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RADICAL NOVELTIES IN CRITICAL TECHNOLOGIES AND SPILLOVERS: HOW DO CHINA, THE US AND THE EU FARE?

ALICIA GARCÍA-HERRERO, MICHAL KRYSTYANCZUK AND ROBIN SCHINDOWSKI

Critical technologies including artificial intelligence, semiconductors and quantum computing are attracting attention because of their indispensable nature and their role in national security strategies. We compare China, the United States and the European Union in these technologies and their subfields.

We use large language models (LLMs) to identify which patents in these technologies can be considered most groundbreaking (not patented before) and worth replicating. These are 'radical novelties.'

We find that the US clearly dominates quantum. Chinese and EU progress is similar. The US does slightly better than China in AI with clear dominance in generative AI, but China stands out in some important subfields, such as aerial vehicle technology. China dominates in a larger number of semiconductor fields but not in the highest value added, which is related to design.

In a second step we assess how quickly radical novelties in these three technologies are transferred from one economic area to another and within each economic area. We find that the fastest transmission overall is for AI. The EU is by far the slowest in replicating radical novelties from the US and China, while the US and China tend to replicate European novel patents relatively quickly. Radical novelties are also replicated quickly between China and the US which is surprising given US controls on exports of critical technologies to China.

Our findings are concerning for Europe because it does not produce enough critical patents in these technologies and because it is slower in replicating patents from the US and China.

JEL: O30, O33, F52
Key words: critical technologies, patents, innovation, AI, quantum computer, semiconductors

Alicia García-Herrero (alicia.garcia-herrero@bruegel.org) is a Senior Fellow at Bruegel. Michal Krystyanczuk (michal.rystyanczuk@bruegel. org) is a Data Scientist at Bruegel. Robin Schindowski is a Research Fellow at MERICS.

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1 Introduction

Economic theory has long held technological progress as the main driver of long-term economic growth (Romer, 1990; Aghion and Howitt, 1992). China has emerged as a centre for technological innovation over the last decade, driven by the desire to shift the economy from a focus on capital deepening to more productivity-driven development. The degree of success of China's innovation drive has been analysed widely in the literature from many different perspectives (He, 2023; Bergeaud and Verluise, 2023). If one focuses on quantitative outcomes, such as the number of scientific publications and/or granted patents, China ranks first worldwide, but outcomes are less clear when qualitative measures are taken into consideration.

China's rise as a technological power is increasingly central to the strategic competition between the United States and China. Defensive measures have been created by multiple US administrations to control the transfer of critical technologies to China, mainly on grounds of national security. These measures include inbound investment screening, export controls and, more recently, outbound investment screening. While the European Union has been less assertive in its overall policy towards China, it developed its own economic security strategy in January 2024 with an eye to reducing dependence on China for some critical raw materials and avoiding losing control of key technologies.

In this Working Paper, we analyse the evolution of frontier innovation in quantum computing, semiconductors and artificial intelligence (AI) in China, the US and the EU by drawing on a measurement of patent novelty based on a large language model (LLM). Specifically, we aim at answering two research questions: (1) How far has China moved in innovating in these three critical technologies compared to the US and the EU? (2) How long does it take for an innovation in one region to appear in another region? In other words, how long do technology spillovers take between these three?

To answer these two questions, we use an LLM model to extract the major innovation from all PCT, USPTO and EPO patents between 2019 and 2023. Innovations within the three technologies (AI, quantum and semiconductors) that appear for the first time in a published patent since the start of our dataset in 1979 and are replicated in subsequent patents, whether in the same jurisdiction or a different one, at least five times, are defined as 'radical novelties'.

To increase the granularity of our analysis, we also create a classification of subfields for the above three technologies, based on the LLM and manual industry research. Finally, we use a semantic similarity index to evaluate how long it takes for technologies similar to a given radical novelty to appear in another region. This measures the speed at which radical novelties are transferred from one country/region to another and is particularly relevant to gauge how much strategic technologies may be delayed in its transfer for economic security reasons. This is particularly relevant considering the US-China technology rivalry.

When looking at the overall share of radical novelties in the three critical technologies analysed, we note China's increased ability to innovate at the technology frontier, especially in semiconductors.

Still, the US dominates innovation in AI and quantum computing. The EU lags behind China and the US in all three technologies, although it is almost on par with China in quantum computing even if well behind the US. Beyond these general trends, we classify these three critical technologies into subfields which will help us find specialisation patterns across the three blocks analysed, which will be covered later.

Finally, we assess the speed at which technologies in radically novel patents appear in regions other than their origin. The EU takes the longest to replicate key patents from the US or China in all three critical technologies. The EU's most relevant patents quickly appear in China and the US. The spillover time for radically novel technologies from China to the US is relatively small, indicating that Chinese firms are in a head-to-head race in independent innovation with their US competitors or that the technology is frequently leaked or copied upon invention. The spillover time from the US to the China is similarly small. AI patents are transferred the fastest, compared to quantum and semiconductors.

In section 2, we describe the three technologies the paper focuses on. In section 3, we review the existing literature on this topic. Section 4 outlines our methodology and the data we are using for analysis. Section 5 offers some stylised facts. Section 6 presents our results as to which of the three countries/economic regions are dominating the different subfields of these critical technologies. In section 7, we report on the speed at which radical novelties are replicated across the economic regions analysed.

2 Why focus on quantum computing, semiconductors and AI?

Quantum computing, semiconductors and AI are at the heart of the US-China rivalry and at the future of human technological progress. Some have even argued that progress in these areas could produce economic singularity, or the point at which machine intelligence is capable of innovating autonomously and beyond human capabilities (Nordhaus, 2021). Whether this is true or not, these three technologies are essential to the future of any leading economy. In that regard, they play a crucial role in the national security strategies of the US and the EU.

AI is at the core of this. It promises to improve human judgement by providing predictive insights from historical data through simulating human intelligence (Agrawal *et al*, 2018). As such, it is projected to lead to substantial productivity gains across many industries. AI-powered processing of visual data can induce progress improvements in autonomous driving, biometrics security and medical imaging. Machine learning will induce improvements in robotics and healthcare analytics. Breakthroughs in generative AI have created applications that go beyond the predictive nature of traditional AI. Importantly, through techniques of computer vision and game simulation, AI has the potential to provide a significant advantage on the battlefield to those powers who can harness it (Scharre, 2024).

The advancement of AI, however, depends on computing power for which the deployment and further development of cutting-edge semiconductors is crucial. While Deepseek's success may have softened

somewhat the direct relation between advanced semiconductors and AI power, it does not fully discard the need for advanced semiconductors. More generally, the semiconductor industry is characterised by a highly globalised supply chain and is therefore particularly subject to geopolitical volatility.

There are three important steps in the chip value chain. During the design phase the structure and technical details of the integrated circuit are defined. Different requirements exist for the design of different types of chips (eg logic, analogue or memory chips) and firms engaged in this step often coordinate with manufacturers or 'fabs' in the process. There has been a trend among original equipment manufacturers to build up capacity for the design of their own integrated circuits, tailored to their end products. Semiconductor manufacturing constitutes the second step. Taiwan and South Korea lead capacity in the fabrication of the most advanced logic chips and are continuously expanding the technology frontier in this area. In the fabrication of legacy chips with process nodes larger than 180 nanometres, China has the highest manufacturing capacity, while also having substantial shares in fabrication of chips between 180 and 10 nanometres (SIA and BCG, 2024). Assembly and testing is the last step, with so far, the lowest value-added. China dominates in terms of capacity in this sector. In the future, the relative value-added of assembly and testing might increase due to the eve of advanced packaging, and China's importance in this subfield might develop into a significant competitive advantage.

Finally, quantum technology is the most embryonic technology in our analysis and relates to many other technologies in as far as its ultimate goal is to increase computing power. The economic implications are potentially huge since, once matured, quantum computing could potentially render traditional semiconductor chips redundant, ending the age of silicon. In addition, it may enable breakthroughs in artificial intelligence, biotechnology, agricultural technology, material sciences, encryption and cybersecurity (Kaku, 2023). This is why the leading economies have grasped the potential importance of advancement in this sector and have started to invest.

In China, quantum computing has been identified as a strategic priority in five-year plans since 2015, and by 2021, the equivalent of $15.3 billion had been earmarked as government investment (McKinsey, 2022). The city of Hefei is the centre of quantum computing, home to Origin Quantum Computing and the National Laboratory for Quantum Information Science. In the US, quantum computing is driven by large incumbent technology firms. In 2019, Google's quantum AI lab announced the creation of 'Sycamore' a 53-qubit processor called. The same year, IBM introduced the 127-qubit IBM Q System One. In Europe, a group of major German industrial companies have formed a consortium to develop industry-related applications for IBM's Q System One.

3 Related literature

Our paper analyses the evolution of frontier innovation across China, the EU and the US in three critical technologies, namely AI, quantum computing and semiconductors.

First, we contribute to the literature measuring China's advances in innovative capabilities. China's technological progress is often assessed using quantitative measures. The quality of innovation is rarely considered[1]. The academic literature also presents doubts regarding the degree of innovation imbedded in Chinese patents. Findings by Hu and Jefferson (2009) suggest that the 2000 amendment to China's patent law has been a decisive factor in the surge of Chinese patents which implies that the number of patents alone cannot be a good indicator of China's ability to innovate. In the same vein, Li (2012) shows that China's surge in patent filings has been largely driven by province-level subsidy programs, suggesting that their actual economic value is overestimated. When looking at citations of Chinese-origin patents filed under the patent cooperation treaty, Boeing and Muller (2016, 2019) showed that China's patent quality has decreased at the same time as the quantity of patents produced has increased. However, findings using natural language processing techniques suggest that there has been a rise in the quality of Chinese patents since the 2010s (Bergeaud and Verluise, 2023; Boeing *et al*, 2024).

Our paper equally contributes to a nascent but growing literature studying the US-China technology rivalry. Fang *et al* (2023) investigated patent quality based on citations and new keywords. Their findings confirm the rising quality of Chinese patents vis-à-vis US patenting. On the issue of spillovers and potential interdependence between the quantum computing, semiconductors and AI, Han *et al* (2024) examined cross-national citations, concluding that innovative activity between the US and China has become more intertwined. From the 2010s, the propensity of Chinese innovators to cite US patents relative to US innovators to Chinese patents has decreased, indicating a decline in dependency of China on the US. However, the analysis by Mueller and Boeing (2024) showed that China remains highly dependent on global innovations for its own inventions.

This Working Paper contributes to the methods for measuring the impact of patented innovation. To estimate the economic value of an invention researchers have commonly used the number of times a patent is cited by subsequent patents (Trajtenberg, 1990; Jaffe *et al*, 2003). However, over the years substantial issues with citation-based indicators have been noted. For instance, Michel and Bettels (2001) find that the cross-country comparability of patents is limited due to differences in practices across patent offices.

Furthermore, since excessive citation of 'prior art' might undermine the novelty of their invention and thus reduce the chance of their patent being granted, applicants might strategically withhold from citing relevant prior art. The patent examiner might face difficulties in identifying the relevant missing

[1] *The Economist,* 'China has become a scientific superpower', 12 June 2024, https://www.economist.com/science-and-technology/2024/06/12/china-has-become-a-scientific-superpower.

prior art, especially when he has limited time to process the application (Lampe, 2012). Finally, Kuhn *et al* (2020) also argued against using citations to determine the quality of patents because of the growing shift that has seen a small but growing number of patents cite an exceptionally high number of prior patents, leading to a decrease in the average technological similarity between citing and cited patents.

To mitigate the measurement error embedded in using citations to analyse the quality of patents, two different methodologies have been used: key words and high frequency textual analysis. For the former, Arts *et al* (2021) developed a keyword-based approach to assess patent significance. Their method involves analysing the frequency and co-occurrence of keywords within patent documents to evaluate technical novelty and impact. For the latter, Kelly *et al* (2021) introduced an indicator of patent significance by analysing textual similarities between patents. They defined a significant patent as one that is both novel – exhibiting low similarity to prior art (backward similarity) – and impactful, meaning it has high similarity to subsequent patents (forward similarity).

While these methodologies are an improvement on traditional indicators, they also have caveats. Starting with keywords, it is hard to apply for new technologies since keywords are not readily available. This method also can miss similar concepts (eg 'AI model' vs. 'machine learning system') and cannot consider the context. High frequency textual analysis is more flexible than keyword search, as it captures word relationships and latent topics, but it still struggles with deep contextual meaning, as it only captures surface-level similarities and may not work well for emerging technologies that lack historical references.

Since 2021, the literature has started to introduce LLMs to evaluate the significance of patents as an improvement relative to key words and high frequency textual analysis. Deep learning is better at capturing semantic meaning and relationships in patent text, not just word similarity. This is particularly important for emerging concepts, which are prevalent in critical technologies. The disadvantage is the computational cost.

