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Firm Networks and Global Technology Diffusion

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Abstract

This study examines the role of multinational firms and global value chain linkages in the cross-country diffusion of emerging technologies. The analysis combines detailed information on the near-universe of online job postings in 17 countries with data on multinational networks and firm-to-firm linkages from 2014 to 2022. Online job postings are utilized to investigate how jobs related to emerging technologies spread through firm networks. The findings show that emerging technology jobs are highly concentrated within multinational firms and their supply chains. Approximately one third of all emerging technology job postings during this period come from Fortune 500 firms, their affiliates, buyers, suppliers, or innovation partners. Although the locations where these technologies originate exhibit a higher prevalence of technology job openings, this advantage diminishes over time as diffusion accelerates in wealthier and geographically closer countries and regions. The study highlights the significant role of firm-to-firm linkages in technology diffusion, with some linkages proving more influential than others. Firms that were previously buyers or innovation partners of establishments in technology-originating locations experienced faster growth in jobs related to these technologies. Moreover, relationships outside corporate boundaries play a particularly critical role, and these connections are influential beyond the factor of geographical distance.

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Firm networks and global technology diffusion [*]

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1 Introduction

The speed with which new technologies spread across nations is key for explaining cross-country differences in economic performance (Comin and Hobijn, 2004, 2010; Comin and Mestieri, 2018). Multinational firms and firm-to-firm relationships through global value chains are believed to play an important role in this process of international technology diffusion (World Bank, 2020). However, understanding the role of firm-to-firm relationships in the cross-country spread of new technologies has proved difficult because of the lack of detailed panel data on both the adoption of new technologies across countries and firms, and on different types of international-firm-to-firm linkages.

In this paper, we leverage a rich combination of granular information on online job postings with data on several types of international firm-to-firm linkages to study the role of multinational firms and global value chains in the cross-country diffusion of new technologies. We examine the diffusion of 29 new technologies across 17 countries and 107,981 firms in the period 2014-2022. Following Bloom et al. (2021), we use the raw text of online job postings and earnings calls data to measure hiring patterns and firm discussions relating to frontier technologies, using this as a proxy for technology diffusion. We combine this information with detailed data on international firm-to-firm linkages, which includes information on buyer-supplier relationships, innovation partners and affiliates in multinational firm networks. To study the process of technology diffusion, we employ various measures of dispersion used in the literature, such as the Gini coefficient and the coefficient of variation, which allow us to document the intensity and spread of emerging technology jobs across countries, regions, and firms.

We first establish four stylized facts about international technology transfer. First, emerging technology hiring has become more dispersed across countries and regions over time. This finding is consistent with evidence on the US only by Bloom et al. (2021). Second, emerging technology jobs are highly concentrated in multinational firms and their supply chains. Around one third of all job postings related to these 29 frontier technologies in the 17 countries are posted by Fortune 500 companies and their buyers, suppliers, affiliates or innovation partners. Third, technology jobs spread faster to richer regions and countries, a finding consistent with the existing literature on cross-country technology diffusion. Finally, technology jobs also spread faster to closer regions and countries to the locations where the technologies emerged.

Given the concentration of emerging technology jobs in multinational firms and their supply chains, we next explore the role of pre-existing firm-to-firm linkages in the diffusion of these technologies. For each technology, we use global patents data to identify the regions where the technology emerged, finding that all of these technologies emerged from cities within the USA. We then identify firms that had ex ante linkages to a firm in the city and industry of the technology's emergence, focusing on the fifteen technologies that emerged after 2005. We evaluate whether firms with such linkages before the takeoff of each technology saw relatively higher growth in job postings related to that technology in the years after the takeoff. We find that *ex ante* buyer and innovation partner linkages play an important role in the spread of jobs related to these technologies, with less evidence of a role of suppliers or affiliates. In addition, we find that the role of these linkages does not dissipate over time.

The faster spread of technology jobs to firms with these pre-existing linkages remains after controlling for distance to the technology emergence location, and we find no evidence of a stronger role of these linkages for firms that are geographically proximate to the technology emergence location. We also explore the role of linkages within and outside firm boundaries. We find that the effects for firms with pre-existing buyer and innovation partner linkages are driven by firms that do not share the same ultimate owner. Finally, we show that there is no differential effect of these *ex ante* buyer and innovation partner linkages for US relative to internationally-linked firms, and the key results are robust to dropping technologies that emerged in Silicon Valley.

Our study contributes to several strands of existing research on the diffusion of innovation, capabilities, and technology, particularly through firm-to-firm linkages and global value chains. A significant body of literature has examined technology diffusion across countries, often using measures of technology adoption at the country level (Comin and Hobijn, 2004, 2010; Comin and Mestieri, 2018). However, these studies have not extensively explored the role of international firm-to-firm linkages in this process. Our research addresses this gap by providing micro-foundational evidence on the importance of these linkages in the diffusion of specific new technologies. Our findings on the positive role of income per capita, and negative role of distance, in the spread of jobs related to emerging technologies, is consistent with this existing literature, while we also highlight the additional important role of firm-to-firm linkages in the cross-country diffusion process.

Our approach for identifying new technologies and pioneer firms draws on Bloom et al. (2021), who use textual analysis of patents, job postings, and earnings calls to study interactions between innovation and employment within the US.[1] We extend their work by examining technology diffusion across 17 countries and highlighting the role of firm-to-firm linkages in the cross-country diffusion of new technologies. This broader scope allows us to uncover the significant impact of international buyer-supplier and innovation

[1] In using online job postings to document technology diffusion, our paper is also related to earlier research that studies the relationship between technology and labor markets, including studies on the diffusion of a single specific technology (Autor et al., 2003; Akerman et al., 2015; Acemoglu and Restrepo, 2020; Graetz and Michaels, 2018; Artuc et al., 2023), specific innovations during important historical episodes (Griliches, 1957; Goldin and , 1998; Caprettini and Voth, 2020), and studies examining impacts of technology progress more generally (Krueger, 1993; Berman et al., 1994; Autor et al., 1998; Michaels et al., 2014).

partner relationships on technology spread, consistent with findings in Haddad and Harrison (1993); Aitken and Harrison (1999); Javorcik (2004); Haskel et al. (2007); Keller and Yeaple (2009); Alfaro (2017).

