: a core–periphery perspective. *Regional Studies,* 54(5), 677–691.

Berman, N., Couttenier, M., Rohner, D., & Thoenig, M. (2017). This Mine Is Mine! How Minerals Fuel Conflicts in Africa. *American Economic Review*, 107(6), 1564-1610.

Biggi, G. and Giuliani, E. (2021). The noxious consequences of innovation: what do we know? *Industry and Innovation*, 28(1), 19-41.

Breul, M., Revilla Diez, J. and Sambodo, M. T. (2019). Filtering strategic coupling: Territorial intermediaries in oil and gas global production networks in Southeast Asia. *Journal of Economic Geography*, 19(4), 829–851.

Bridge, G. (2008). Global production networks and the extractive sector: governing resource-based development. *Journal of Economic Geography*, 8(3), 389-419.

Brixner, C., Isaak, P., Mochi, S., Ozono, M., Suárez, D., Yoguel, G. (2020). Back to the future. Is industry 4.0 a new tecno-organizational paradigm? Implications for Latin American countries. *Economics of Innovation and New Technology* 29(7), 705–719.

Cantwell, J. (1995). The globalisation of technology: what remains of the product cycle model?. *Cambridge Journal of Economics*, *19*, 155-155.

Church, C., & Crawford, A. (2018). Green conflict minerals: The fuels of conflict in the transition to a low-carbon economy. IISD, Winnipeg.

Coenen, L. & Morgan, K. (2020). Evolving geographies of innovation: existing paradigms, critiques and possible alternatives, *Norsk Geografisk Tidsskrift – Norwegian Journal of Geography*, 74:1, 13-24.

Crescenzi, R. & Iammarino, S. (2017). Global investments and regional development trajectories: the missing links, *Regional Studies*, 51:1, 97-115.

de Rassenfosse, G., Dernis, H., Guellec, D., Picci, L., & van Pottelsberghe de la Potterie, B. (2013). The worldwide count of priority patents: A new indicator of inventive activity. *Research Policy*, 42(3), 720-737.

Dosi, G. (1998). Sources, Procedures, and Microeconomic Effects of Innovation. *Journal of Economic Literature*, 26(3), 1120-1171.

Emel, J., Huber, M. T. and Makene, M. H. (2011). Extracting sovereignty: Capital, territory, and gold mining in Tanzania. *Political Geography*, 30(2), 70–79. doi: 10.1016/j.polgeo.2010.12.007.

European Commission. Conflict Minerals Regulation Explained. Accessed 21 January 2020. https://ec.europa.eu/trade/policy/in-focus/conflict-minerals-regulation/index_en.htm.

Feldman, M., Guy, F. and Iammarino, S. (2021). Regional income disparities, monopoly & finance. *Cambridge Journal of Regions, Economy and Society*, 14(1), 25-49.

Feng, S. and Magee, C. L. (2020). Technological development of key domains in electric vehicles: Improvement rates, technology trajectories and key assignees, *Applied Energy*, 260.

Frankel, T.C. (2016). Cobalt Mining for Lithium Ion Batteries Has a High Human Cost - Washington Post. Accessed 22 January 2020. https://www.washingtonpost.com/graphics/business/batteries/congo-cobalt-mining-for-lithium-ion-battery/?noredirect=on.

Gereffi, G. and Korzeniewicz, M., eds. (1994). *Commodity chains and global capitalism* (No. 149). ABC-CLIO.

Giuliani, E. (2018). Regulating global capitalism amid rampant corporate wrongdoing—Reply to "Three frames for innovation policy". *Research Policy*, 47(9), 1577-1582.

Hall, B. H., Jaffe, A. B., & Trajtenberg, M. (2001). *The NBER patent citation data file: Lessons, insights and methodological tools.* National Bureau of Economic Research.

Hao, H., Liu, Z., Zhao, F., Geng, Y., & Sarkis, J. (2017). Material flow analysis of lithium in China. *Resources Policy*, 51, 100-106.

Hayter, R. and Patchell, J. (2016). Resources and development. In *International Encyclopedia of Geography: People, the Earth, Environment and Technology: People, the Earth, Environment and Technology* (Vol. 1). Oxford, UK: John Wiley & Sons.

Iammarino, S. and McCann, P. (2013). *Multinationals and Economic Geography. Location, Technology, and Innovation*, Edward Elgar, Cheltenham UK and Northampton (MA) USA.

Jaffe, A. B., & Rassenfosse, G. d. (2017). *Patent citation data in social science research: Overview and best practices* (Vol. 68): John Wiley & Sons, Inc.

Kiggins, R. D. (Ed.) (2015). *The political economy of rare earth elements: rising powers and technological change*. Basingstoke: Palgrave.

Kim, J., Jun, S., Jang, D., & Park, S. (2018). Sustainable technology analysis of artificial intelligence using Bayesian and social network models. *Sustainability*, 10(1).

Kim, Y. H., & Davis, G. F. (2016). Challenges for Global Supply Chain Sustainability: Evidence from Conflict Minerals Reports. *Academy of Management Journal*, 59(6), 1896–1916.

Lebdioui, A., Lee, K. and Pietrobelli, C. (2020). Local-foreign technology interface, resource-based development, and industrial policy: how Chile and Malaysia are escaping the middle-income trap. *Journal of Technology Transfer*, 46(3), 660-685.

Lee, J. and Gereffi, G. (2021). Innovation, upgrading, and governance in cross-sectoral global value chains: the case of smartphones. *Industrial and Corporate Change*, 2020, 1–17.

Lema, R., Pietrobelli, C., Rabellotti, R., & Vezzani, A. (2021). Deepening or delinking? Innovative capacity and global value chain participation in the ICT sectors. UNU-MERIT Working Papers No. 2021–007.

Linton, J. D. (2017). Emerging Technology Supply Chains. *Technovation*, 62-63, 1-3.

Marañon, M. and Kumral, M. (2019). Kondratiev long cycles in metal commodity prices, *Resources Policy*, 61, 21-8.

Martin, R. and Trippl, M. (2017). The evolution of the ICT cluster in southern Sweden – Regional innovation systems, knowledge bases and policy actions, *Geografiska Annaler, Series B: Human Geography*, 99(3), 268–283.

Mun, C., Yoon, S., Kim Y., Raghavan, N., Park, H. (2019) Quantitative identification of technological paradigm changes using knowledge persistence. PLoS ONE 14(8): e0220819

Murphy, J. T. and Schindler, S. (2011). Globalizing development in Bolivia? Alternative networks and value-capture challenges in the wood products industry. *Journal of Economic Geography*, 11(1), 61–85.

Petralia, S., Balland, P. A. and Rigby, D. L. (2016) Unveiling the geography of historical patents in the United States from 1836 to 1975. *Scientific Data*. 1–14.