Some key references, also using LLMs to classify patents according to novelty as we do, include Schmitt and Denter (2024), who proposed a statutory novelty indicator trained on actual US patent office (USPTO) rejection decisions, demonstrating that many established novelty measures fail to align with legal standards of patentability. Their findings suggest that deep learning models can predict novelty rejection likelihood with higher accuracy than citation-based proxies. Additionally, Ikoma and Mitamura (2025) showed that large language models (LLMs) significantly improve semantic prior art search and novelty detection. By leveraging contextual embeddings rather than surface-level keyword similarity, these models more effectively identify prior disclosures that could invalidate a patent claim.

In a similar vein, Parikh and Dori-Hacohen (2024) developed ClaimCompare, a data pipeline that generates labelled datasets of patent claims to train models for assessing novelty. Their approach resulted in significant improvements in retrieval accuracy and demonstrated the effectiveness of machine learning in enhancing novelty evaluation. Furthermore, Yassine and Lipizzi

(2023) proposed a text-based patent novelty measure using natural language processing (NLP) techniques, applying it to patents within the same classification to derive novelty-value profiles. Their approach provides an alternative to citation-based novelty assessments and highlights the potential of NLP in refining patent landscaping and innovation evaluation. These studies reinforce the importance of LLMs in patent evaluation, as they enable more nuanced assessments of technological novelty and patent significance.

Finally, we also contribute to the literature of classifying patents into technology categories. This is particularly difficult for emerging technologies since no readily available taxonomies exist. Patent registries usually use pre-defined categories to delimit technologies. The two most common classifications are the International Patent Classification (IPC) system used by the World Intellectual Property Organization (WIPO) and the Cooperative Patent Classification (CPC) system, a more specific version of the IPC which was adopted by the USPTO. While this is the easiest way to classify patents, it comes with the caveat that they are primarily designed for patent examiners and are based on *techniques* rather than an economic understanding of technology (Griliches, 1990).

In a seminal paper, Trajtenberg (1990) manually delimited US patents, but manual methods alone are now considered too time consuming and subject to human error and bias, especially since the usage of the patent system has become increasingly common since the 1990s. With the advancement in machine learning and NLP, the academic literature has offered several workarounds. Bergeaud *et al* (2017) used network analysis techniques to classify technologies based on common keywords. Abood and Feltenberger (2018) proposed a method of automated patent to technology matching based on a small group of manually matched 'seed' patents. Li *et al* (2018) proposed a deep learning algorithm based on convolutional neural network (CNN) and word vector embedding. Lee and Hsiang (2020) used Google's BERT model to generate patent classifications.

Recent advancements in large language models and generative AI offer new possibilities, not only in the extraction of patent novelties, but equally in the classification of patented technologies. This is the path we follow but we add our own supervision to the classification obtained through LLM models. In particular, we obtain subfields for each of the three critical technologies by LLM which we then confirm manually using industry expertise.

4 Data and methodology

4.1 Using Large language models (LLMs) for patent analysis

Our methodology builds on prior work using NLP to quantify technological novelty across jurisdictions. Unlike and Arts *et al* (2021) and Kelly *et al* (2021) who relied on high frequency textual analysis and keywords respectively, we opt for using an LLM model, following the most recent literature. Our choice is LLAMA3 for the classification of patents and to extract their novelty. LLAMA 3 is a state-of-the-art LLM that can extract novel concepts embedded in patent abstracts.

A similar approach was used by Boeing *et al* (2024), who applied LLMs to vectorise patent abstracts and computed semantic distances to identify high-impact patents. Our methodology extends theirs by not only measuring semantic novelty but also identifying radical innovation concepts, defined as previously unseen technological descriptors with demonstrated influence on subsequent filings. Finally, our definition of radical novelty, following Arts *et al* (2021), requires two criteria to be fulfilled, Firstly, for a patent to be considered relevant enough, its key innovation should not have appeared in the description of any patent since 1979. Secondly, the key concept should appear in at least 5 subsequent patents in any jurisdiction, which should ensure its relevance. Appendix I offers more details about the methodology used.

4.2 Data

The basis for our analysis consists of the merger of two datasets. First, we use a dataset covering the universe of PCT patent grants from 1979 to 2023 which we acquired from WIPO[2] to have a full account of all pre-existing innovations. This will provide the basis to determine whether any of the patents in critical technologies thereafter are novel enough. We then scrap all the patents from WIPO Patentscope that were made available publicly from 2019 to 2023 whether filed in the USPTO, the EU patent office (EPO) or the Chinese patent office (CNIPA), which resulted in a PCT application. We also include US and EU domestic filings in these critical technologies, namely USPTO and EPO, respectively. We do not include China's domestic patents filed at CNIPA to avoid artificially inflating the number of patents to be reviewed without much hope that they will constitute radical technologies.

It is well-established that subsidy programs are behind, at least partially, the massive increase in patenting in China (Li, 2012). As patents surge, reviewers at the CNIPA are swamped with applications leading to a reduction in the degree of scrutiny regarding the technical content of these patents. Patents might thus fit our definition of radical novelty but might be technically irrelevant, and hence, artificially inflate China's radical novelty count. Furthermore, we believe that since the three technologies under observation are essential to international competition, Chinese firms will prefer to file patents in these fields through internationally recognised systems. This is evidenced by the extensive use of the PCT patent system by Chinese firms[3]. In fact, the number of radical novelties in Chinese patents might still be inflated as Chinese applicants also receive subsidies for international applications.

US and EU domestic filings, namely USPTO and EPO, are included because they serve as an alternative to the PCT system. This is particularly the case for the USPTO since the US consumer market is one of the largest and most competitive globally with very strict legal protection of intellectual property rights. If a foreign firm infringes on a USPTO patent the patent holder can seek redress at the US International Trade Commission to obtain an exclusion order, blocking the imports of goods of the infringer to the US.

[2] Specifically, the dataset consists of the PCT backfiles in Asian and non-Asian languages; see https://www.wipo.int/patentscope/en/data/.
[3] Aaron Wininger, 'China Remains Top Patent Cooperation Treaty Filer in 2021', China IP Law Update, 11 February 2022, https://www.chinaiplawupdate.com/2022/02/china-remains-top-patent-cooperation-treaty-filer-in-2021/.

It has been argued that this has reduced the risk of IP theft for vertically integrated semiconductor firms and induced them to outsource part of the value chain to East Asian economies (Barnett, 2020), resulting in the globalised chip ecosystem of today.

Second, administration fees and maintenance fees at the USPTO tend to be lower compared to other offices. Including the EPO is also important as most European companies file there, in addition to US and Chinese companies, as it is particularly known for its high-quality examination services (van Pottelsberghe de la Potterie, 2010).

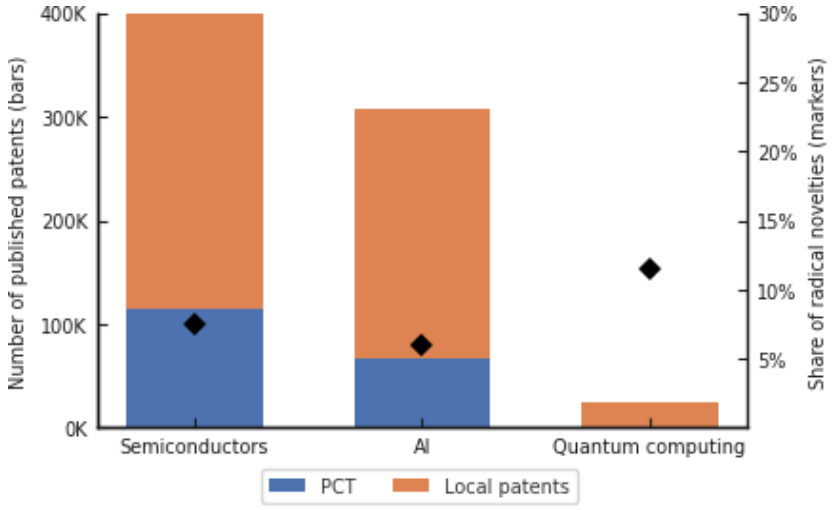
In the next section we use a few stylised facts to describe our rich database before moving to our results, starting with the subfields that we identify to be most relevant for each critical technology and which country dominates each of them. We then move to estimating how fast radical novelties may be adopted by another country/economic region.

5 Stylised facts

We first examine the PCT patents filled in the three patent registries analysed (PCT, USPTO and EPO) from 2019 to 2023. Figure 1 shows the number of patents in our sample across the three sectors of interest, both PCT patents and non-PCT patents. Patents in AI and semiconductors by far outnumber those in quantum computing. Over the period of observation, 390,327 patents have been published in semiconductors with 303,326 in AI, compared to only 33,768 in quantum computing. The data also reveals that the propensity to file PCT patents, measured as the percentage of PCT patents to total number of patents, is highest in semiconductors (29.80 percent), followed by AI (23.39 percent) and quantum computing (12.94 percent).

The right-hand side of Figure 1 shows the share of patents which we identified as novelties based on our previously described methodology. First, we note that 9.72 percent of patents in AI are characterised as a radical novelty based on our definition, while the share is about 50 percent higher for quantum computing with 14.42 percent of the patents being classified as radical novelties. Finally, about 11.04 percent of semiconductor patents are classified as radical novelties.

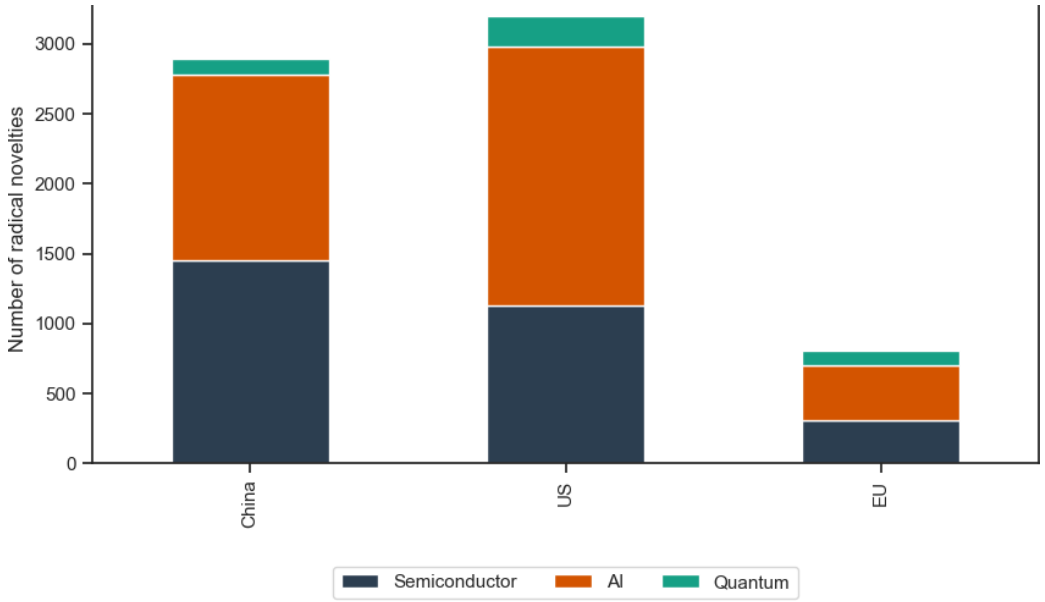
Figure 1: Published patents by sector (2019-2022)



Source: Bruegel based on WIPO.

Figure 2 shows the decomposition of radical novelties by the location of the filing entity's origin. The US has the highest number with a total of 3,203 radical novelties, closely followed by the China with a total of 2,892. EU firms only account for 804 radical novelties in total. China's dominance in the number of radical novelties is largely driven by its activity in semiconductors, constituting 52.7 percent of its novelties. This is not surprising since US firms themselves are only a part of the global chip ecosystem. As we will briefly explore in the next section, Japan, Taiwan and South Korea, combined, surpass annual patenting in the semiconductor sector in the USPTO.

Figure 2: Novelties by firm headquarters (2019-2023)



Source: Bruegel based on WIPO.

In AI and quantum computing, China still lags the US, which holds the largest number of radical novelties in these two technologies with a total of 1,852 and 222 respectively. China has significantly more radically novel patents in semiconductors compared to the US and even more so compared to the EU. In quantum computing, China slightly surpasses Europe with 116 compared to 102 radical novelties. Europe comes last in AI and semiconductors but the share of quantum computing novelties in its novelties (12.64 percent) is higher than the respective shares of quantum computing in the US (6.93 percent) and China (4.01 percent).