Additionally, our paper is related to the extensive theoretical and empirical literature on the effects of multinational activity and global production networks on firm performance and technology diffusion. Previous studies have suggested that multinational corporations (MNCs) facilitate significant technology transfer and R&D activities through their roles in Global Value Chains (GVCs) (Yeaple, 2013; Yoshino and Rangan, 1995; Alfaro et al., 2015). Engagement in GVCs often leads to enhanced skill development since it requires high levels of explicit coordination between firms and hence cooperative learning (Caliendo and Rossi-Hansberg, 2012), and increased demand for high-skill labor (Verhoogen, 2008; Brambilla et al., 2012). Moreover, domestic firms linked to MNCs frequently experience productivity and innovation spillovers (Alfaro-Ureña et al., 2022), and compliance with global standards imposed by MNCs drives technological upgrades (Antràs and Helpman, 2004; Garcia-Marin and Voigtländer, 2015). Yet, previous research was unable to measure the diffusion of specific new technologies through firm-to-firm international linkages.

Our empirical findings align with these insights, showing that pre-existing relationships with buyers and innovation partners, rather than suppliers or affiliates, are critical for the rapid diffusion of new technologies; and suggesting that relationships with counterparts external to the corporate boundaries are particularly important. This evidence indicates that the nature of the firm-to-firm linkages is crucial, as only specific types of linkages foster the diffusion of emerging technologies. The direct measurement of emerging technologies and different types of firm-to-firm linkages allow us to uncover these channels of technology transfer, thereby deepening our understanding of how multinational networks and GVCs facilitate the transfer of emerging technologies on a global scale.

The remainder of this paper is structured as follows. In section 2, we describe the data and the main measures we employ in the empirical analysis. In Section 3, we document stylized facts about the geographic spread of new technologies across countries, and regions. We also investigate sector and firm concentration of such technology hiring. In Section 4, we document the role of multinational supply chains in technology diffusion. In doing so, we first investigate the technological advantage of firms located in pioneer locations and its evolution over time and we then study the role of various types of firm-to-firm linkages to pioneer firms in shaping technology diffusion. Section 5 concludes the paper.

2 Data and measurement

This paper uses data on online job postings from Lightcast to capture jobs related to emerging technologies, and matches this at the firm level with data on firm-to-firm linkages from Factset. In this section, we first describe the online job postings dataset, the classification of new technologies, and the matching process with FactSet firms. We then discuss additional data cleaning and complementary sources. Finally, we provide different measures of technology concentration including the Gini coefficient and the coefficient of variation.

2.1 Online job postings

Our primary dataset includes 573 million scraped online job postings from Lightcast (formerly Burning Glass Technologies). Our sample covers 17 advanced economies from 2014 to 2022.[2]

We use the job postings data to identify jobs relating to emerging technologies for several reasons. First, it allows us to identify jobs related to specific and granular technologies over time. In the absence of detailed data on the deployment of multiple technologies across firms, regions, and countries, real-time rich text data sources have been increasingly used as a barometer for the diffusion of new technologies, as reflected through their skills demand footprint or extent of discussion in company boardrooms (see for example Acemoglu et al. (2022) and Bloom et al. (2021)). These datasets are particularly useful for studying rapid advances in new technologies that have not yet been clearly defined or captured by statistical agencies using traditional data sources. Moreover, Lightcast provides not only the raw text of each job description, but also additional information about the industry, occupation, and location of each job posting, allowing us to trace diffusion through each of these channels.

The main potential shortcoming of the Lightcast data on online job postings concerns the representativeness of actual vacancies. First and most notably, it only includes jobs posted online and this subset of vacancies may not be fully representative of all vacancies, while vacancies are also a flow measure of labor demand, rather than a measure of the stock of employment. A growing literature has now shown that online job postings tend to be over-representative of higher-skilled occupations and industries, although recent research has generally found that in advanced economies a very high share of jobs are now posted online. For the US, Hershbein and Kahn (2018) show that the share of jobs online as captured by Lightcast is roughly 90% of the jobs in JOLTS. Bloom et al. (2021) also show that the trend in Lightcast postings after 2010 parallels that of JOLTS openings in the US.

[2]The sample includes: Austria, Belgium, Denmark, France, Germany, Italy, Luxembourg, Netherlands, Norway, Sweden, Switzerland, United Kingdom, Singapore, Australia, New Zealand, Canada and the United States.

For the UK, Javorcik et al. (2019) show it covers just above 85 percent of all (online and offline) job vacancies as measured by the UK Vacancy Survey. Bastos et al. (2023), exploiting the same dataset across 35 countries, find a close relationship between total job vacancy rates as measured by official statistical agencies and each country's ratio of Lightcast job postings to total employment.

We complement the above evidence by comparing Lightcast job postings as a share of each country's working age population, shown in Appendix Table A1. We find that Belgium, Switzerland and Luxembourg have the highest ratios of vacancies to working age population, while New Zealand, Norway and Italy have much lower shares. Another limitation of the data on online job postings is that they only measure stated but not necessarily realized demand. We therefore note that these measures of high-tech job postings serve as a proxy to track technology diffusion in the labor market, but future work expanding this with measures relating to the hires, separations, wages and internal training might provide a more complete picture. At this point,however, such consistent data is not available for such a wide sample of countries over time.