Phelps, N. A., Atienza, M. and Arias, M. (2018). An invitation to the dark side of economic geography. *Environment and Planning A: Economy and Space*, 50(1), 236–244.

Pietrobelli, C., Marin, A., & Olivari, J. (2018). Innovation in mining value chains: New evidence from Latin America. *Resources Policy*, 58, 1–10.

Roelich, K., Dawson, D. A., Purnell, P., Knoeri, C., Revell, R., Busch, J., & Steinberger, J. K. (2014). Assessing the dynamic material criticality of infrastructure transitions: A case of low carbon electricity. *Applied Energy*, 123, 378-386.

Sachs, J. D., & Warner, A. M. (2001). The curse of natural resources. *European Economic Review*, 45(4), 827-838.

Stoop, N., Verpoorten, M. and Windt, P. C. van der (2019). Artisanal or Industrial Conflict Minerals? Evidence from Eastern Congo. SocArXiv.

Sukhodolov, Y. A. (2019). The Notion, Essence, and Peculiarities of Industry 4.0 as a Sphere of Industry, in Popkova, E. G., Ragulina, Y. V. and Bogoviz, A. V. (Eds). Industry 4.0: Industrial Revolution of the 21st Century, pp. 3-10. Springer International Publishing, Cham.

Sun, X., Hao, H., Liu, Z., Zhao, F., & Song, J. (2019). Tracing global cobalt flow: 1995–2015. *Resources, Conservation and Recycling*, 149, 45-55.

Tseng, C. Y., Ting, P. H. (2013). Patent analysis for technology development of artificial intelligence: A country-level comparative study. *Innovation: Management, Policy and Practice*, 15(4), 463–475.

UNCTAD/FAO. (2017). *Commodities and Development Report 2017: Commodity Markets, Economic Growth and Development.* New York/Geneva.

Unruh, G. (2000). Understanding carbon lock-in. *Energy Policy*, 28(12), 817-830.

Young, S., Fernandes, S. and Wood, M. (2019). Jumping the Chain: How Downstream Manufacturers Engage with Deep Suppliers of Conflict Minerals. *Resources*, 8(1), 26.

Ziemann, S., Weil, M., & Schebek, L. (2012). Tracing the fate of lithium—The development of a material flow model. *Resources, Conservation and Recycling*, 63, 26-34.

Figures

Figure 1

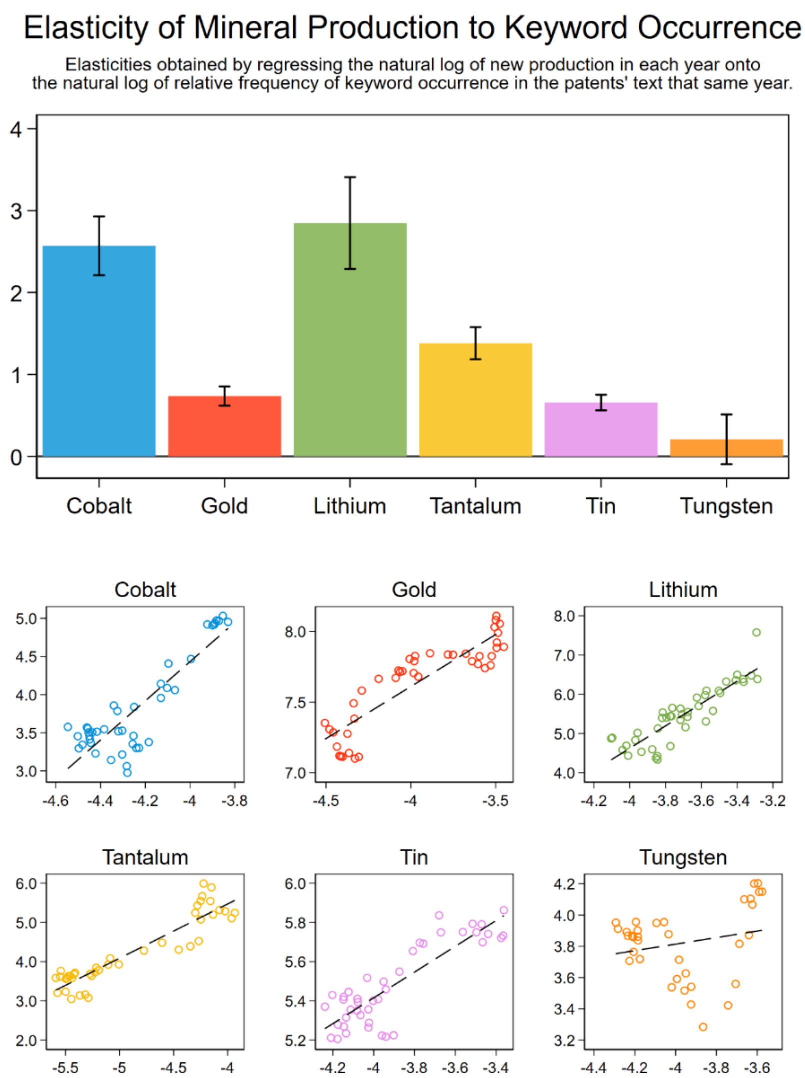
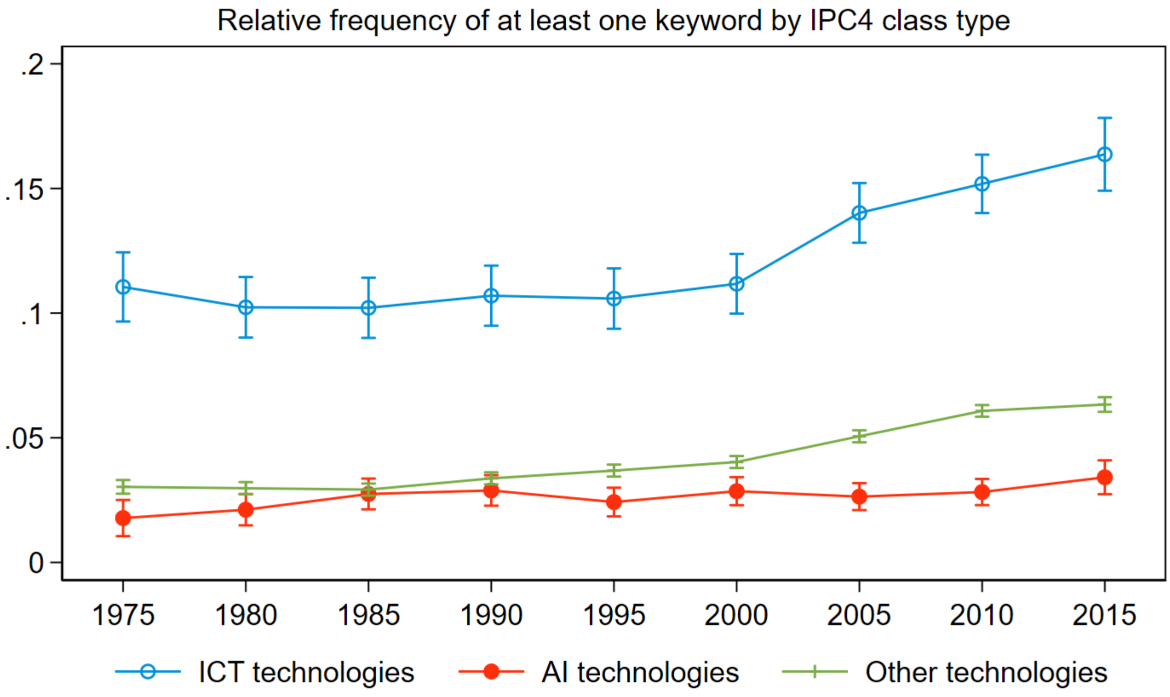
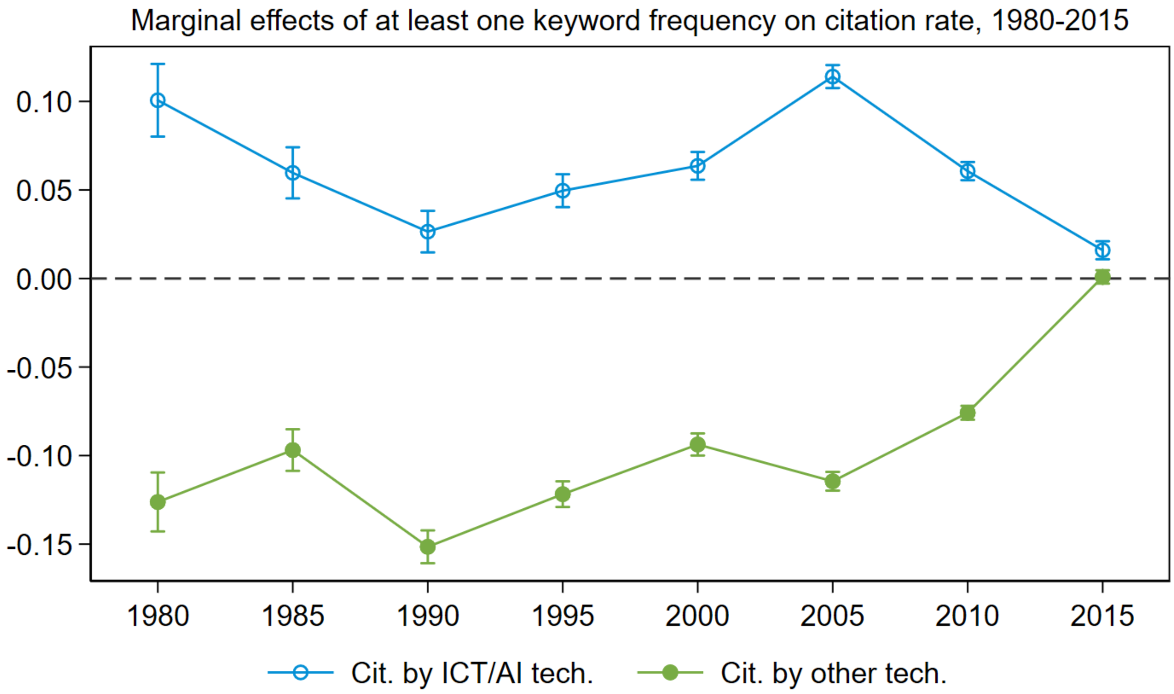