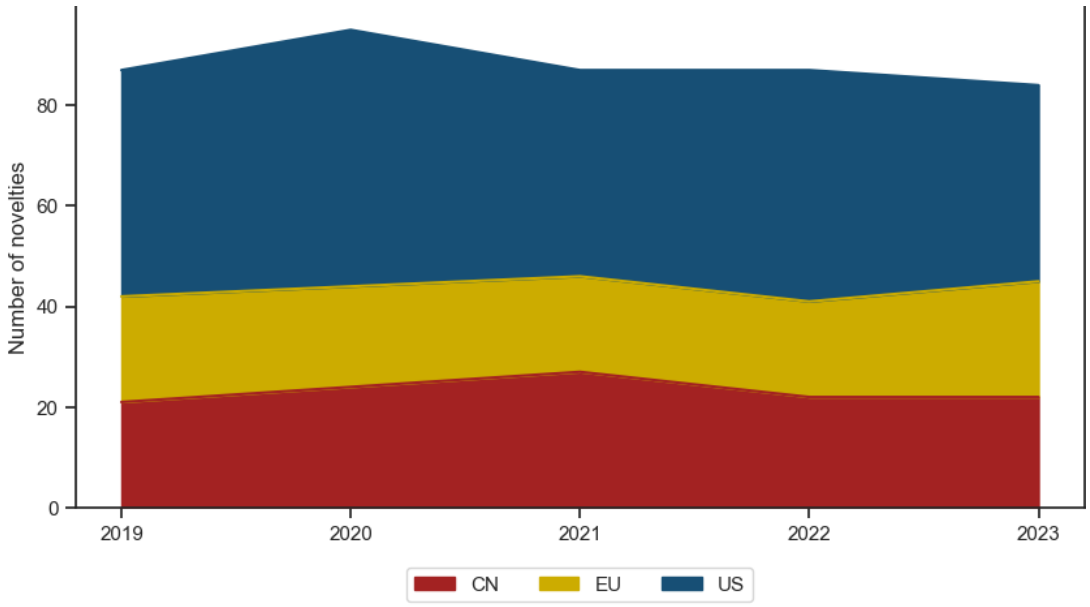
In the next section, we will look deeper into how different economies dominate different subsectors of these three critical technologies and how quickly radical novelties diffuse from one economic region to another.

6 Results

6.1 General findings

First, we show the evolution of radical novelties across jurisdictions since 2019. Figure 3 displays the case of quantum computing. The number of radical novelties obtained per year hovers between 80 and 90 but appears trendless since 2020. The US dominates the sector, accounting for roughly half of all radical novelties on average. EU and Chinese patenting remained stable, hovering between 15 to 30 novelties and reaching a combined share of 53.71 percent by 2023.

Figure 3: Evolution of novelties in quantum computing (2019-2023)



Source: Bruegel based on WIPO.

In semiconductors, the total number of annual patented novelties published peaked at 668 by 2021, declining to 493 in 2023 (Figure 4). China has a strong position when compared with the EU, and even the US, since it consistently maintains a share of novelties of around 50 percent. The US comes second with a strong lead over the EU but has recently contracted, from 257 novelties in 2019 to 173 in 2023.

The relatively low share of US firms is not surprising when considering the particularities of the global semiconductor ecosystem. Many prominent US chip firms are highly vertically disintegrated. Firms such as Qualcomm and Nvidia mostly specialise in chip design and outsource most of the production of their cutting-edge logic chips to TSMC in Taiwan. Japan and South Korea equally play a significant role in the global chip ecosystem, providing crucial display technology for TSMC's most advanced fabs. South Korea has also made strong progress in semiconductor manufacturing at the technology frontier.

When adding these three jurisdictions to the analysis, the picture changes (Figure 5). Taiwan almost catches up with the US in the number of radical novelties, experiencing a sharp increase from 38 novelties in 2019 to 156 in 2023. In other words, China's dominance in terms of radical novelties in semiconductors is much less evident when including other relevant jurisdictions. A key question is whether the radical innovations from these different jurisdictions are integrated with the US chip ecosystem compared to the Chinese chip ecosystem. This is an interesting research question but goes beyond the scope of this paper.

Figure 4: Evolution of radical novelties (2019-2023)

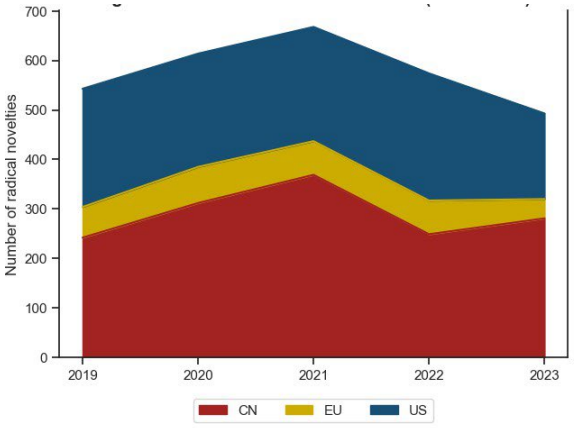
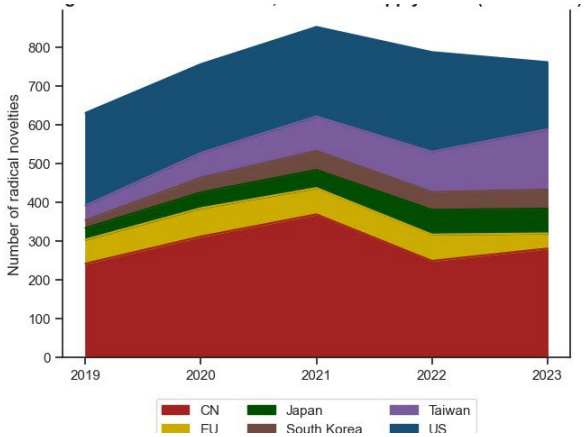


Figure 5: Radical novelties, extended supply chain (2019-2023)

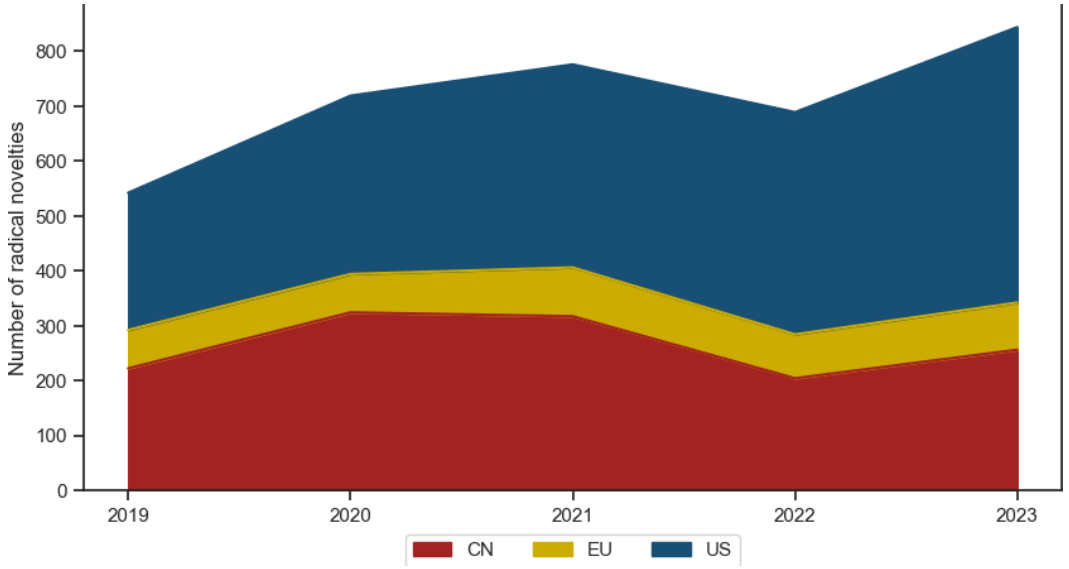


Source: Bruegel based on WIPO.

Finally, for AI, the US dominates, accounting for a significantly higher number of radical innovations than the EU and China (Figure 6). In 2019, US firms were published 250 radical novelties, a share of 46.13 percent of total novelties in China and the EU. In 2023, the number of US radical novelties almost doubled to 502, while its share increased to 59.48 percent, an absolute as well as relative increase in AI innovation in the US over our period under observation. China's number of annual radical novelties decreased in 2022 to a total number of 204 radical novelties, or a share of 29.61 percent,

with a small recovery in the absolute number of novelties in 2023. The EU's absolute number of radical novelties in AI is small compared to China and the US, increasing from 70 in 2019 to 86 in 2023, while its share increased slightly from 12.92 percent in 2019 to 10.19 percent in 2023.

Figure 6: Evolution of radical novelties in AI (2019-2023)



Source: Bruegel based on WIPO.

6.2 Getting more granular

Given the complexities of these three radical technologies, general dominance by a certain country or economic area, in terms of number of overall radical novelties, might not be very meaningful for policy purposes. Some subfields may be more relevant than others for specific applications or may be used upstream for other subfields, which means that that they could create bottlenecks to other innovation processes. In other words, some subfields might be more indispensable than others so that, if a certain country dominates one of those subfields, it can leverage by becoming indispensable for other technologies which depending on it. To further delve into the potential relationships between subfields, we can take the AI subfield 'computer vision' as an example. It has a knock-on effect on 'advanced medical technologies' as surgery apparatuses and medical imaging make extensive usage of techniques developed in this field. In the same vein, breakthroughs in 'quantum hardware' enable further progress in other quantum-related fields such as quantum machine learning and quantum semiconductor technology.

Given the above, it seems important to conduct a more granular analysis of the critical novelties in the key subfields of AI, quantum and semiconductors. This is harder than it seems because there is not yet an official classification of subsectors for these new technologies. To address this limitation, we develop our own categorisation of key subfields for each technology by clustering all of the previously identified radical novelties into subfields based on a combination of manual industry research and LLM models. Any radical novelty which falls outside of the identified subfields is classified as 'Other'

but there are very few which fall in this residual category, confirming the mutual exclusivity of our categorisation.

With the final list of subfields for each technology, we calculate the share of radical novelties per subfield for China, the EU and the US respectively. Finally, to grasp how the subfield focus has changed within our jurisdictions of interest, we analyse the decomposition of subfields over time separately for each of the three.

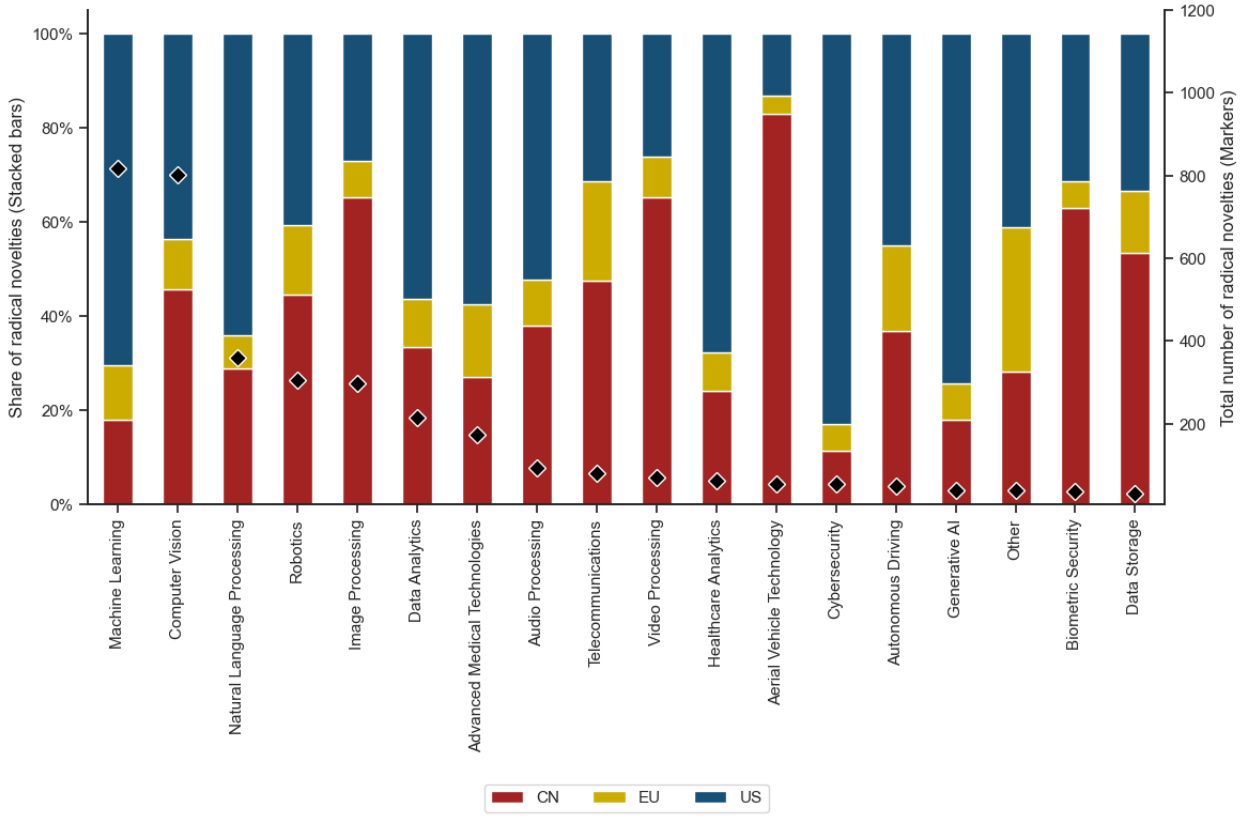
Artificial intelligence

Figure 7 presents our decomposition by subfield in AI. The two subfields in which by far the most innovative activity takes place are machine learning, accounting for 816 radical novelties and computer vision with 803 radical novelties. While China accounts for the largest share in computer vision (45.7 percent), machine learning is dominated by the US (70.47 percent).