2.1.1 Identification of new technologies

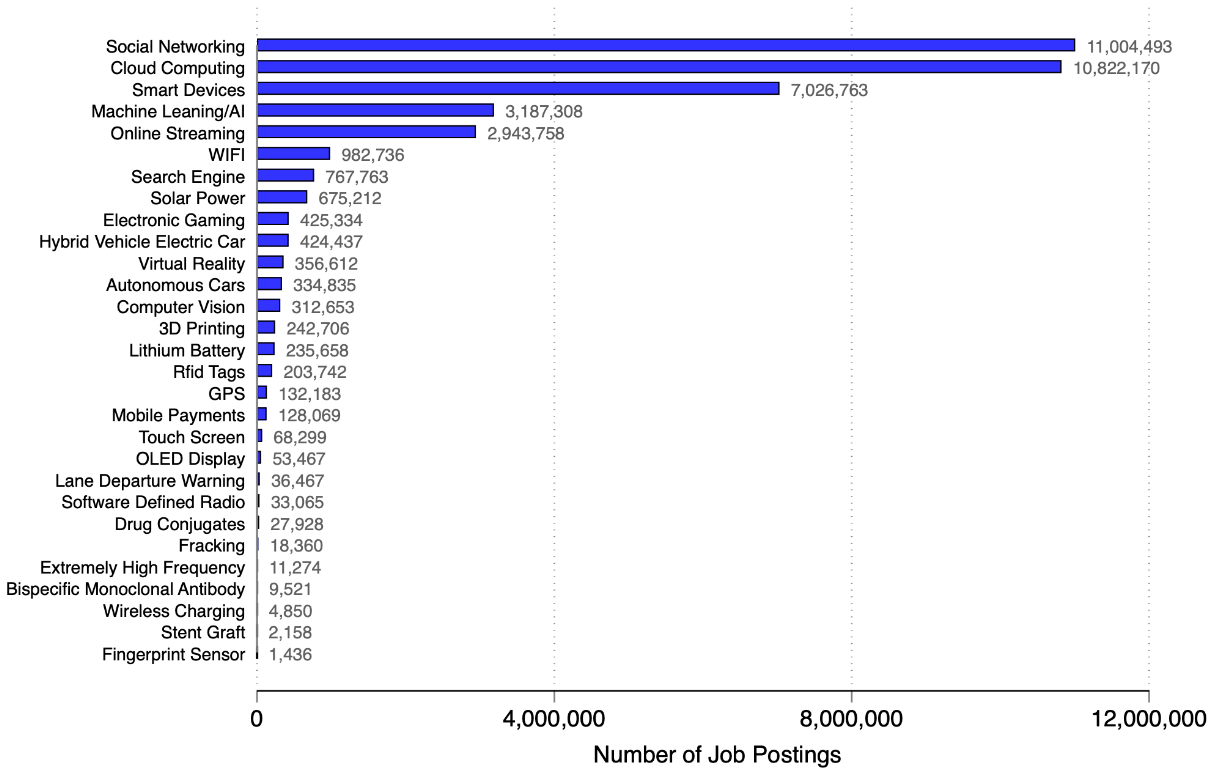
We use the raw text of the job postings to search for the 305 technology keywords from the classification of 29 technologies identified by Bloom et al. (2021).[3] We use Google translate to translate these keywords into all of the official languages of the 17 countries. We search for the keywords in both English and all official languages of the country. We then classify each job posting as being related to a specific technology if it includes at least one keyword for that technology.

This classification by Bloom et al. (2021) represents one classification of influential innovations that have been discussed prominently by investors and executives of publicly listed companies in the last two decades. Given that 53% of utility patents filed by USPTO are of foreign origin as of 2019 and that one-third of the earning calls were hosted by non US-based firms, these 29 technologies should also be suitable for studies examining diffusion outside the US.

Figure 1 lists the number of job postings mentioning each of the 29 technologies. Cloud Computing and Social Networking were mentioned the most, with more than 10 million job postings identified for each of these technologies, followed by Smart Devices then Machine Learning or AI and Online Streaming.

[3]For example, *"cloud environment"*, *"cloud solution"*, *"cloud storage"* and *"cloud service"* all belong to Cloud Computing technology.

Figure 1. Job postings by technology



Note: This figure displays the total number of job postings for each of the 29 technologies across all 17 countries from 2014Q1 to 2022Q4.

2.1.2 Industry and region classifications

We extract the industry code from each Lightcast job posting. As most countries in our sample are in the EU and have the 4-digit ISIC industry classification, we use crosswalks to convert all other national industry classifications to ISIC. This results in 88 industries with highly unequal distribution of technology-related hiring (see Section 3 for details). The crosswalks used are shown in Appendix A2.

We adopt a similar standardised procedure for region classifications to ensure consistency and comparability of data across the 17 countries. For European countries, we use the Nomenclature of Territorial Units for Statistics (NUTS) 2021 classification to achieve a consistent unit of measurement. For anglophone countries, we group them into states or provinces for the United States, Canada, Australia/New Zealand, ITLS1 for the United Kingdom, and at the country level for Singapore. Our approach results in 156 regions across 17 countries. Appendix A2 provides more details for region level aggregation.

2.2 FactSet data on firm-to-firm relationships

We use data on firm relationships from FactSet, a private company specializing in market intelligence on firm networks, including inter-firm and intra-firm linkages. FactSet collates data from various sources, including annual reports, investor presentations, press releases, and company websites. Among FactSet's offerings, the FactSet Fundamentals dataset provides consolidated financial statements and firm information for publicly traded companies, while FactSet Relationships dataset covers supply chain relationships, including suppliers, customers, and partnerships, as well as firm-to-affiliate relations.

The FactSet Revere Supply Chain Relationships database is recognized as one of the most comprehensive sources for global firm supply chain information (Huang et al., 2023). This dataset integrates information from official firm filings (10-K, 10-Q, and 8-K reports submitted to the SEC), investor presentations, press releases, and company websites (FactSet, 2021).[4] FactSet analysts normalize relationship types by cross-referencing a firm's records with its partners' ("reverse" links), providing a comprehensive view of supply chain linkages compared to other databases like Compustat Segment (Huang et al., 2023).

As of March 2024, FactSet actively monitored over 54,000 "source" companies, resulting in a dataset of more than 2 million relationship links involving approximately 360,000 firms. Each link includes information on start and end dates, with historical data available from 2003 and global coverage starting in 2014, expanding to Latin America in 2016.[5] The database specifies the nature of each relationship. For our study, we focus on buyer, supplier, and innovation partner relationships, supplemented with information on ownership ties and other firm characteristics. At any given time, we observe the parent and ultimate parent firm of a company, and any subsidiaries, if applicable.[6] The dataset also includes firm name, industry affiliation, headquarters country, and entity type, which we use in our analysis. Annual sales data, converted to constant 2020 U.S. dollars, are available but not used in our study.

We combine the two aforementioned FactSet data modules to construct a final dataset of 169,420 firms with bilateral relationship information from 2012 to 2022. These are defined as de jure corporate institutions, with 27% (46,000 firms) having available information from FactSet Fundamentals for at least one year within the sample period.

[4] In financial reporting, a 10-Q is a company's quarterly report with unaudited financial statements, while the 10-K is an annual report with audited financials. An 8-K updates shareholders on significant unscheduled events. U.S. listed firms must detail any customer accounting for more than 10% of revenue (Gofman and Wu, 2022), with some firms voluntarily disclosing additional customers (Huang et al., 2023).

[5] Many Latin American records from 2014 suggest backward updating for these firms.

[6] The parent or ultimate parent is identical to the company itself for self-owned firms.