Figure 2



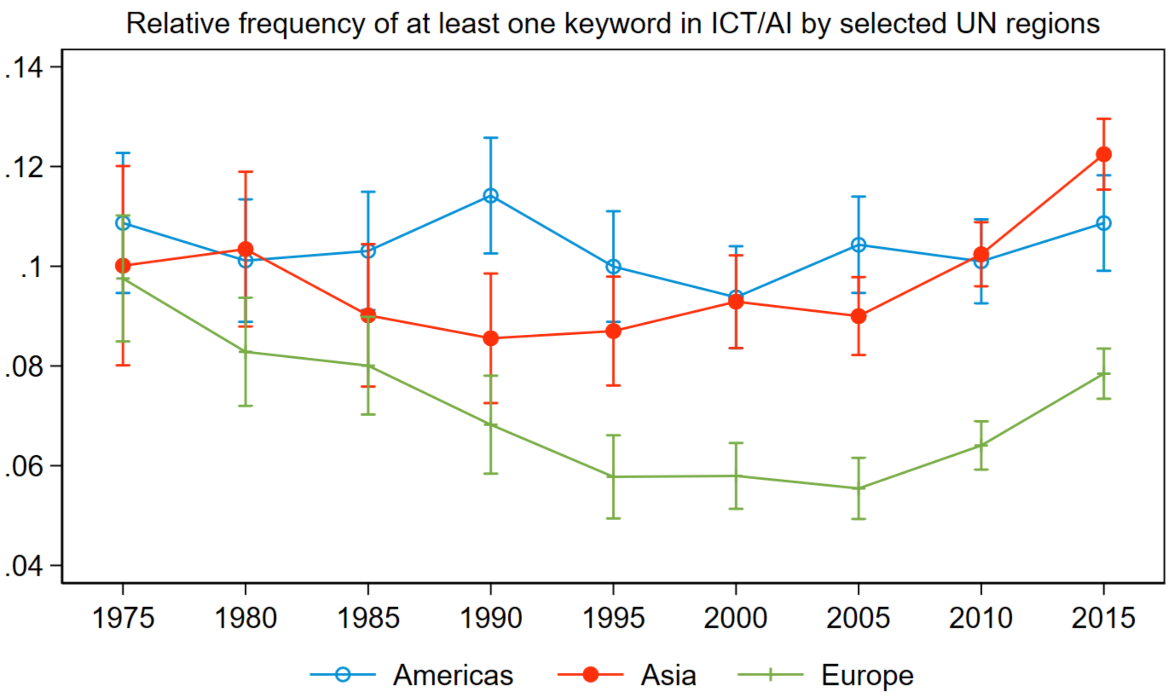
Calculations exclude IPC subclasses with less than ten patents and, for 'other tech.', belonging to chemistry and metallurgy. Vertical bars give 90% confidence intervals. All AI technologies are a subset of ICT ones.

Figure 3



Citation rates are de-meaned by year. Calculations exclude citing and cited IPC subclasses with less than ten patents. Vertical bars give 90% CIs. All regressions control for period trends and citing IPC dummies.