Other important subfields include natural language processing, robotics, image processing, data analytics and advanced medical technologies. In natural language processing, data analytics and advanced medical technologies the US is the leader with respective shares of 64.07 percent, 56.28 percent and 57.27 percent. China outperforms the EU and the US in robotics and image processing with shares of 44.59 percent and 65.32 percent, respectively. China leads on innovation in a range of other less patented subfields such as telecommunications, aerial vehicle technology, video processing, autonomous driving, biometric security and data storage. The US, on the other hand, is the leader in audio processing, healthcare analytics, cybersecurity and generative AI, accounting for shares of 52.17 percent, 67.74 percent, 83.02 percent and 74.36 percent.

It is important to highlight that like quantum technology, AI is an emerging field with an evolving set of subfields. The quantity of radical novelties is therefore an imperfect representation of the importance of the subfield. For instance, while still comparatively small in our sample, generative AI is driving much of the investment activities in the sector and promises a large variety of applications, with substantial gains in productivity for many industries.

Figure 7: Share of radical novelties in AI by subfield and entity origin

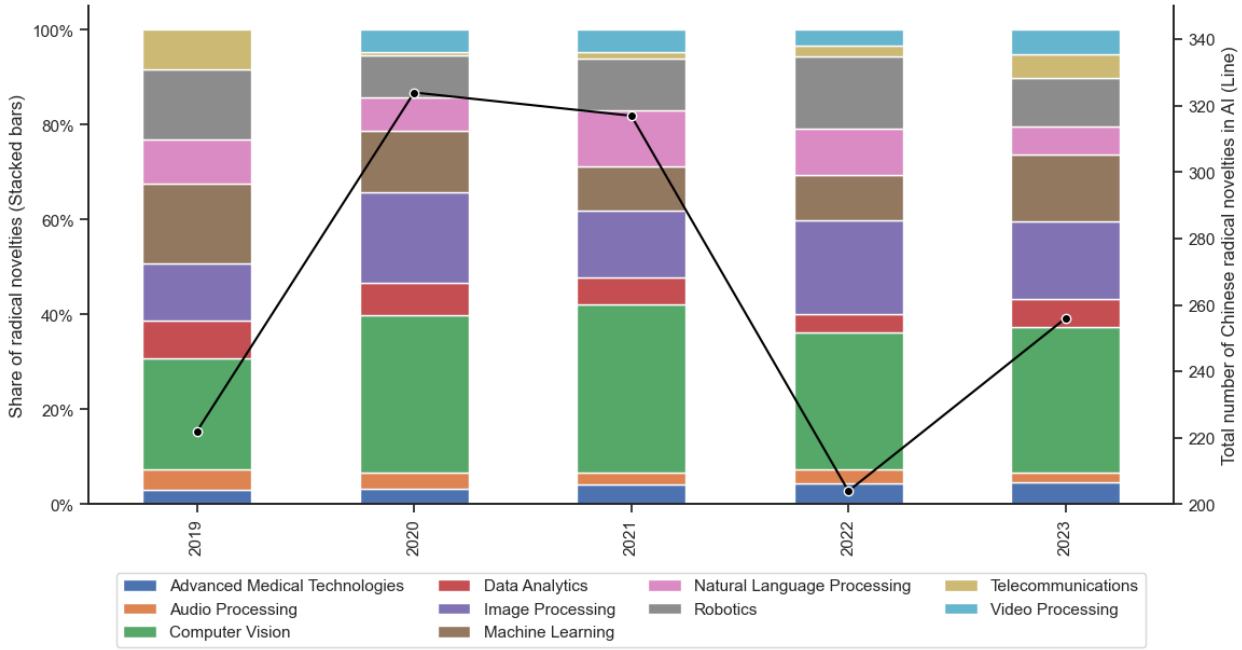


Source: Bruegel based on WIPO.

The evolution of subfield focus reveals that Chinese innovative activity has remained relatively stable over our period of observation. In line with the subfields in which large Chinese technology incumbents such as Huawei and ByteDance are active, China's main focus is the processing of visual data. China's push for advanced manufacturing and automation is equally represented in the results.

Radical novelties by Chinese firms in the subfield of robotics and machine learning have consistently taken shares between 31.41 percent in 2019 and 24.15 percent in 2023. Smaller shares are taken by data analytics, advanced medical technologies and telecommunications.

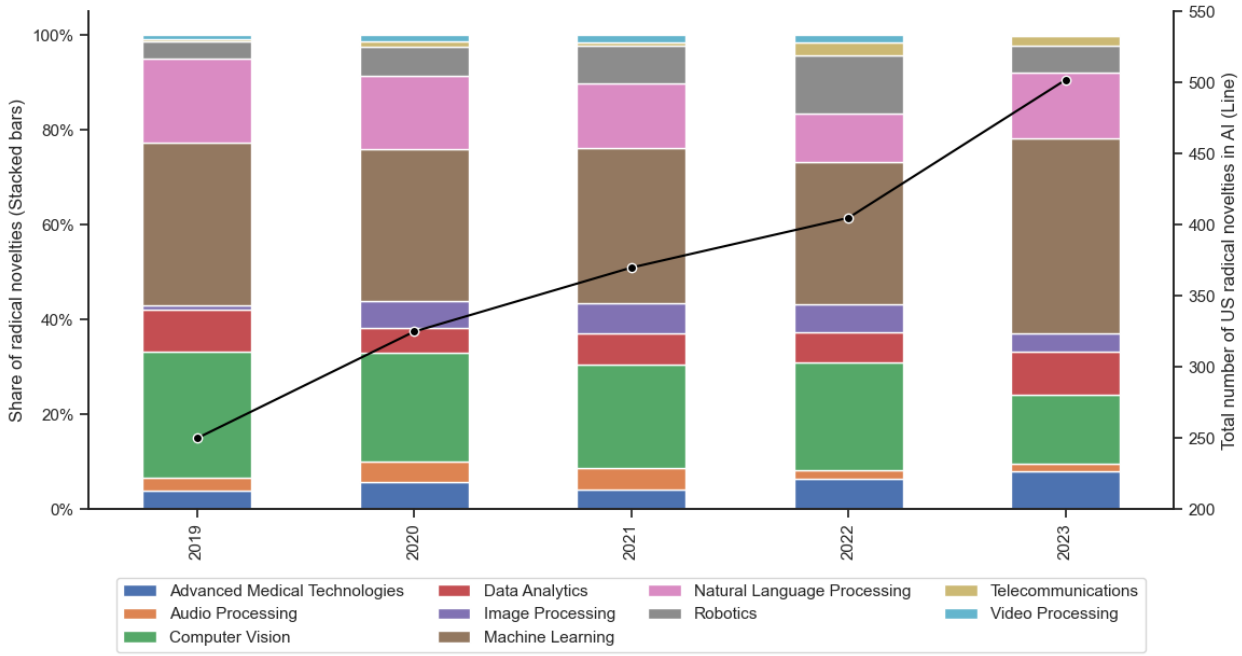
Figure 8: Chinese radical novelties in AI by subfields (2019-2023)



Source: Bruegel based on WIPO.

While the US excels in computer vision and natural language processing as well, its comparative advantage lies in machine learning which in 2023 took a share of 41.08 percent in its radical novelties. Data analytics, robotics and advanced medical technologies have equally contributed to the strength of the US in AI, reaching shares of 9.03 percent, 5.64 percent and 8.13 percent in 2023, respectively. Like the Chinese case, the composition of radical novelties has remained quite stable. Compared to China, however, video processing, audio processing and telecommunications account for a relatively smaller share in the US AI portfolio.

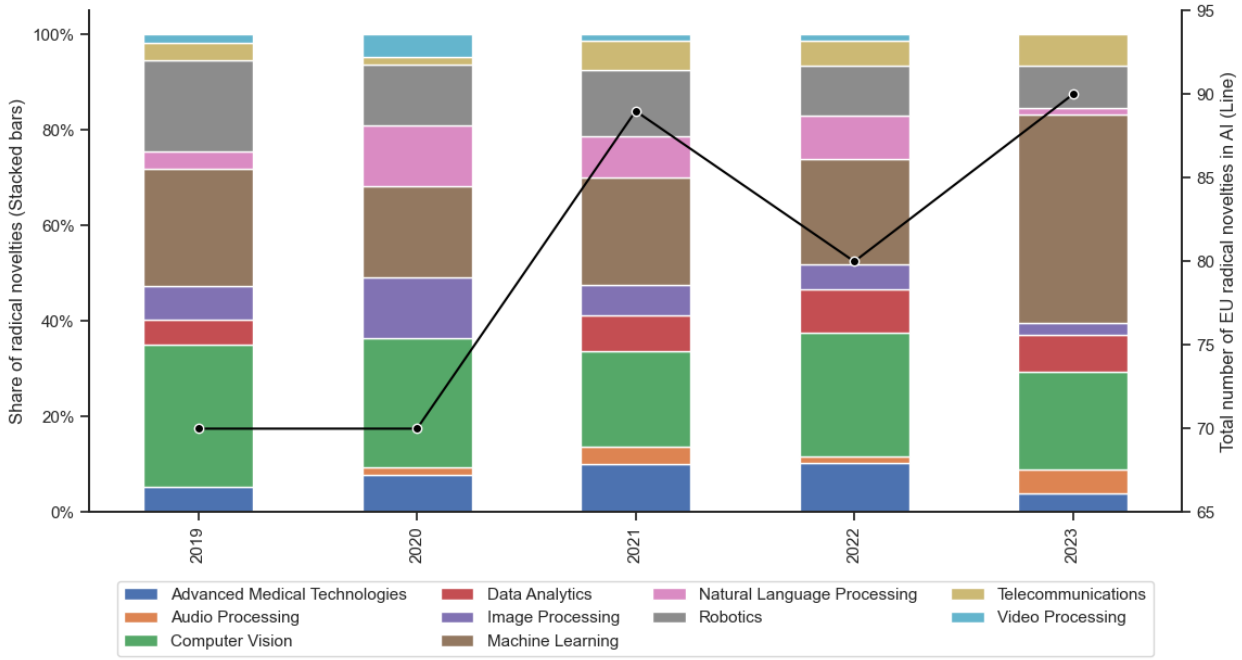
Figure 9: US radical novelties in AI by subfields (2019-2023)



Source: Bruegel based on WIPO.

Relative to the US and China, the EU's share of radical novelties has been somewhat more volatile (Figure 10). First and foremost, robotics accounts for a substantial share of radical novelties throughout the years, although it has diminished from 19.30 percent in 2019 to 8.97 percent in 2023. Secondly, computer vision and machine learning are two important fields that consistently take major shares in its portfolio of radically novel patents, the latter reaching a percentage of 43.59 in 2023. Smaller shares are taken by natural language processing, telecommunications, data analytics, image processing and audio processing. Interestingly, the EU also innovates substantially in advanced medical technologies, reaching a share of 10.39 percent in 2022.

Figure 10: EU radical novelties in AI by subfields (2019-2023)



Source: Bruegel based on WIPO.