2.2.1 Matching Lightcast job postings to Factset

We identify 10 million unique Lightcast company names associated with at least one job posting spanning from 2012 to 2022 across 17 countries. The set of company names are extracted from the raw text of all job postings and are not cleaned or standardized, nor cross-referenced with other postings, allowing for several variations in the naming of a single company. To overcome this issue, we draw on the legal names of all entities in the FactSet Relationships dataset, and define a list of name variations to help us matching both Lightcast and FactSet datasets. We take these variations by converting company names to lowercase, removing punctuation and special characters, and eliminating company suffixes (e.g., Ltd., Inc., LLC, etc.). The specific list of variations is in Appendix A4.

We then use both exact and fuzzy matching approaches to match the Factset firm names to company names in Lightcast. As a first step, we narrow down both matching approaches to the country where each company's headquarters are legally registered, according to FactSet. Using the different company name variations, we proceed to search for each FactSet company name within Lightcast, delimited by the headquarters' country. This sequential exact matching allow us to reduce the list of Lightcast company names by eliminating those already exactly matched with FactSet before the fuzzy matching procedure. The additional fuzzy matching approach was considered necessary due to potential variations in spelling and punctuation in company names that could not be captured by the exact matching, leading to inaccurate matching rates. We utilize lowercase company names without punctuation marks to conduct the fuzzy matching approach, employing the term frequency-inverse document frequency (TF-IDF) method as the primary fuzzy matching technique, complemented by the Levenshtein distance method for additional verification of name matches. Merging the results from both exact and fuzzy matching, we then obtain an initial subset of 80,000 matched FactSet firms out of the total 169,420.

As a second step, we expand the FactSet Relationships dataset by integrating ownership and structural information, enabling us to search for affiliates of the 169,420 firms as well. For instance, if the FactSet firm were 'Microsoft', using the relationship structure data we can access the entire family of affiliates, including 'GitHub', 'LinkedIn' and 'Skype Technologies'. This integration yielded a newly expanded dataset of nearly 2.5 million Factset entities, including parent companies from the original sample. Subsequently, we conduct a second exact and fuzzy matching exercise searching for this expanded list of company names in the Lightcast data without restricting the matching process to the headquarters country. This procedure allow us to identify 440,000 affiliated entities from FactSet in the Lightcast data, which are associated with 108,000 firms in the FactSet Relationships dataset. After consolidating the outcomes from both steps and removal of duplicate matches[7], our final

[7] The duplicate-elimination criteria is detailed in Appendix A4.

dataset comprises 109,000 FactSet firms (representing 65% of the 169,420 firms from the supply chain data) linked with nearly 1.5 million company names in Lightcast.

To identify the FactSet firms with potential operations in the 17 Lightcast countries, we refined the original sample, keeping only those firms with at least one affiliate in any of the 17 Lightcast countries, according to information reported by FactSet or Lightcast data. For instance, although Samsung's headquarters may not be in any of the 17 Lightcast countries, FactSet might report it has an affiliate in the US, while Lightcast might include job postings an affiliate in the UK. However, certain FactSet firms, primarily located in Asia, do not have an affiliate in any of the 17 Lightcast countries and are therefore excluded, resulting in a sample of 128,764 firms. Then, we removed every affiliate without location information on the subnational region, leaving us with 126,358 firms. Out of this 126,358 firms, we successfully identified 107,981 in Lightcast, resulting in a final match rate of around 85%.

Our final matched dataset is aggregated at what we define as the establishment level, with establishments firm-country-subnational region triplets (subnational regions are typically the highest-level administrative subdivision in each country[8]). Using this definition, the total number of establishments is 1,476,936, belonging to the 107,981 matched firms in the 17 countries.

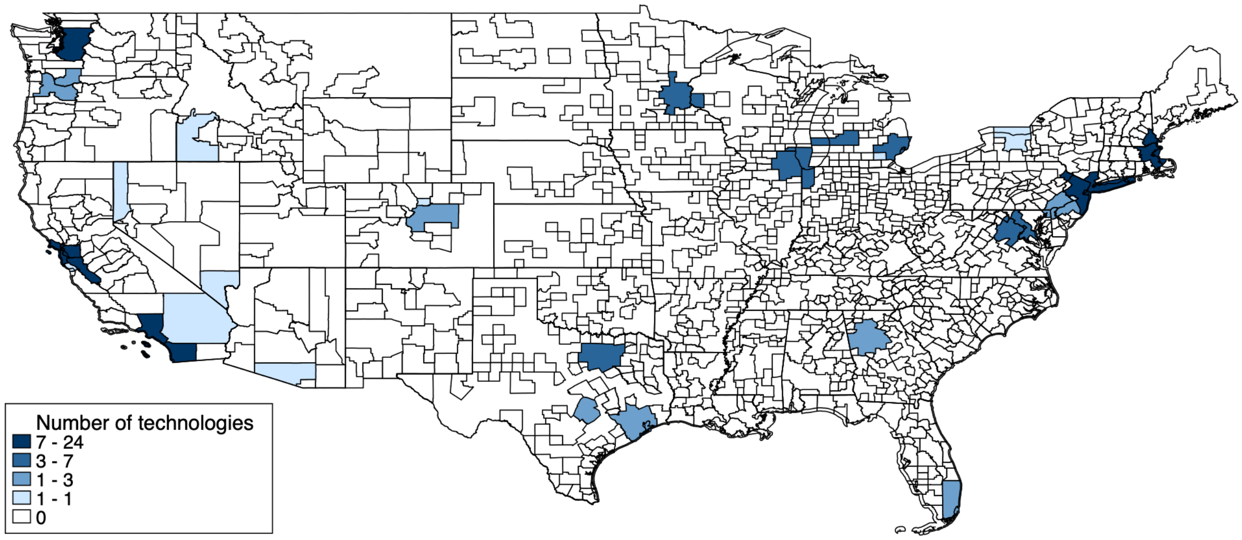
2.3 Measuring technology pioneer locations and additional datasets

2.3.1 Pioneer regions and firms

To measure technology diffusion globally, it is important to identify where the technologies first emerged. For each of the 29 technologies identified, Bloom et al. (2021) define the 'pioneer' locations for these technologies as the core-based statistical areas (CBSA)s that collectively accounted for 50% of the global citation-weighted patent grants for that technology during the ten years before its emergence year. While their analysis of pioneer locations is focused only on the US, a robustness check repeating their exercise using global patents data demonstrates that all pioneer locations for these technologies globally are indeed in the US. All the regions globally with the highest number of patent citations for these technologies are located within the U.S., as shown in Figure 2. We hence proceeded using the US CBSA pioneer locations for each technology.