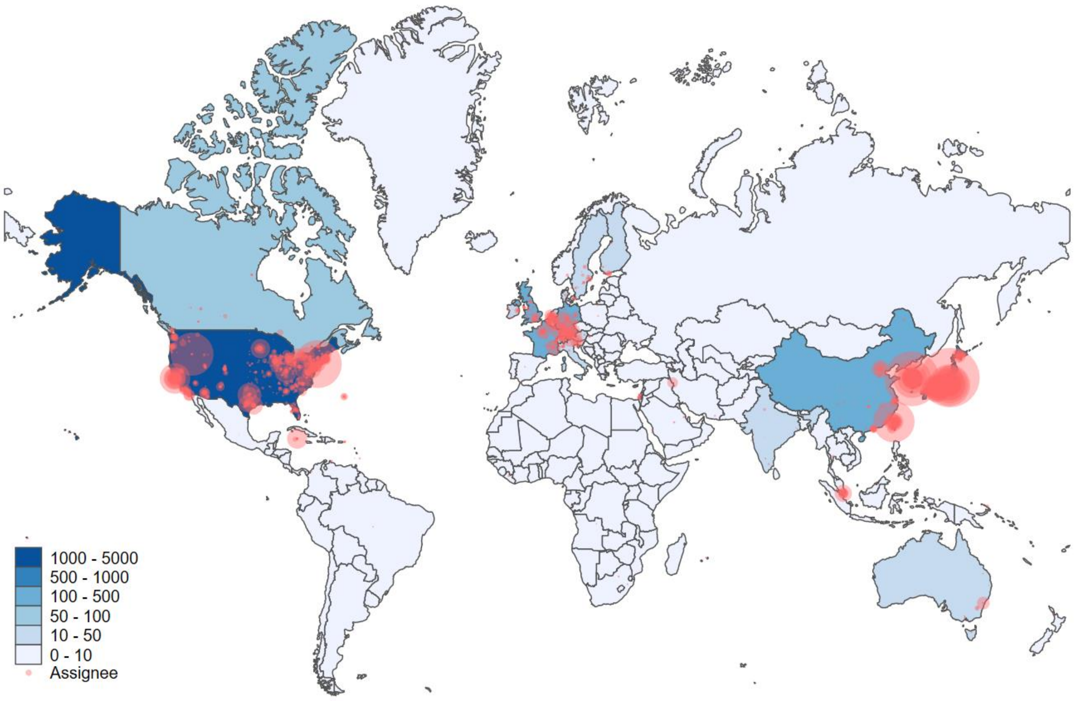
Figure 4



Calculations exclude IPC subclasses with less than ten patents. Vertical bars give 90% confidence intervals. All AI technologies are a subset of ICT ones.

Figure 5

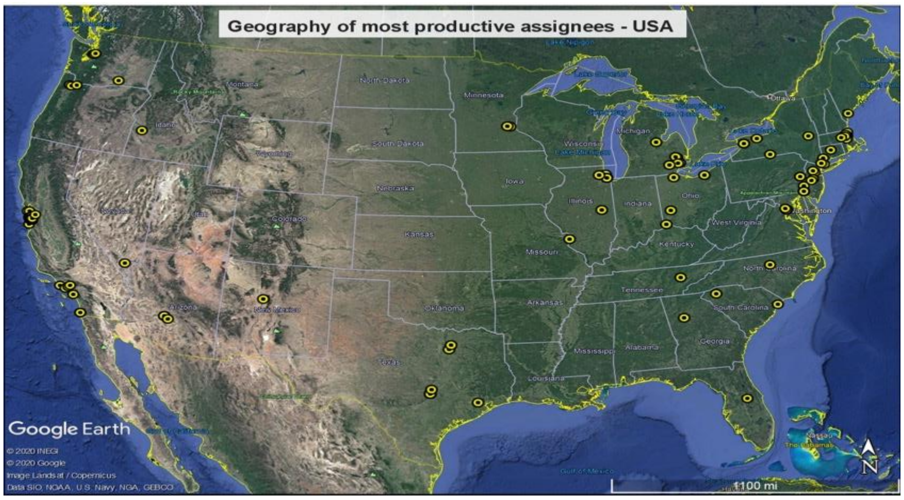
Counts of assignees in ICT/AI with patents mentioning at least one keyword, 2000-2017



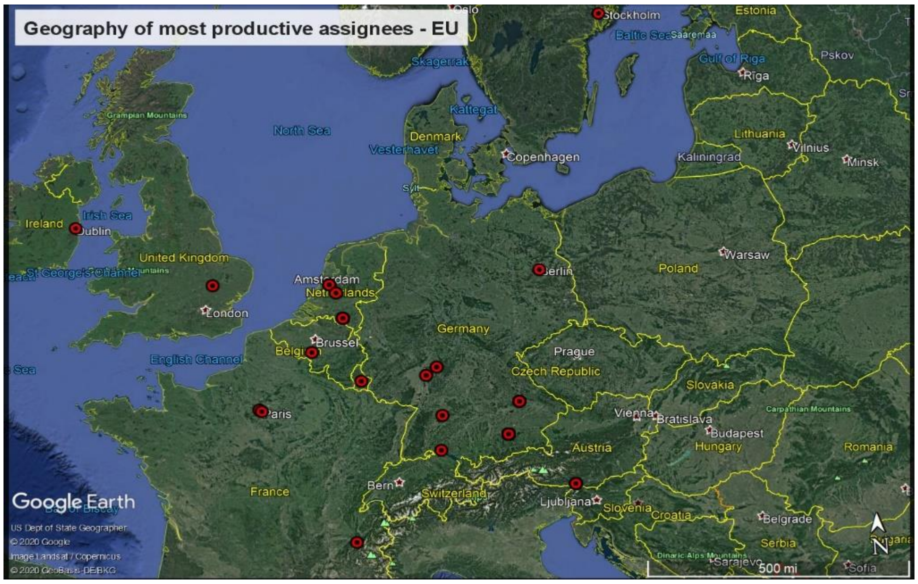
The marker size of assignees is proportional to the number of assignees' patents mentioning at least one keyword

Maps 1a,b,c: Location of top assignees in terms of number of CMM-related patents in ICT/AI

Map 1.a – USA (threshold >100 patents)