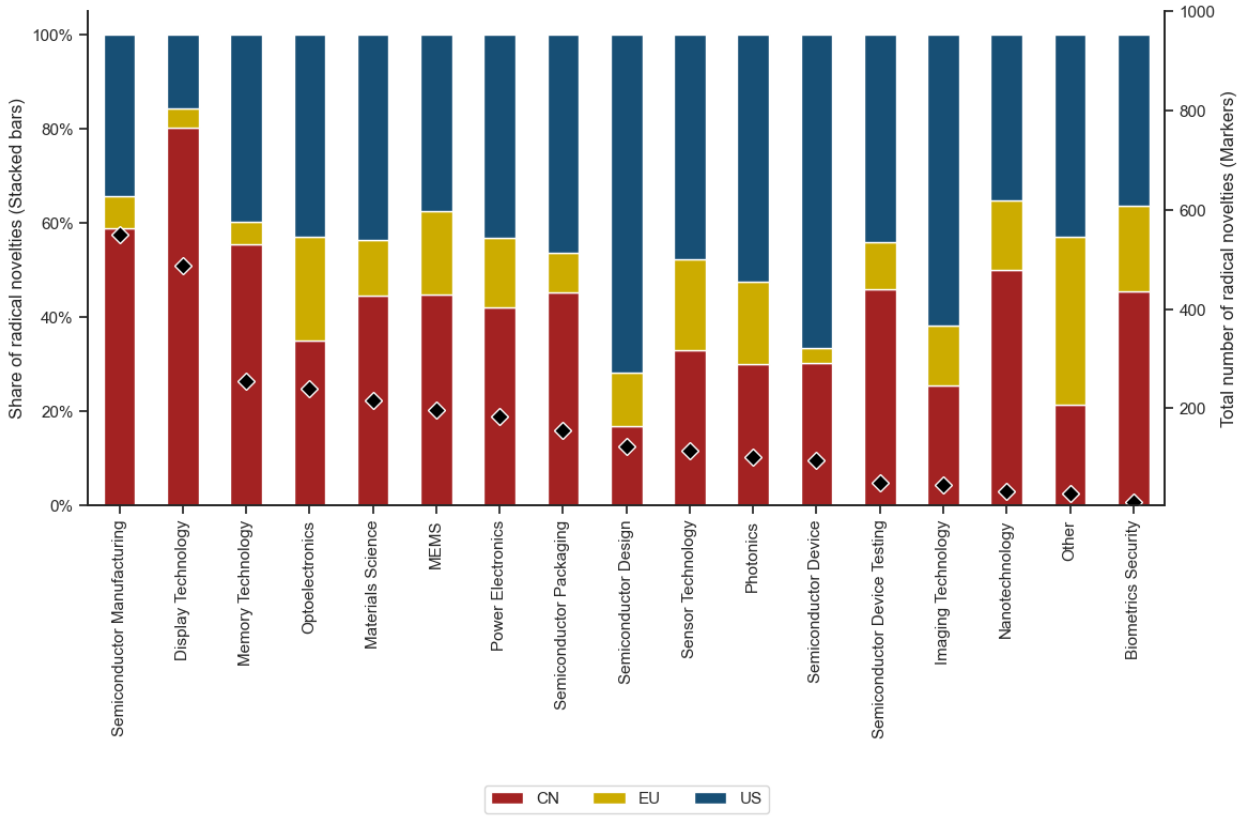
One interesting pattern that our analysis reveals is that the US and China specialise in subfields in which both have a comparative advantage in data availability. In China, the data generated by large-scale deployment of surveillance technology and the widespread usage of Douyin (the Chinese version of TikTok) has led to a spring of inventions regarding the processing of image and video, including computer vision (Scharre, 2024). Often, local governments collect and share this data with private suppliers of AI applications which then use the data for further commercial innovation (Beraja *et al*, 2023). The US has the advantage of a fairly unregulated internet, and internet services (ie social media applications, search engines, e-commerce) that are used across the globe. The collected data forms the basis of natural language processing and machine learning algorithms, and now, generative AI, the fields of comparative advantage for the US.

Semiconductors

Figure 11 displays the relative innovative strength of China, the EU and the US in various semiconductor subfields. Unsurprisingly, in view of the importance and complexity of chip fabrication in the advancement of the sector, semiconductor manufacturing is the sector's focus on innovation,

accounting for a total number of 551 radical novelties. Display technology follows closely, with a total number of 488 radical novelties. Memory technology, optoelectronics, materials science, microelectromechanical systems (MEMS) and power electronics appear as substantial subfields as well. For the latter four, China and the US are roughly on par. China dominates in memory technology, while the US leads innovation on semiconductor design, sensor technology and imaging technology.

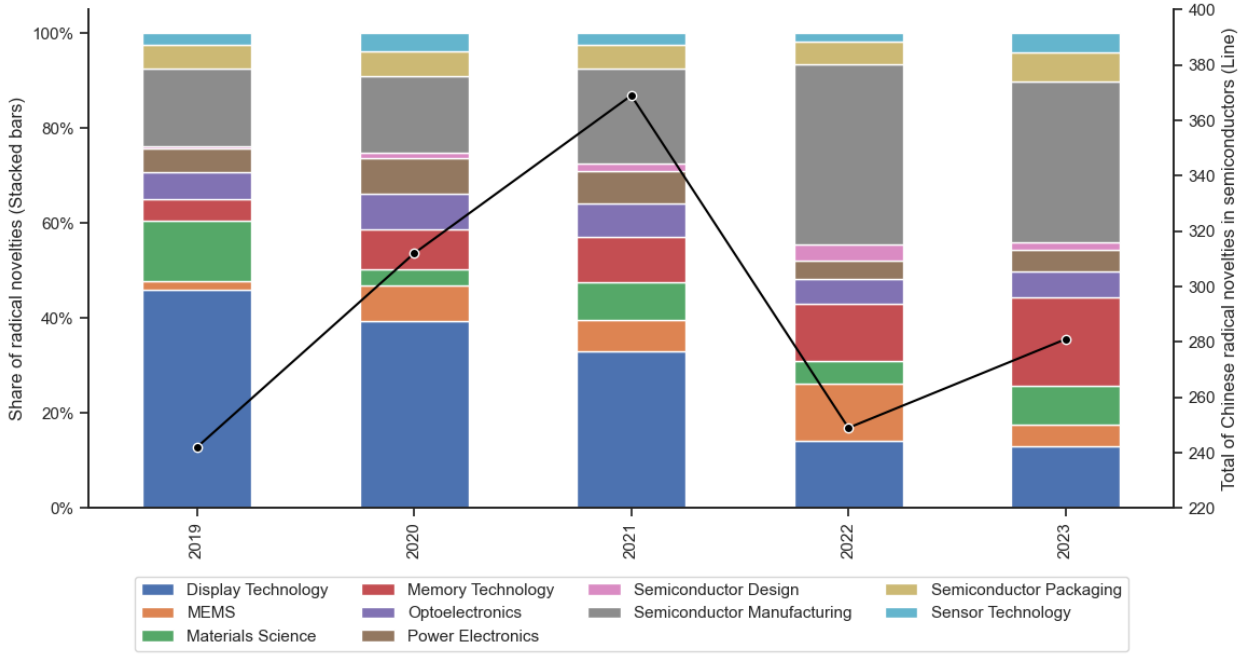
Figure 11: Share of radical novelties by subfield and entity origin



Source: Bruegel based on WIPO.

Given the government's decisive push for the development of a domestic chip ecosystem, it is not surprising that the composition of China's radical novelties across subfields has changed substantially (Figure 12). Until 2021, Chinese semiconductor firms were largely focused on display technology which made up 46.05 percent of all radical novelties in 2019, and 33.14 percent in 2021. This aligns well with China's general strength in consumer electronics manufacturing. However, a significant shift has taken place since 2021. Semiconductor manufacturing and memory technology are now the dominant subfields in China's chip innovation portfolio, with shares of 33.73 percent and 18.43 percent in 2023, respectively. A manual check of the data revealed that this has mainly been driven by two large firms, namely Yangtze Memory Technology and Changxin Memory Technology.

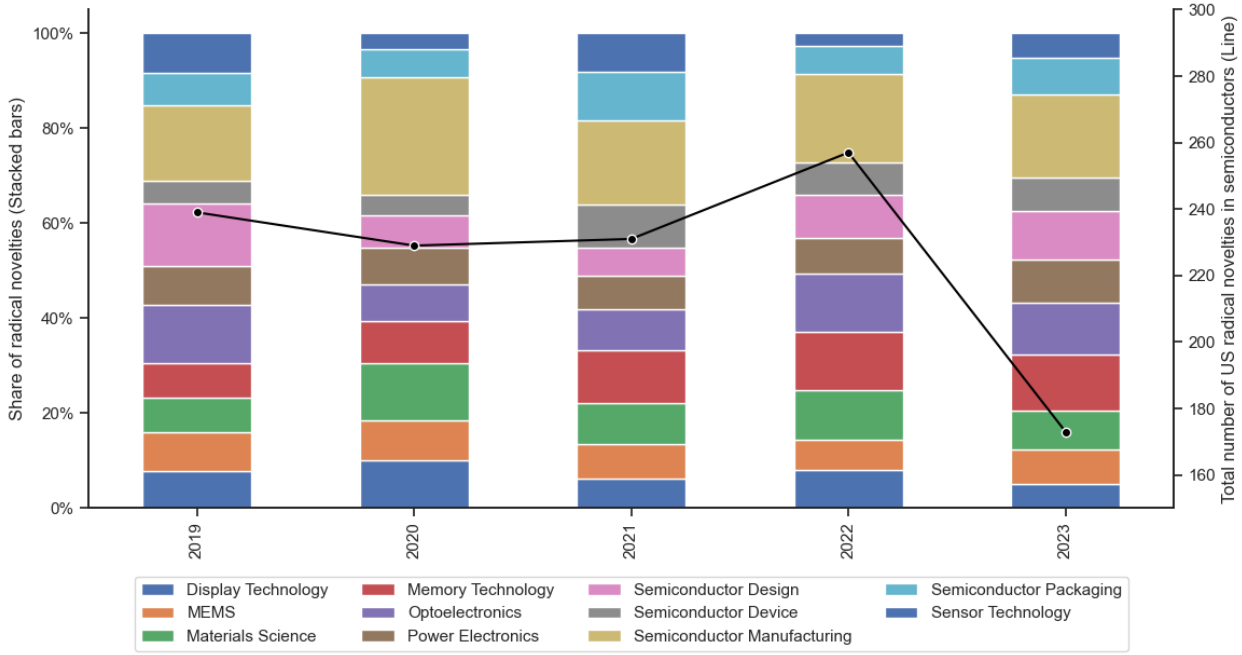
Figure 12: Chinese radical novelties in semiconductors by subfields (2019-2023)



Source: Bruegel based on WIPO.

While China's innovation heavily centres around semiconductor manufacturing and memory technology, the US portfolio appears more diversified. Figure 13 shows the evolution of subfields of radical novelties in semiconductors for the US. As can be seen, semiconductor manufacturing equally has the most significant share, hovering around 20 percent among the top 10 subfields. However, semiconductor design, optoelectronics, memory technology, power electronics and material science equally hold shares of about 5-15 percent each. The composition has remained largely stable, despite the US experiencing a significant drop of published novelties in 2023, from 256 down to 173.

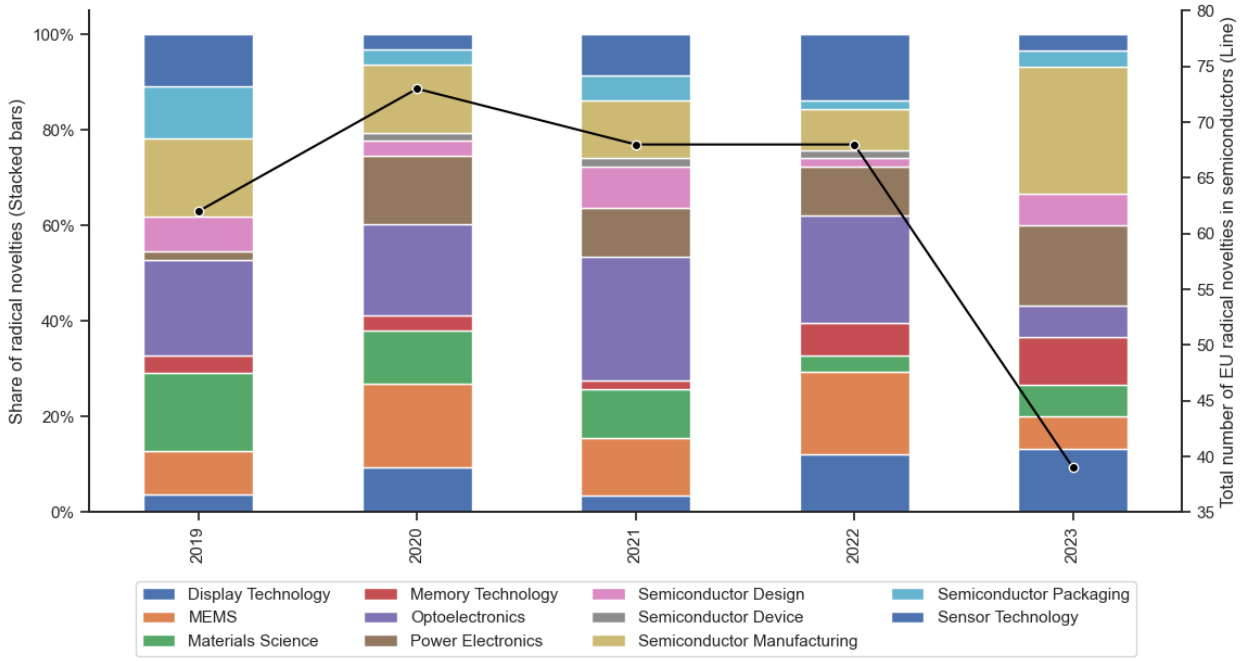
Figure 13: US radical novelties in semiconductors by subfields (2019-2023)



Source: Bruegel based on WIPO.