[8]This follows Acemoglu et al. (2020) who define establishments of a firm as the collection of firm job vacancies in each US commuting zone. Sub-national regions are generally defined at Territorial Level 2 (TL2) in OECD Regional Statistics, the "first government layer after the national or federal one." https://www.oecd.org/regional/regional-statistics/geographical-definitions.htm

Figure 2. Pioneer locations for 29 technologies using global patents data



Note: This figure shows the pioneer locations covering all 29 technologies, identified based on global patent data (not limited to the US). Specifically, the pioneer locations are defined as those which collectively accounted for 50% of the global citation-weighted patent grants for that technology during the ten years before its emergence year.

To identify pioneer firms for each technology, we first limit firms that are located in the pioneer CBSAs using the zip code of the firms. Next, from this sample we select firms that belong to a pioneer industry based on the 4-digit NAICS code.[9] Finally, we label the firm as a pioneer if it was in the pioneer location at least 1 year before the technology emerged, with the year of emergence as defined in Bloom et al. (2021). We identify in total 5031 pioneer firms for the 29 technologies using this method. Figure 3 plots the distribution of pioneer firms for selected new technologies that emerged after 2005.[10]

[9]The pioneer industry is identified by Bloom et al. (2021) following the same approach for pioneer locations.

[10]We do not use the pioneer firms as identified in Bloom et al. (2021) due to the small number of firms, which, once matched with the Factset data sample would result in a sample size that is too small.

Figure 3. Geographic location of pioneer firms by technology

Note: This figure shows the geographic locations of pioneer firms for each technology that emerged after 2005. The size of the red circles is proportional to the average normalized share of technology-related job adverts.

2.3.2 Distance to pioneer regions and firms

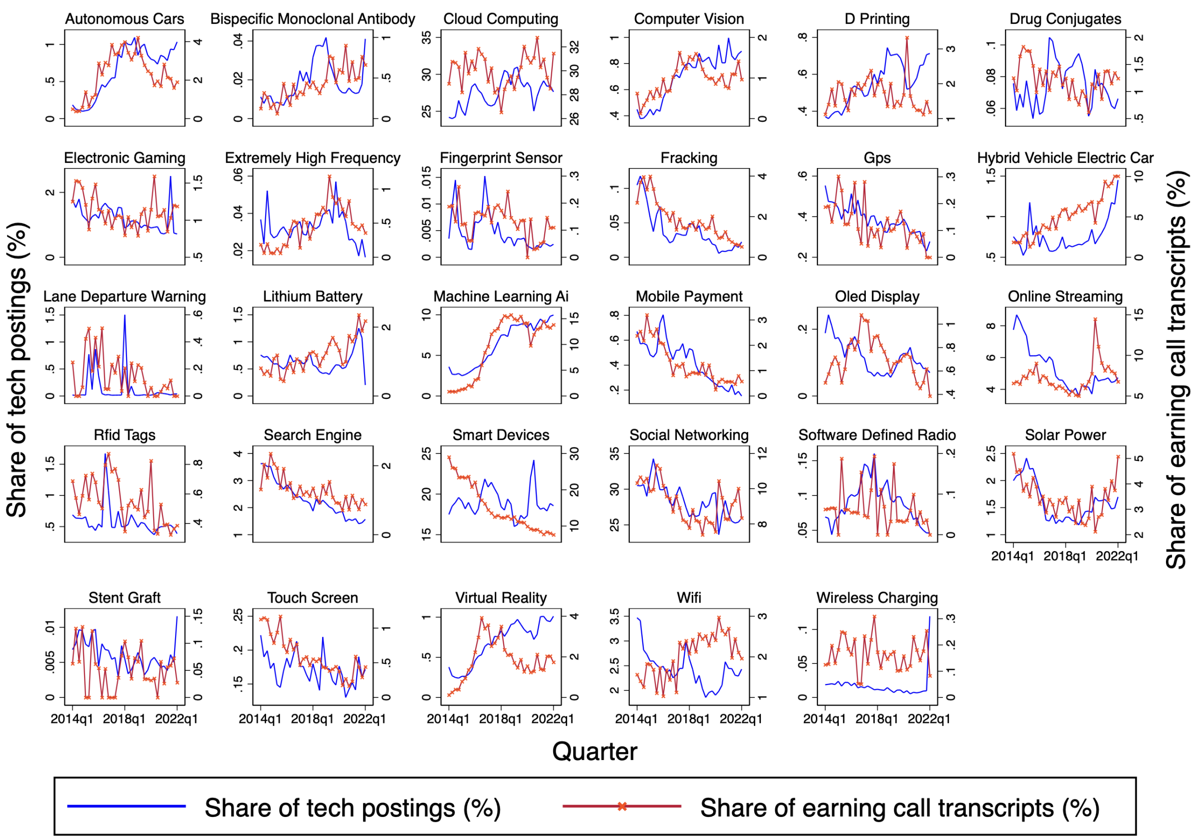
We are interested in the role that distance plays in technology diffusion. Using the region of each Lightcast job posting, we retrieve the latitude and longitude parameters of the most populous city in every macro-region or US state to build the distance-to-pioneer-region dataset for the 29 new technologies using information from Simplemaps.com and World Cities Database. Likewise, for the distance to pioneer firms, we use the exact latitude/longitude-coordinates from FactSet.

2.3.3 Earnings calls transcripts

We also use data from Refinitiv Eikon on 214,685 transcripts from quarterly shareholder earnings calls meetings of publicly listed firms. This type of data has been increasingly used by economists to measure firm uncertainty (e.g. Hassan et al. (2019)), firm sentiment (e.g. Hassan et al. (2020)) and proxies for whether new technologies are 'disruptive' in terms of being widely discussed in boardrooms (e.g. Bloom et al. (2021)). Our sample covers 6,525 firms in the same 17 countries and years for which there is Lightcast data. Over two-thirds of these earning calls were held by US-based firms (62% percent of all earnings calls since 2014).

Figure 4 plots the time series for both the share of Lightcast job postings and the share of earnings calls transcripts mentioning each of the 29 technologies across all 17 countries from 2014 to 2022. We see that growth in technology hiring is highly correlated with growth in earnings calls mentions – the correlation is statistically significant at the 5% level with a coefficient of 0.825.

Figure 4. Share of technology-related earnings calls and job postings



Note: This figure displays the share of technology related job postings and the share of quarterly earnings calls in all 17 countries, from 2014Q1 to 2022Q4.