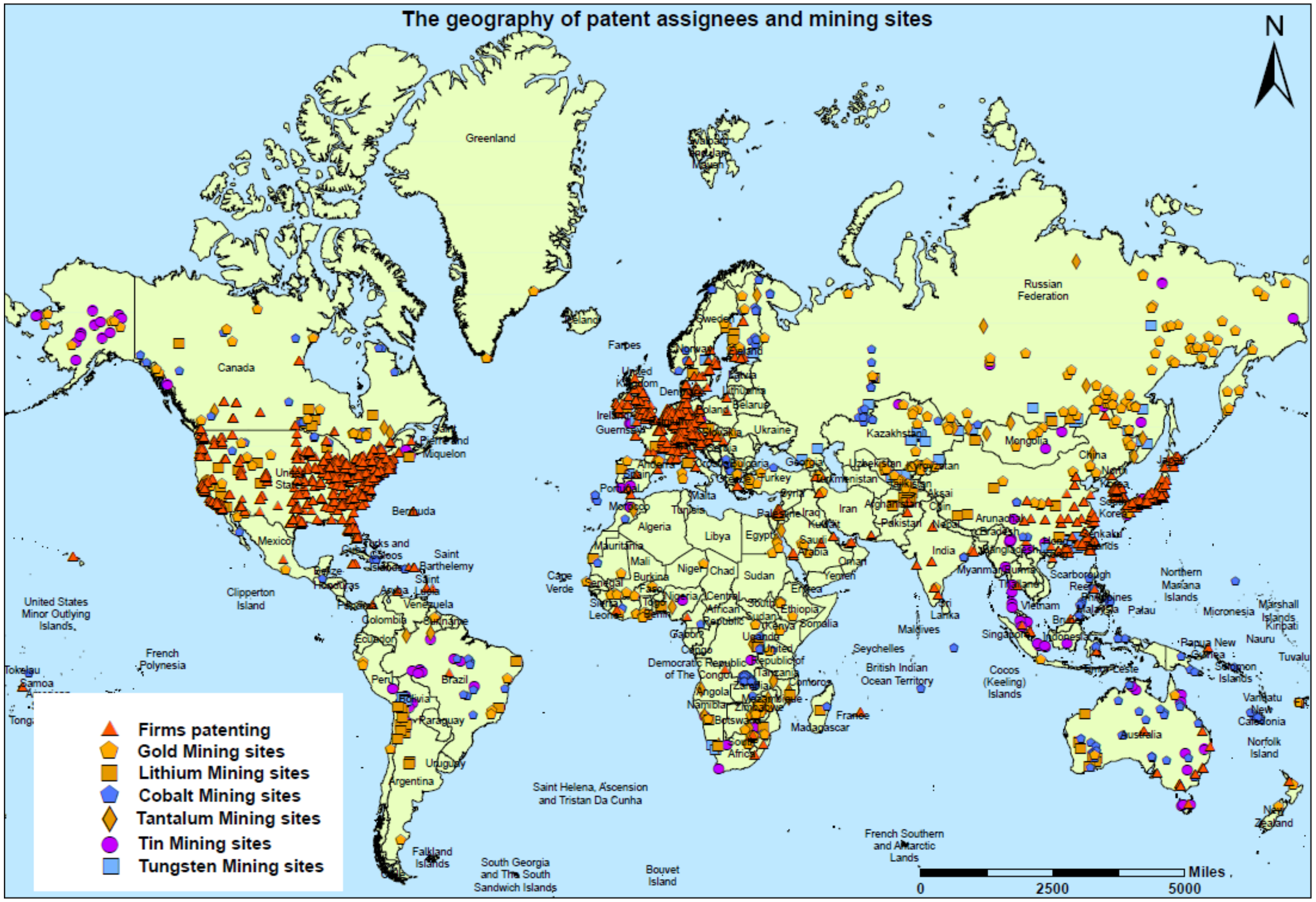


Map 1.b – Europe (threshold >100 patents)



Map 1.c – Asia (threshold >500 patents)

Figure 6: The subnational geography of patent assignees and CCM mining sites



Appendix

Figure A.1. Relative frequency of at least one CCM keyword in patents and CCM global production