Finally, Figure 14 shows the EU's evolution of subfields in semiconductors. Traditionally, three sectors stand out, semiconductor manufacturing, optoelectronics and MEMS of which optoelectronics takes the dominant share throughout the years of combined 45.45 percent in 2019 to 40.01 percent in 2023. Sensor technology, memory technology, display technology, power electronics and materials science equally contribute significant shares of around 5-15 percent on average. Smaller shares are taken by semiconductor packaging and semiconductor design, with respective shares of 6.67 percent and 3.34 percent in 2023. Similar to the US, however, the number of radical novelties in semiconductors shrank by over half from 2022 to 2023.

Figure 14: EU radical novelties in semiconductors by subfields (2019-2023)



Source: Bruegel based on WIPO.

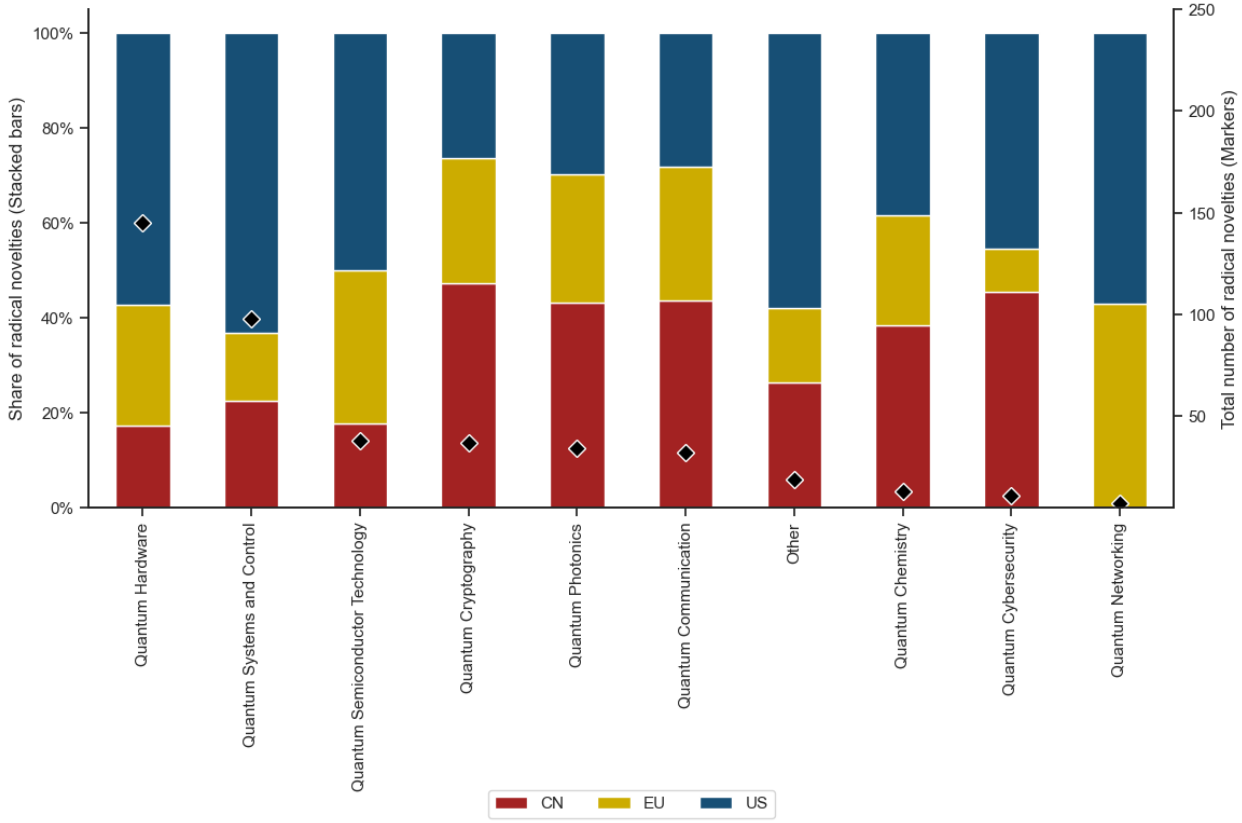
In sum, while China is advancing in radical novelties in semiconductor manufacturing and memory technology, the US has a fairly diversified portfolio, and, most notably, a strong presence in semiconductor design. The EU lags in all fields but is still a strong player in optoelectronics, MEMS and sensor technology. Our findings reflect the structure of the global semiconductor ecosystem. The US is home to many large technology firms who specialise in the high value-added parts of the semiconductor value chain, ie semiconductor design. China excels in memory technology and semiconductor manufacturing and has a strong presence in display technology, which reflects its dominance in consumer electronics. China's shift to the former two subfields also indicates that it has moved up the chips value chain.

Quantum computing

Figure 15 displays the relative share of China, the US and the EU for each subfield in quantum computing. The analysis reveals that quantum hardware and quantum systems and control are the subfields in which the largest amount of radical progress is conducted, leading to a sum of 145 and 98 novelties, respectively. Considerable activity is equally noted in quantum cryptography (38), quantum photonics (37), quantum semiconductor technology (34) and quantum communication (32).

The US dominates innovation in quantum computing in absolute number. The subfields where it captures the highest share are quantum hardware, quantum systems and control and quantum semiconductor technology, where the US accounts for 57.24 percent, 63.27 percent and 50 percent, respectively. China is most dominant in quantum cryptography, quantum photonics, quantum communication and quantum chemistry, reaching shares of 47.37 percent, 43.24 percent, 43.75 percent and 38.46 percent, respectively. Europe doesn't dominate any of the subfields but captures a significant share of novelties in quantum hardware (25.52 percent), quantum semiconductor technology (32.35 percent), quantum photonics (27.03 percent) and quantum communication (28.13 percent).

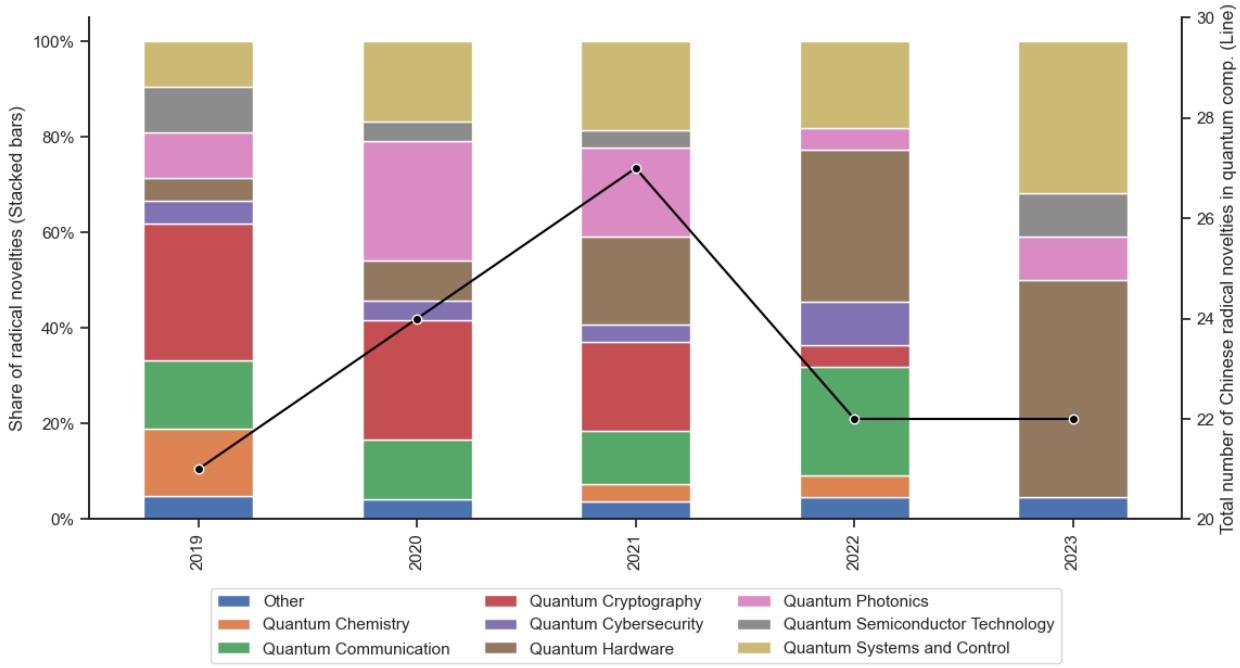
Figure 15: Share of radical novelties by subfield and entity origin



Source: Bruegel based on WIPO.

Moving to the decomposition of the evolution of subfield concentration for each of the three economies separately, Figure 16 shows the Chinese case. Between 2019 and 2021, activity in patenting of radical novelties mostly focused on quantum cryptography, quantum communication and quantum photonics. At the same time, quantum systems and control gained in significance in terms of China's radical novelties in this subfield. In 2022 and 2023, the focus shifted significantly. While quantum hardware constituted only 4.76 percent of all Chinese quantum technology novelties in 2019, this share rose to 45.45 percent by 2023. Our data shows that in 2023, the most significant innovations focused on quantum hardware and quantum systems and control, with a combined share of 77.27 percent. Quantum cryptography, quantum communication, quantum chemistry and quantum cybersecurity disappeared in radical novelties in 2023.

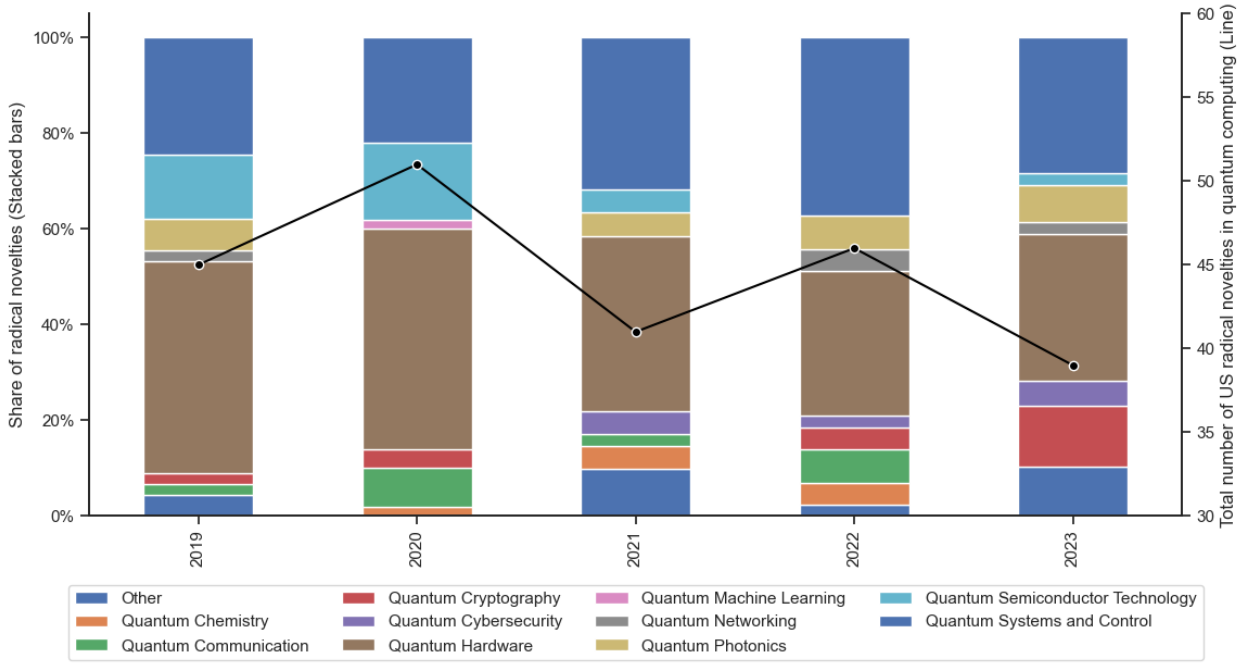
Figure 16: Chinese radical novelties in quantum computing by subfields (2019-2023)



Source: Bruegel based on WIPO.

In the US, an opposite trend is visible (Figure 17). While quantum hardware and quantum semiconductor technology dominated quantum technology innovation in 2019 (50.73 percent and 15.94 percent, respectively), these values dropped to 30.43 percent and 4.35 percent in 2023. At the same time, quantum systems and control and quantum cryptography gained a more significant share, at 30.43 percent and 10.87 percent respectively.