2.4 Concentration measures

Our key measure of labor-market diffusion is the ratio of technology-related job postings to total job postings at the country, region, and firm levels. As the Lightcast data offers variation at multiple dimensions, we are also interested in the distribution of technology postings across countries, regions and firms. For example, are technology-related postings concentrated within a few countries or more dispersed across countries? Is technology hiring distributed equally across firms? To answer these questions, we follow Goldfarb et al. (2019) and construct the Gini Coefficient at the country, region, and firm levels across the 29 technologies. As a robustness check, we also compute the Coefficient of Variation (CV), which is the measure of dispersion employed by Bloom et al. (2021).[11]

To account for the fact that different technologies may accumulate different scales of job postings, and that different regions, countries or firms may also have systematically different size of postings, normalization provides a robust measure to gauge the extent to which technology-related hiring for each firm, region and country compares to their overall distribution. For each technology τ and year t, we construct the normalized share of job postings by each region, country, or firm - denoted by i, using the equation below:

$$\text{Normalized share}_i, \tau, t \ = \frac{\text{share jobs exposed}_{i,\tau,t}}{\text{share jobs exposed}_{\tau,t}} \tag{2}$$

3 Stylized facts about the global dispersion of new technologies

3.1 Technology hiring has become more dispersed across countries and regions over time

We begin by establishing the extent to which jobs related to these technologies have spread across countries, by measuring the dispersion of the technology share of job postings across 17 countries and 156 regions, for each of the 29 technologies from 2014 to 2022.[12] As described above, we use the Gini Coefficient and CV as our concentration measures.

For each technology T and year t, we regress the concentration measures $Y^T_{j,\ t}$ on the years since the emergence of a technology across the country, region and firm dimensions denoted by j, accounting for technology and year fixed effects:

$$Y^T_{j,\ t} \ = \ \alpha + \beta * \textit{Years since emergence}^T_t + \mu_T + \mu_t + \epsilon_{j,\ t,\ T} \tag{3}$$

where *Years since emergence* is defined as the number of years since the year when a tech-

[11]The CV for each technology T and year t is calculated as:

$$CV^T_t \ = \ \frac{sd(Y^T_t)}{mean(Y^T_t)} \tag{1}$$

[12]As described above, we use state as region for the US and Australia, province for the EU and Canada, and city for the UK. There is only one region for Singapore, New Zealand and Luxembourg.

nology first appeared in the earnings calls transcripts following the definition by Bloom et al. (2021).

Consistent with expectations, hiring related to these technologies has become more dispersed across countries and regions over the past decade. The negative coefficients (hence the decline in the values of Gini and CV) across both panels, displayed in Figure 1, demonstrate that technology hiring has become more dispersed over time both across countries and country-region pairs. The stronger coefficients for the country-region pair regressions suggests greater diffusion across country-regions over time than across countries alone. In terms of magnitude, for the country-level regression, an increase in 1 year since the emergence of the technology is associated with a 4.9% decline in the coefficient of variation, and a 3.4% decline in the Gini.

Table 1. Dispersion of technology hiring across countries and regions

	Coefficient of Variation	Gini
	(1)	(2)
	Panel (a): Across countries	
Years since emergence	-0.0160*	-0.0279*
	(0.0106)	(0.0048)
Adjusted R-squared	0.8408	0.7933
Observations	232	232
Tech FE	Yes	Yes
Year FE	Yes	Yes
	Panel (b): Across country-regions	
Years since emergence	-0.1747***	-0.0872***
	(0.0506)	(0.0190)
Adjusted R-squared	0.8168	0.8365
Observations	232	232
Tech FE	Yes	Yes
Year FE	Yes	Yes

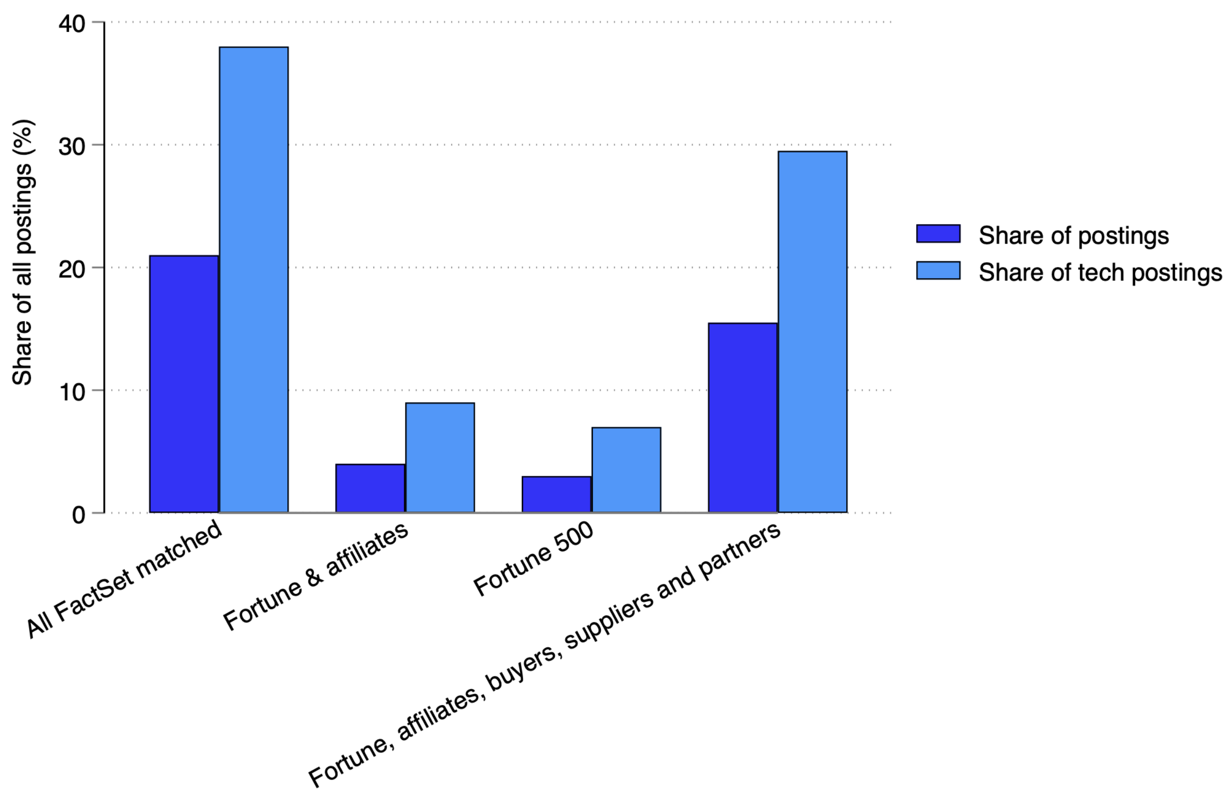
Notes: This table displays regression results of the two concentration measures in columns 1-2 on the years since the technology's first emergence across 17 countries and 156 regions, controlling for technology and year fixed effects. Standard errors are clustered by technology. The coefficient of variation is defined as the standard deviation of normalized technology share of job adverts divided by the mean. The Gini is defined as the inequality of the distribution of tech share of job adverts, computed using Stata's ineqdeco command. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