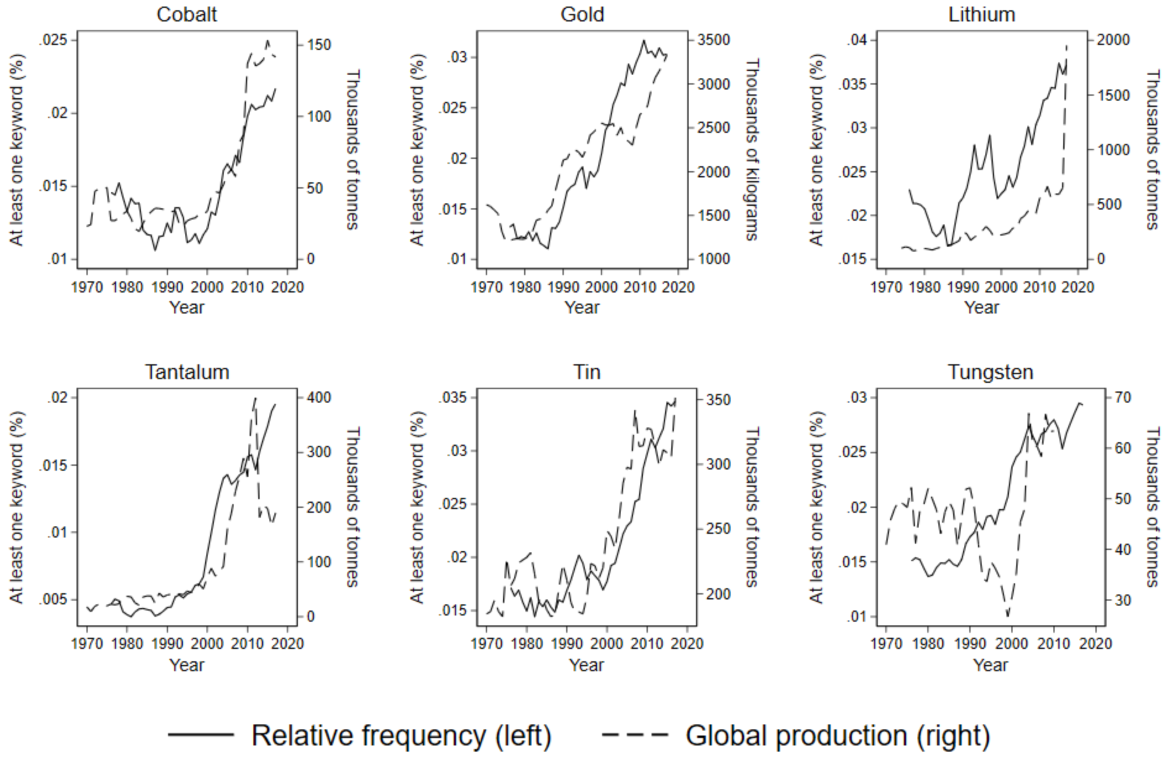


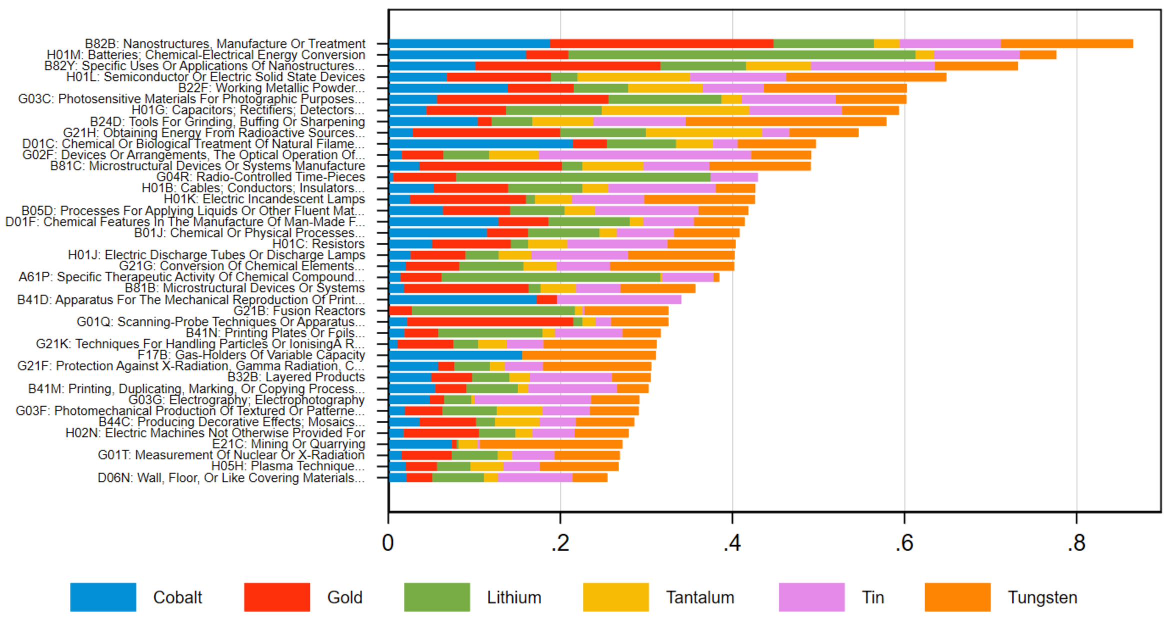
Table A.1 List of WIPO Fields related to ICT

WIPO Field	Sector Title	Field Title
1	Electrical engineering	Electrical machinery, apparatus, energy
2	Electrical engineering	Audio-visual technology
3	Electrical engineering	Telecommunications
4	Electrical engineering	Digital communication
5	Electrical engineering	Basic communication processes
6	Electrical engineering	Computer technology
8	Electrical engineering	Semiconductors
21	Chemistry	Surface technology, coating
22	Chemistry	Micro-structural and nano-technology

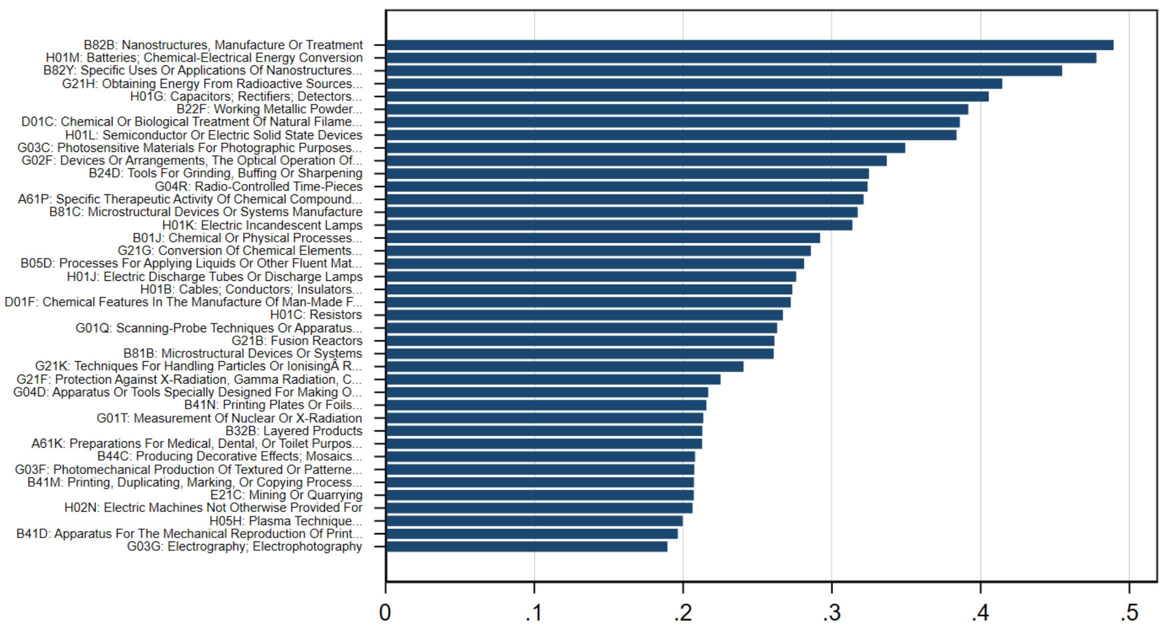
Table A.2: IPC4 subclasses within ICT belonging to AI technologies

IPC4	Title (truncated)	WIPO Field Sector and Title
G06E	Optical Computing Devices	Electrical engineering: Computer technology
G06F	Electric Digital Data Processing	Electrical engineering: Computer technology
G06G	Analogue Computers	Electrical engineering: Computer technology
G06J	Hybrid Computing Arrangements	Electrical engineering: Computer technology
G06K	Recognition of Data; Presentation of Data...	Electrical engineering: Computer technology
G06N	Computer Systems Based on Specific Computational Methods	Electrical engineering: Computer technology
G06Q	Data Processing Systems or Methods	Electrical engineering: IT methods for management
G06T	Image Data Processing or Generation, In General	Electrical engineering: Computer technology
G09G	Arrangements or Circuits for Control of Indicating...	Electrical engineering: Audio-visual technology
G10L	Speech Analysis or Synthesis; Speech Recognition...	Electrical engineering: Computer technology
G11B	Information Storage Based on Relative Movement Bet...	Electrical engineering: Audio-visual technology
H04B	Transmission	Electrical engineering: Telecommunications
H04L	Transmission of Digital Information	Electrical engineering: Digital communication
H04M	Telephonic Communication	Electrical engineering: Telecommunications
H04N	Pictorial Communication	Electrical engineering: Telecommunications
H04R	Loudspeakers, Microphones, Gramophone Pick-Ups	Electrical engineering: Audio-visual technology
H04W	Wireless Communication Networks	Electrical engineering: Digital communication

Figure A.2: Relative frequency of selected keywords (a) and of at least one keyword (b) by IPC4 class (excl. C)