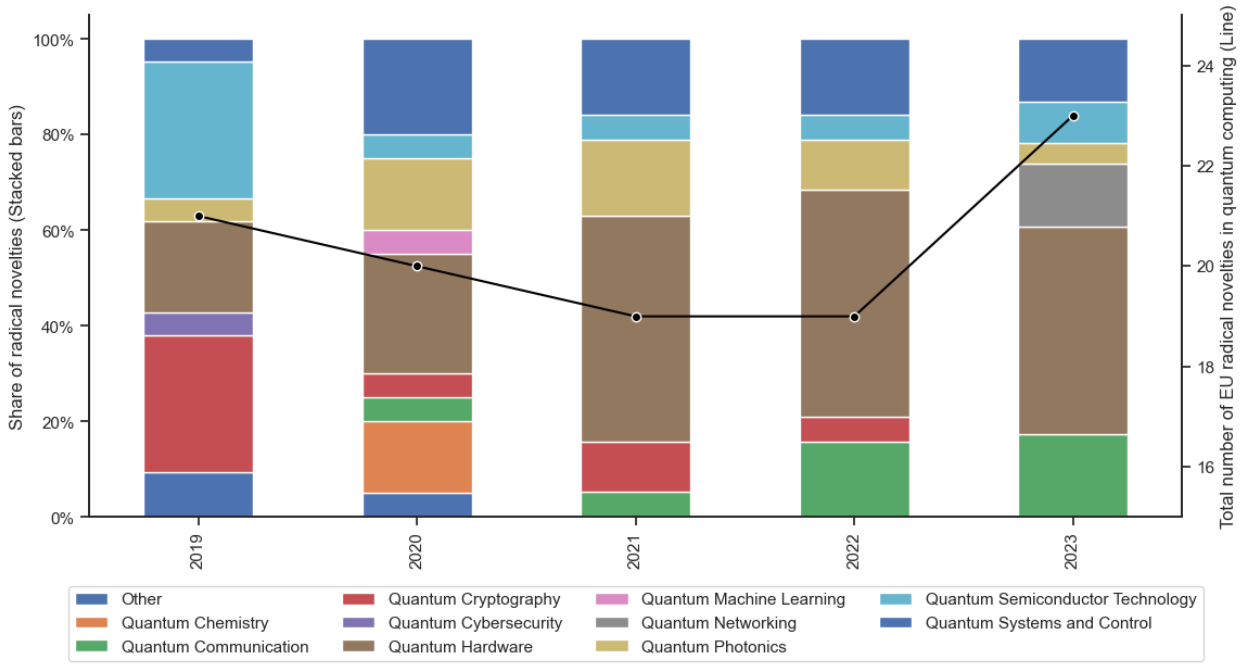
Figure 17: US radical novelties in quantum computing by subfields (2019-2023)



Source: Bruegel based on WIPO.

Finally, the EU's radically novel patents in quantum computing are mostly situated in quantum hardware, as in the US, with shares between 21.74 percent in 2019 up to 47.83 percent in 2022 (Figure 18). Quantum photonics and quantum communications have equally played a significant role, although with the latter only gaining importance from 2021 onwards. While quantum cryptography reached a significant share of 26.09 percent in 2019, that percentage dropped to 3.23 percent by 2023.

Figure 18: EU radical novelties in quantum computing by subfields (2019-2023)



Source: Bruegel based on WIPO.

In general, it must be noted that the overall number of quantum computing-related radical novelties remains small. The above findings should therefore not be overinterpreted. Since quantum technology is a young industry that is developing quickly, rapid changes in the concentration of subfields might occur. Our analysis, however, suggests that China has shifted from quantum cryptography and communication to hardware-related subfields. On the contrary, the EU and the US have retained stable shares of quantum hardware over the years, while equally making progress in quantum communication and quantum cryptography in recent years.

7 Cross-regional patterns

7.1. Measuring patent spillovers

We move to estimating how quickly regions catch up to the technological advancements of other regions or, how long it takes for a technology of a radical novelty filed by region A to appear in the patent of region B. To this end, we track the first appearance of a relevant innovation using a keyword-based approach. To improve the accuracy of our methodology, we apply stemming, a method that reduces words to their root form to ensure consistency in keyword matching across patents. For example, 'innovation', 'innovates' and 'innovative' are reduced to innovate, allowing us to catch instances of the same concept even when phrased slightly differently. As a second step, we extract stemmed keywords from patent abstracts and check when they first appear in other filings. Finally, we validate our approach by manually reviewing a sample of 100 innovations, confirming that keyword matches reliably capture repeated technological concepts.

The spillovers are then quantified by measuring the time between the publication date of the repeated patent and the initial radically novel patent, which is then averaged out across subfields of critical technologies. The following equation illustrates our results:

$$t_{i,j,p} = date_{i,p} - date_{j,p}$$

where $t_{i,j,p}$ is the lag between economy i and j of patented novelty p in days. We then average the lag for each subfield:

$$T_s = \frac{\sum_p t_{i,j,p,s}}{n_s}$$

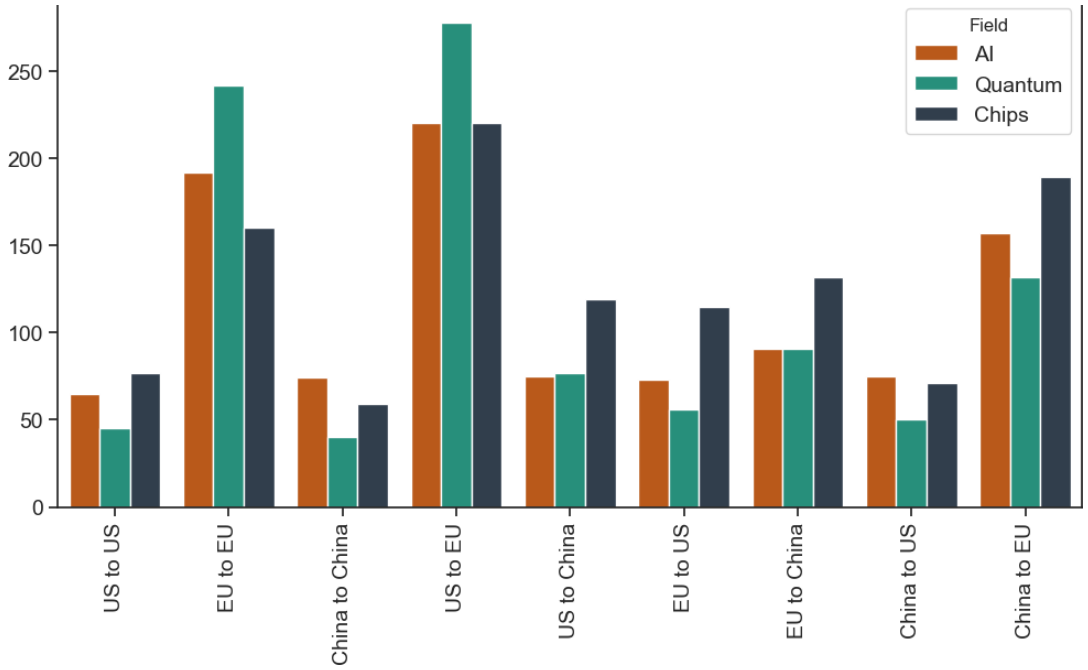
where n_s is the sum of patented novelties from economy i that are repeated in economy j. Since patents typically take at least one and a half years to be published—depending on the jurisdiction—it is important to acknowledge that we remain agnostic about the precise channels through which these spillovers occur. In most cases, it is likely that the technology was not directly copied from the patent itself. Instead, it could be that the scientific basis for the technology was already well-known, and regions were in a head-to-head race in developing a product. It could also be that the technology was leaked through inter-regional development cooperation or the movement of people between regions.

7.2. How fast do countries/regions replicate critical novelties?

We now look into the speed at which critical novelties may be replicated in the same economic area or in another one.

Figure 19 shows the average spillovers for radical novelties in the three technology fields. In general, the EU needs on average the longest to replicate radically novel patents from other regions. It takes particularly long for technologies coming from the US, less so from China. On the contrary, technologies from the EU are much faster to be found in patents from US entities than the other way around. China is closely following the EU and the US although with slightly larger spillover times than the US has vis-à-vis the other two regions. The EU does not only need a considerable amount of time to innovate in technologies from other regions but equally to progress radically novel innovations within its own domestic market. This could be due to several reasons such as nation state barriers, the weak absorptive capacity of its high-tech firms, or more tedious administrative processes for R&D. In any case, this is a point of concern for EU policymakers.

Figure 19: Cross-regional spillovers per field by direction (in average number of days)

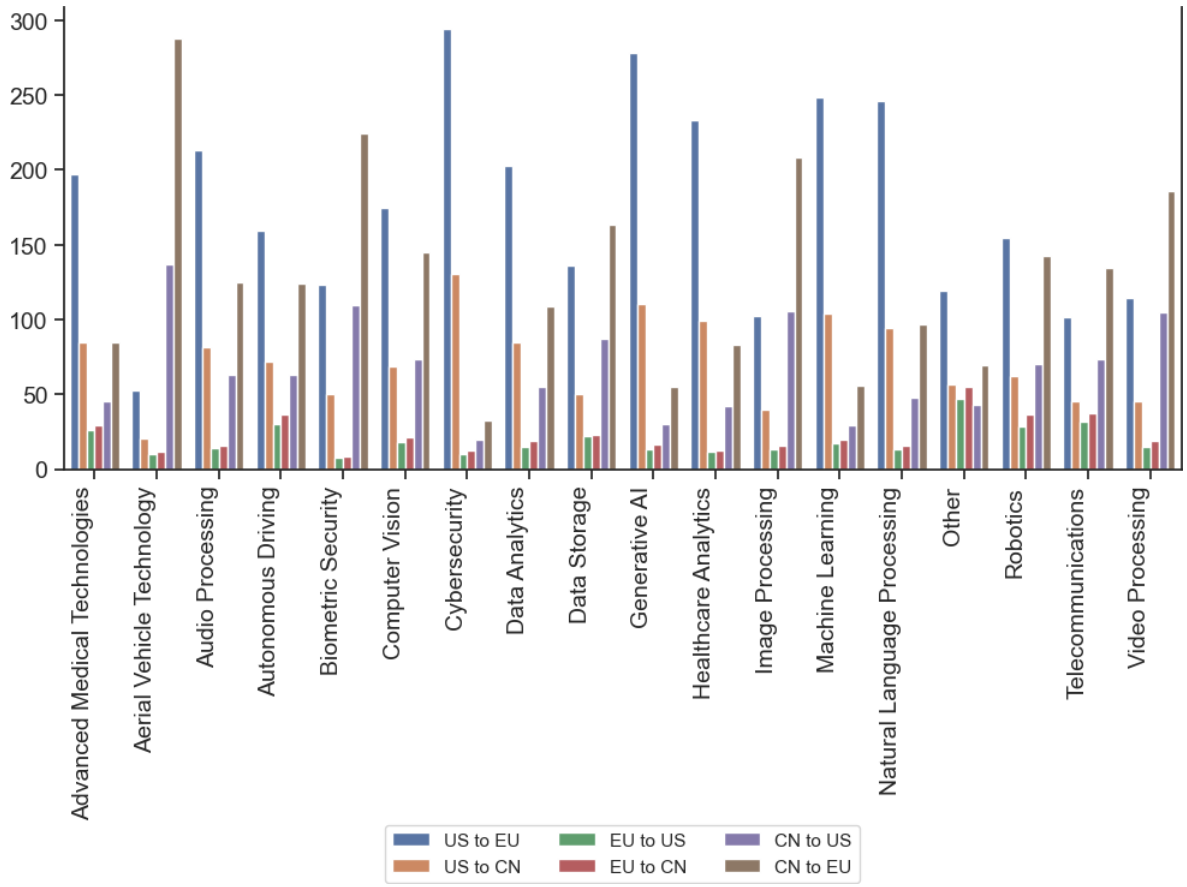


Source: Bruegel based on WIPO.

Artificial intelligence

Moving to a much more granular analysis of the different subfields of AI, we find the largest spillover times from the US to the EU is in cybersecurity and generative AI, averaging 294 and 278 days, respectively (Figure 20), and the smallest in aerial vehicle technology, image processing and telecommunications. Clearly, as EU economies have so far advanced little in generative AI, this finding is not surprising. Furthermore, as cybersecurity is often connected to military applications, the EU's underinvestment in this area may have impeded progress on this front. The spillover time for the US to the EU are also quite long for natural language processing and machine learning. For Gen AI, the spillover time from the US to China is around 40 percent of that of the US with the EU, hinting already to China's current rise as a generative AI market.