3.2 Technology hiring is highly concentrated in multinational firms and their supply chains

We proceed by using the FactSet-Lightcast matched dataset to explore the role of multinationals and their supply chains in technology hiring. While our matched dataset of 107,981 firms accounts for only just above 20 percent of all online job postings in these 17 countries, they account for nearly 40 percent of all technology postings. In addition, Fortune 500 firms alone account for around 7 percent of all technology job postings, while Fortune

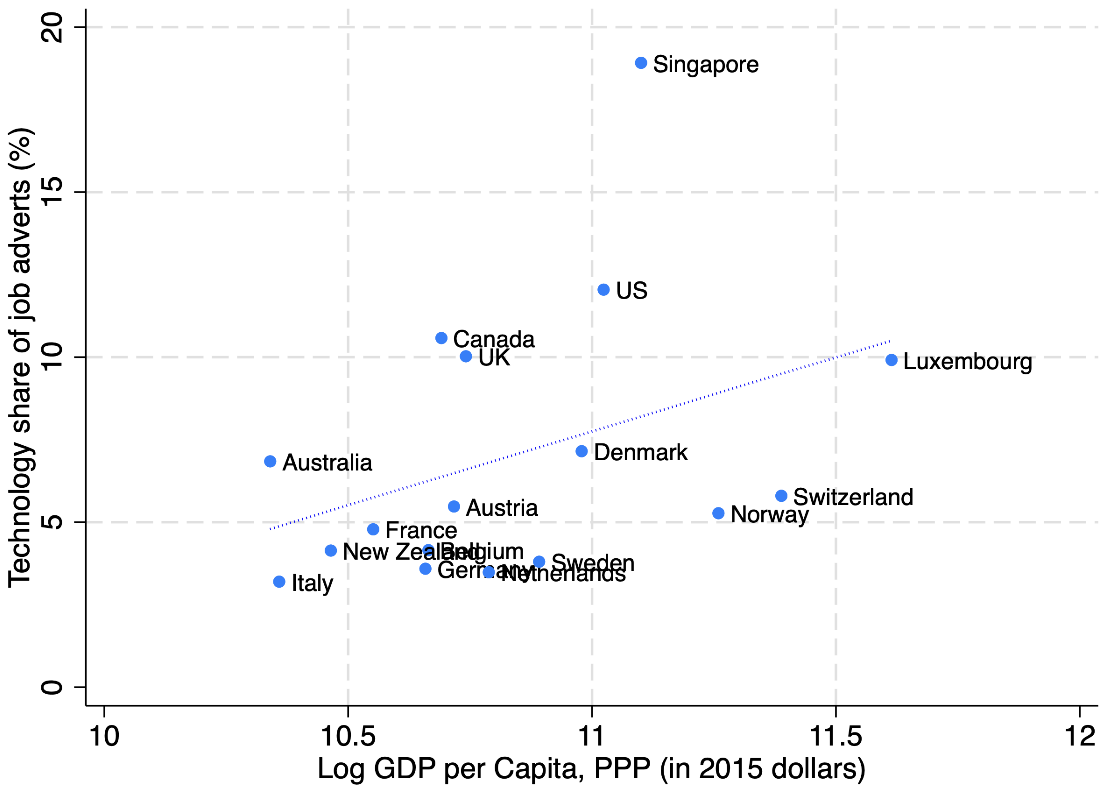
500 and their affiliates, buyers, suppliers and innovation partners account for nearly 30 percent of all technology-related job postings, as is shown in Figure 5.

Figure 5. Technology job postings in multinationals and their supply chains



3.3 Technology hiring intensity is higher in richer countries

Figure 6. Income and technology job posting share in 2022



Note: This figure plots the number of technology-related job postings as a share of total job posting in 2022, and the log GDP per capita in PPP (2015 dollars) in the same year for each of the 17 countries.

Consistent with a broad literature on the patterns of technology diffusion (see, e.g, Comin and Mestieri (2018)), we also find that the share of all hiring related to these new technologies is higher in richer countries. Figure 6 shows that countries are far from displaying similar levels of technology hiring. The figure plots the relationship between the technology share of job adverts and the log of GDP per capita on a PPP basis in 2022, displaying a strong positive correlation. The correlation is statistically significant at the 5% level with a coefficient of 0.6259. The countries with the highest technology-share of job adverts are Singapore, Luxembourg, the US, UK and Canada, which is consistent with the findings of Autor et al. (2006) and Aghion et al. (2018). The relationship between income and technology hiring is further explored in Section 3.4.

3.4 Geographic proximity matters for the diffusion of technology jobs

We next evaluate the role of distance in shaping technology diffusion across countries and regions. We begin by constructing distance to the pioneer region for each technology and country. As discussed in Section 2.3.2, pioneer locations for each technology are defined as the US CBSAs that jointly accounted for 50 percent of citation-weighted patents during the ten years before the technology emerged.

To examine the role of distance from pioneers in technology diffusion, we run the following specification:

$$Y^T_{c,\ t} \ = \ \alpha + \beta d^T_{c,\ t} + \gamma x^T_{c,\ t} + \mu_T + \mu_t + \epsilon_{c,\ t,\ T} \tag{4}$$

We use the normalized share of technology-related job postings for technology T in country c and year t, as the dependent variable, $Y^T_{c,\ t}$. The log of distance to the pioneer region for technology T in country c and year t is represented by $d^T_{c,\ t}$. Then $x^T_{c,\ t}$ is the additional control measuring the log of income per capita (PPP in 2015 US dollars). We also include year, technology and country-technology fixed effect dummies – μ_t and μ_T respectively.

Results for the baseline distance regression are displayed in Table 2. The significant and positive coefficient on income suggests that the share of technology-related job postings is positively associated with a country's income per capita. This is in line with the positive correlation between income per capita and the share of technology-related job adverts discussed above in Section 3.3. The distance coefficients across all specifications are also statistically significant and negative. These results suggest that emerging technology jobs spread faster to closer locations, in line with much of the previous literature on technology diffusion.