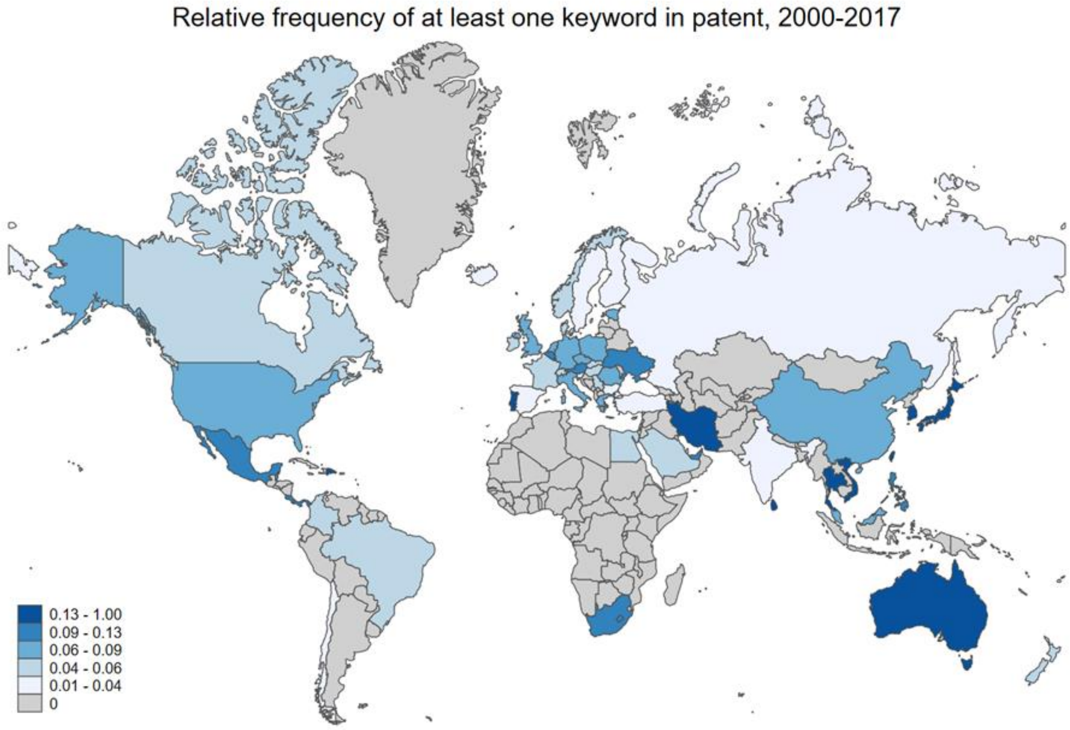


Notes: The above graph in panel (a) displays the share of patents in each IPC4 class mentioning at least once one of the keywords reported in the legend. Each patent is counted only once for each keyword appearance. However, there could be double-counts of the same patent across keywords if multiple keywords are mentioned. Only patents issued after year 2000 are used.



Notes: The above graph in panel (b) displays the share of patents in each IPC4 class mentioning at least once any of the keywords: cobalt, gold, lithium, tantalum, tin, or tungsten. Each patent is counted only once if any of the keywords are mentioned, so that there are no double-counts if two or more keywords appear on the same patent. Only patents issued after year 2000 are used.

Figure A.3



Note: Polygons are coloured in varying shades of blue, with darker shades reflecting higher quintiles of the distribution taken over all countries with at least one patent mentioning a keyword (grey-shaded areas are countries with no such patents).

Technological demand for CCMs and conflict/violence: preliminary evidence

To establish a correlation between technological demand for CCMs and conflict/violence, we obtain yearly data on state and non-state armed conflicts from the Uppsala Conflict Data Program (UCDP).[13] A conflict is defined as "The use of armed force between two parties which results in at least 25 battle-related deaths in a calendar year". Details on these data and definitions are available in Gleditsch et al. (2002), Sundberg et al. (2012), and Pettersson et al. (2021), as well as the respective codebooks.[14] We break down conflict counts by UN macro-regions used in Section 5.1. Counts for each area are treated as separate outcomes, that we then merge into our time series data detailing relative frequency of keyword appearance and mineral production across the world (already described in Section 3.2).[15] We consider the period between 1976 and 2017. Finally, we regress conflicts in a given region and year on the three-year lagged relative frequencies of keyword counts. We do this separately for each macro-region and mineral using OLS. In addition, we provide instrumental variable regressions (2SLS), where relative frequencies are used to predict resource extraction in the first stage regression. This allows to isolate the effect that demand for CCMs embedded in new technologies has on armed conflict, via the channel of resource extraction. Effectively, OLS regressions can be interpreted as the reduced-form of 2SLS regressions.

Table A.4 shows correlations of our measures with conflict data. As stated, each coefficient (for each area and mineral) was obtained from running a separate, univariate, regression. This allows to compare how CCM-based technologies and resource extraction over time differentially affect conflict and violence in different parts of the world. Interestingly, we learn that for all minerals except Tungsten[16] there is a strong and significant positive association between our independent variables and armed conflict in the Middle East, Africa, and the Americas. By contrast, this association is entirely absent in Europe and Asia (excluding Cobalt in the latter case). Note that even though Americas include US and Canada, very few conflicts are actually recorded in these areas. In unreported results, we dropped these two countries from the definition of Americas altogether, confirming all our findings. Neither US nor Canada, therefore, are driving the results on conflict, which take place mostly in Central and South America. We also considered removing the three-year lag on relative keyword frequencies, with no effect on our results. Encouragingly, therefore, this analysis provides non-causal but consistent and robust evidence supporting our theoretical argument about armed conflict and violence, and the geographical mismatch characterising this relationship.

References

Gleditsch, Nils Petter; Peter Wallensteen, Mikael Eriksson, Margareta Sollenberg & Håvard Strand (2002) Armed Conflict 1946–2001: A New Dataset. *Journal of Peace Research* 39(5): 615–637.

Sundberg, Ralph, Kristine Eck & Joakim Kreutz (2012). Introducing the UCDP Non-State Conflict Dataset. *Journal of Peace Research* 49(2):351-362.

Pettersson, Therese, Shawn Davis, Amber Deniz, Garoun Engström, Nanar Hawach, Stina Högbladh, Margareta Sollenberg & Magnus Öberg (2021). Organized violence 1989-2020, with a special emphasis on Syria*. Journal of Peace Research* 58(4).

[13] The program's webpage is: https://ucdp.uu.se/.

[14] The data and associated codebooks are available at this link: https://ucdp.uu.se/downloads/.

[15] We consider aggregate evidence for keyword counts and mineral production because it would be very difficult to do this at regional or even just country level without relying on a much more extensive and complex analysis. In particular, it is unclear how demand for minerals (captured in patents keywords) relates to the geography of supply, without precise information on trade flows for each commodity. For instance, how do we assign a surge in demand of gold observed in, say, South Korean patents, to all the countries that actually produce gold, and through this to conflict in these countries? We leave this to future work and focus on high-level evidence at this stage.