Figure 20: Spillovers in AI across different countries/regions (average number of days)



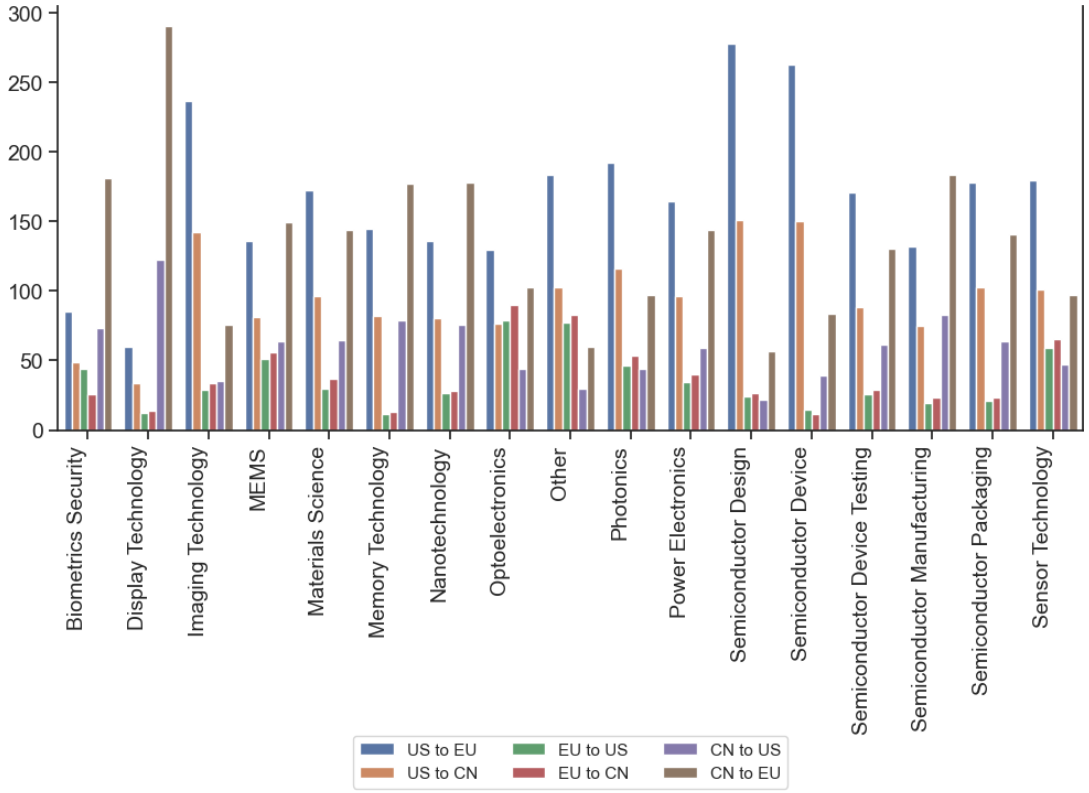
Source: Bruegel based on WIPO.

In the same vein, spillovers from China to the US tend to be longer than from China. This is the case of computer vision and image processing, with durations extending beyond 73 days to the US. These findings are clearly concerning for the EU. From the US to China, the longest spillovers are in data storage, but many are short. Spillovers from the EU to China or from the EU to the US tend to be very short. All in all, we find that the speed at which radical novelties in specific AI fields are transferred varies widely from one technology to another and one country to another. The EU suffers the longest delays while its own novel patents are replicated rather quickly.

Semiconductors

Moving to diffusion of semiconductor technology within a country's borders, Figure 21 reveals that the replication time within the EU are again the longest (303 days) compared to the US (170 days) and even more so China (132 days). While the US and China show relatively efficient internal diffusion, the EU again experiences longer delays. This trend is consistent with the cross-country spillover data, where the EU also faces delays in adopting semiconductor innovations from other regions. This suggests that both internal and external factors are contributing to slower technology diffusion in the EU, potentially impacting its competitiveness in this critical sector.

Figure 21: Cross-regional spillovers in semiconductors by subfield (in average number of days)



Source: Bruegel based on WIPO.

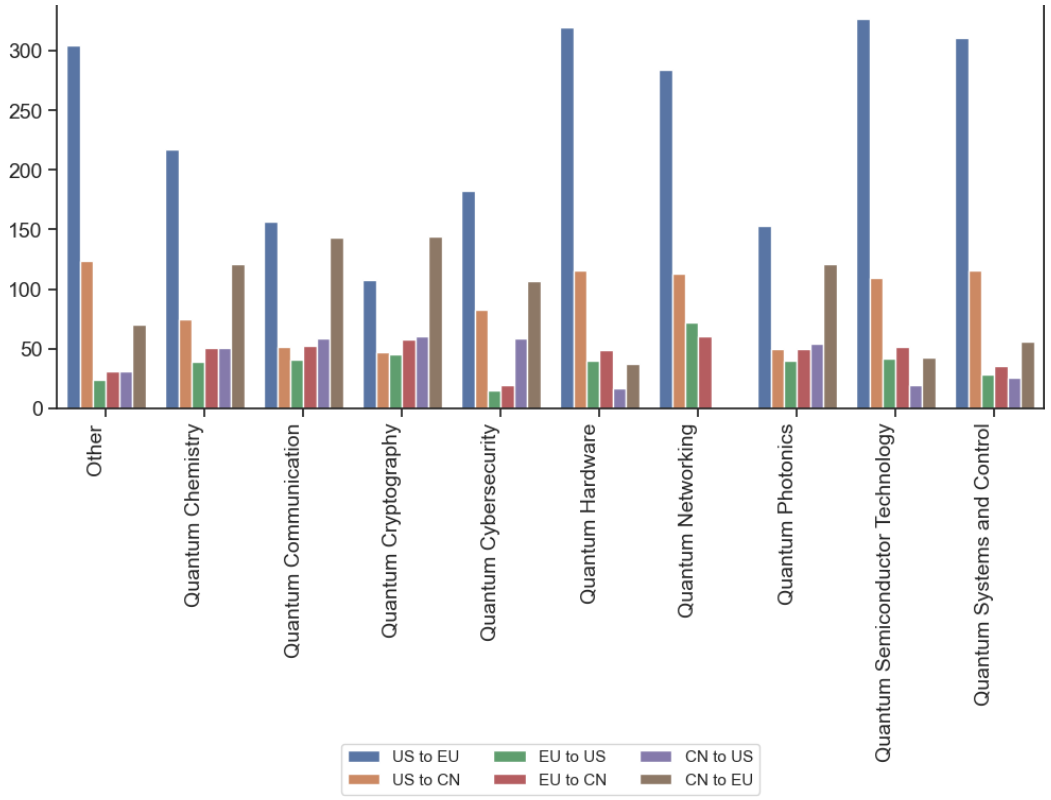
Finally, moving to the different subfields of semiconductor technologies, we find that the innovation field with the longest spillover time from the US to the EU is semiconductor design, with an average of 278 days (Figure 24). Conversely, fields such as memory technology and power electronics show much shorter spillover time, especially from China to the US, with durations as low as 59 days. Additionally, fields like semiconductor manufacturing and photonics exhibit relatively balanced replication times across different regions, with China to the EU reaching up to 183 days. Our findings for the semiconductor sector suggest that, while some semiconductor innovations get replicated relatively quickly, others, particularly in advanced manufacturing and testing, experience notable delays, especially when those EU innovations originating in the US.

Quantum computing

Finally, at a more granular level, the field of quantum semiconductor technology experiences the slowest diffusion from the US to the EU, with 326 days on average (Figure 22). Similarly, quantum cryptography shows a longer spillover time, particularly from the EU to China and from China to the EU, with durations extending up to 60 days. However, certain fields like quantum photonics exhibit much shorter the spillover time from the US to China and from the EU to the US, with durations as low as 50 and 41 days, respectively. These patterns indicate that while some quantum innovations are

rapidly adopted across regions, others, especially those like quantum communication, encounter substantial delays in their diffusion, particularly from the US to the EU and within the EU itself.

Figure 22: Cross-regional spillovers in quantum computing by subfield (in average number of days)



Source: Bruegel based on WIPO.

8 Conclusions

Our findings are concerning for Europe for two reasons. First, the EU seems to have fallen behind the US and China in core innovation capabilities in the technologies of the future. The EU sees most of its success in quantum computing, but it is too early to say whether this success will continue. This critical technology is much less mature in general terms, evident in its fewer radical novelties and total number of patents. Second, the much slower replication of radical novelties by Europeans points to a certain isolation for the EU's innovation in critical technologies compared to China and the US. The fact that radically novel patents are also replicated more slowly within the European single market than within the US or China points to the fragmentation of the single market as a potential root cause of the problem.

Our results do not indicate that either China or the US is an overall frontrunner in the innovation race, although the sub sectoral analysis offers some clues as to the winners in specific subsectors. Their innovation ecosystems are far more integrated with one another than they are with the EU when measured by the speed of spillovers (or technology replication) in critical technologies, despite US introduction of export controls in critical technologies.

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Appendix 1: Methodology

Definition of radical novelty

Let C_i be the unique concept extracted from patent P_i, and let H represent the historical corpus of all patents. We formally define radical novelty as:

$$N_{\mathrm{r}}(C_{\mathrm{i}}) = \begin{cases} 1 \; if \; C_{\mathrm{i}} \notin \mathcal{H} \; and \; |S(C_{\mathrm{i}})| \geq k \\ 0, otherwise \end{cases}$$

where $S(C_i)$ represents the set of patents citing or adopting concept C_i within a set time window.

Novelty detection

The novelty detection procedure consists of three key steps:

1. Concept Extraction with LLAMA3:

   Given an abstract of patent P_i, we extract its main innovation concept C_i using LLAMA3 via a structured prompt. The extracted concept is then embedded into a high-dimensional semantic space R^d for further analysis:

$$\mathrm{E}(\mathrm{A_i}) = \mathrm{LLAMA3}(\mathrm{A_i})$$

2. Clustering with DBScan:

   - To classify new concepts into innovation clusters, we apply DBScan, which groups similar embeddings based on density.
   - The distance metric used for clustering is the cosine similarity of concept embeddings:

$$sim(E_{\mathrm{i}}, E_{\mathrm{j}}) \; = \; (E_{\mathrm{i}} \; \cdot \; E_{\mathrm{j}}) \; / \; (\|E_{\mathrm{i}}\| \; \|E_{\mathrm{j}}\|)$$

   - This method allows discovery of meaningful technological clusters without assuming a fixed number of clusters (as opposed to k-means).

3. Validation of radical novelty:

   - For a concept C_i to be classified as a radical novelty, it must:
     1. Appear for the first time in our dataset.
     2. Be referenced at least *k* times in subsequent patents.

- The validation score is computed as:

$$V(C_i) = |S(C_i)| /$$

where $V(C_i) \geq 1$ ensures significant adoption of a novel concept.

Aggregation of the innovation fields

To illustrate major innovation domains in AI, quantum computing and semiconductors, we aggregate clustered innovation concepts into macro-fields. These fields are curated using a semi-supervised approach, where:

- DBScan cluster labels are reviewed manually.
- Clusters are merged based on semantic proximity into broader innovation themes.

The resulting categories enable a clearer interpretation of radical innovations across key technological domains (Annex 1).

Country of origin

A critical aspect of our analysis is identifying the country of origin for each patent and its radical technology. Since WIPO data does not include headquarters location, we use an automated search pipeline via ChatGPT 4o.

1. Entity normalisation: We first clean entity names to resolve typos and inconsistencies in legal abbreviations (eg Ltd., GmbH, S.A.).
2. Automated web querying: For each entity, we prompt ChatGPT 4o to search the web and extract the headquarters location.
3. Classification rules:
    - Subsidiaries of multinational corporations are classified based on their legal country of registration rather than the parent company's location.
    - Manual verification ensures accuracy of classifications.

These steps provide a robust classification of patent origin.

Appendix 2: Innovation Fields and Number of radical novelties per field and per country/region

Artificial Intelligence

Classified concept	CN	EU	US	Total
Advanced medical technologies	47	27	100	174
Aerial vehicle technology	44	3	7	54
Audio processing	35	9	48	92
Autonomous driving	18	10	22	50
Biometric security	22	2	11	35
Computer vision	367	87	352	806
Cybersecurity	6	3	44	53
Data analytics	72	22	121	215
Data storage	16	4	10	30
Generative AI	7	3	29	39
Healthcare analytics	15	5	42	62
Image processing	195	23	80	298
Machine learning	146	97	575	818
Natural language processing	104	29	231	364
Other	10	14	16	40
Robotics	137	57	126	320
Telecommunications	38	17	25	80
Video processing	45	6	18	69

Quantum computing

Classified concept	CN	EU	US	Total
Other	5	3	13	21
Quantum chemistry	5	3	5	13
Quantum communication	16	10	9	35
Quantum cryptography	17	11	10	38
Quantum cybersecurity	5	1	5	11
Quantum hardware	24	43	93	160
Quantum networking	0	3	4	7
Quantum photonics	16	10	12	38
Quantum semiconductor technology	6	11	18	35
Quantum systems and control	22	20	65	107

Semiconductors

Classified concept	CN	EU	US	Total
Biometrics security	9	2	4	15
Display technology	688	38	92	818
Imaging technology	15	8	33	56
MEMS	125	59	82	266
Materials science	132	40	119	291
Memory technology	243	17	110	370
Nanotechnology	23	5	21	49
Optoelectronics	115	159	107	381
Other	6	10	13	29
Photonics	39	28	55	122
Power electronics	92	32	102	226
Semiconductor design	30	15	128	173
Semiconductor device	41	8	90	139
Semiconductor device testing	37	6	27	70
Semiconductor manufacturing	517	71	245	833
Semiconductor packaging	96	19	90	205
Sensor technology	53	42	64	159

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Bruegel, Rue de la Charité 33, B-1210 Brussels
(+32) 2 227 4210
info@bruegel.org
www.bruegel.org