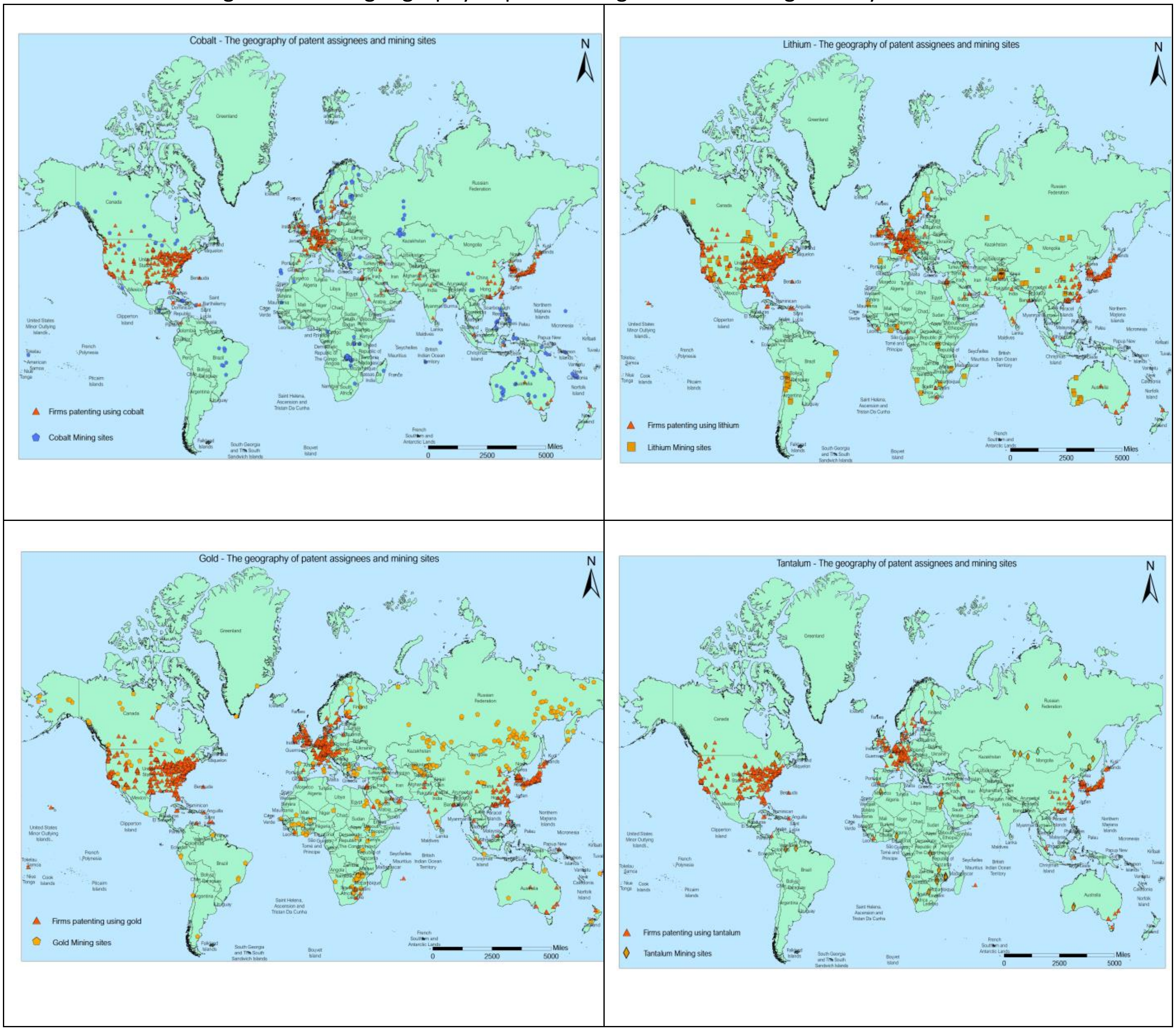
[16] Here, only the 2SLS results do not align with our prediction, but we also point the reader to the fact that these particular regressions have a very weak first stage (low F stat), which entails that the coefficients we obtain cannot really be trusted.

Table A.3: Regressions for conflict data (state and non-state)

	Cobalt		Gold		Lithium		Tantalum		Tin		Tungsten	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
Europe	-120.3	-0.00919	-51.93	-0.000762	-49.32	-0.00111	-104.7	-0.00553	-35.12	-0.00413	-89.97	0.0631
	(146.1)	(0.0109)	(56.15)	(0.000843)	(75.21)	(0.00171)	(84.52)	(0.00423)	(74.94)	(0.00842)	(71.01)	(0.0629)
Mid. East	2489.5	0.190	738.9	0.0108	1227.1	0.0277	1140.3	0.0602	1382.5	0.163	765.9	-0.537
	(519.6)^{a}	(0.0404)^{a}	(263.8)^{a}	(0.00349)^{a}	(348.1)^{a}	(0.00978)^{a}	(392.1)^{a}	(0.0257)^{b}	(299.0)^{a}	(0.0459)^{a}	(332.1)^{b}	(0.201)^{a}
Asia	-242.9	-0.0186	75.04	0.00110	81.31	0.00184	38.47	0.00203	36.97	0.00435	108.1	-0.0758
	(138.5)^{c}	(0.0108)^{c}	(71.26)	(0.000982)	(111.3)	(0.00247)	(102.7)	(0.00524)	(89.75)	(0.0101)	(98.07)	(0.0845)
Africa	2101.5	0.161	1516.7	0.0223	2329.3	0.0526	1996.1	0.105	1998.8	0.235	2009.9	-1.409
	(803.1)^{b}	(0.0576)^{a}	(254.2)^{a}	(0.00242)^{a}	(301.0)^{a}	(0.0124)^{a}	(425.1)^{a}	(0.0300)^{a}	(319.5)^{a}	(0.0425)^{a}	(360.6)^{a}	(0.587)^{b}
Americas	610.1	0.0466	257.9	0.00378	305.8	0.00690	390.9	0.0206	380.9	0.0448	308.9	-0.217
	(104.1)^{a}	(0.00638)^{a}	(49.37)^{a}	(0.000641)^{a}	(83.38)^{a}	(0.00214)^{a}	(71.96)^{a}	(0.00483)^{a}	(52.70)^{a}	(0.00739)^{a}	(70.22)^{a}	(0.0923)^{b}
SW F Stat.		225.67		101.32		10.98		64.92		108.33		3.85

Robust standard errors in parentheses. Significance levels: ^{c} $p < 0.1$, ^{b} $p < 0.05$, ^{a} $p < 0.01$. Dependent variable: yearly count of state and non-state conflicts by macro region according to the Uppsala Conflict Data Program (UCDP). Independent variables: three year lagged relative frequencies of keyword counts. Instrumental variable regressions use the latter variable to predict resource extraction in the first stage regression. Effectively, OLS regressions can be interpreted as the reduced-form of 2SLS regressions. Each coefficient (for each region and mineral) was obtained from running a separate, univariate, regression.

Figure A.4: The geography of patent assignees and mining sites by CCM



Published by
Department of Geography and Environment
London School of Economics and Political Science
Houghton Street
London
WC2A 2AE

geog.comms@lse.ac.uk
www.lse.ac.uk/Geography-and-Environment