Table 2. Regression of diffusion on distance, across 17 countries

	Dep variable: Normalized share of tech-related postings	
	(1)	(2)
Mean distance from pioneer, logs	-0.121**	-0.147***
	(0.052)	(0.050)
Income per capita, logs		0.940***
		(0.230)
Technology FE	Yes	Yes
Year FE	Yes	Yes
Adjusted R-squared	0.067	0.111
Observations	4,176	4,176

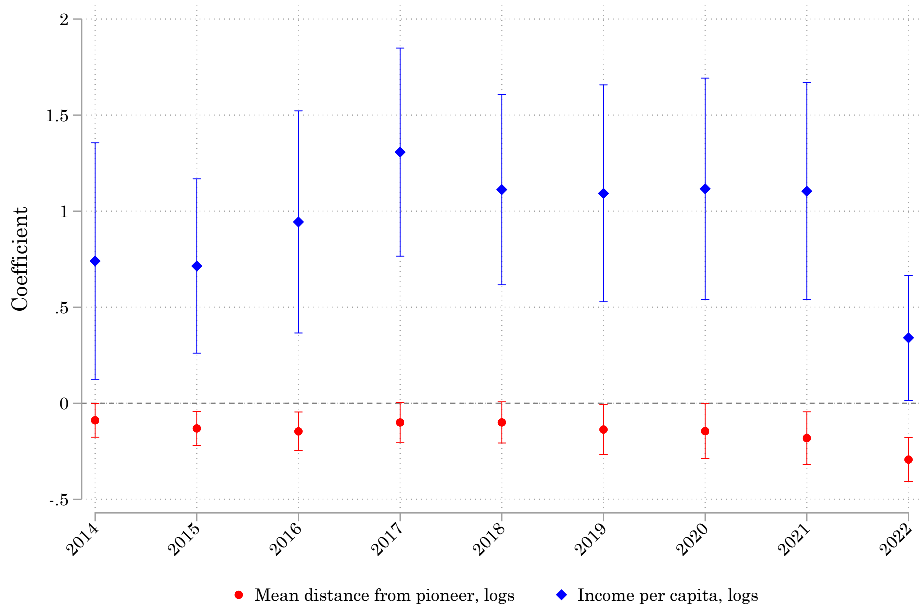
Note: This table displays country-technology level regression results of the normalized share of technology job postings for each technology on log of mean distance to pioneer cities for that technology and log of income per capita from 2014 to 2022, controlling for technology and year fixed effects. Mean nearest distance calculated over the regions within the 17 countries. Income per capita is PPP in 2015 US dollors. Robust standard errors are clustered by technology. *** p<0.01, ** p<0.05, * p<0.1.

We next run cross-sectional regressions to estimate how the role of distance has changed over time from 2014 to 2022. Additionally, to account for non-linear distance effects, we also include the square of distance in the specification and control for technology fixed effects as is shown below, where $Y_{c,T}$ is the share of job postings for technology T in country c, $d_{c,T}$ and $d^2_{c,T}$ are (log) distance and (log) square of distance for technology T in country T, and x_c is the log of income, for each country c:

$$Y_{c,T} \; = \; \alpha + \beta d_{c,T} + \theta d^2_{c,T} + \gamma x_{c,T} + \mu_T + \epsilon_{c,T} \tag{5}$$

We plot the distance coefficients over time following specification (5), shown in Figure 7. In line with our findings so far, we observe that the coefficient on distance has been fairly steady over time, although became larger in 2022. The coefficient on income per capita is larger in magnitude and has a higher statistical significance in most years, although the coefficient dropped in magnitude and significance in 2022.

Figure 7. Distance and income effects from 2014 to 2022



Note: This figure displays the coefficients on distance and income per capita (and corresponding standard errors at the 10% level) from 2014 to 2022 following the cross-sectional regression in equation 5. These regressions include all 17 countries.

For comparison, and considering that all pioneer locations are in the US, we proceed by exploring the distance effect within the US alone. We apply the same specification as equation (4), for each of the 29 technologies across 51 US states from 2014 to 2022. Again, while there is evidence of a negative association between distance from pioneer locations and technology job postings within the US, the distance effect is weaker than the role of income per capita.

Finally, we explore the role of distance to pioneer cities for each technology and firm. In particular, for each technology, we build the nearest distance of each firm to the technology's pioneer city, controlling for technology and year fixed effects. We also control for each firm's sales and country fixed effects for an additional robustness check. Our results, shown in Table 4, are consistent with those from the previous country-level analysis. Across columns (1) to (4), we observe significant and negative distance coefficients and positive income effects.

Table 3. Distance and income effect on technology hiring within the US

	Dep variable: Normalized share of tech-related postings	
	(1)	(2)
Mean distance from pioneer, logs	-0.004**	-0.004***
	(0.000)	(0.000)
Income per capita, logs		0.012***
		(0.004)
Technology FE	Yes	Yes
Year FE	Yes	Yes
Adjusted R-squared	0.079	0.083
Observations	13,311	13,311

Notes: This table displays regression results of the share of technology-related job posting on the (log) distance and (log) median household income in the US, for technology T in state s and year t, controlling for technology, year and state-technology fixed effects. The median household income for each state is measured in 2022 US dollars with data the Federal Reserve Bank of St. Louis. Standard errors are clustered by technology. *** p<0.01, ** p<0.05, * p<0.1

Table 4. Distance and income effect on technology hiring, across 107,981 global firms

	Dep variable: Normalized share of tech-related postings			
	(1)	(2)	(3)	(4)
Nearest distance from pioneer city, logs	-0.075***	-0.104***	-0.087***	-0.100***
	(0.016)	(0.021)	(0.019)	(0.026)
Firm sales in USD, logs			0.034**	0.030**
			(0.013)	(0.013)
Technology FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Country FE		Yes		Yes
Adjusted R-squared	0.001	0.002	0.001	0.001
Observations	18,709,716	18,709,716	3,907,761	3,907,761

Notes: Standard errors clustered at the tech level in parentheses. The normalized shared is calculated by Normalized share$_{i,\tau,t} = \frac{share\ jobs\ exposed_{i,\tau,t}}{share\ jobs\ exposed_{\tau,t}}$. The normalized share is capped at the 99^{th} percentile of non-zero observations. The specification excludes observations before the year of emergence of a technology.

4 Diffusion through multinational supply chains

The results reported in the previous section showed that emerging technology jobs are disproportionately concentrated in Fortune 500 firms and their supply chains. In this section, we examine empirically the role of various types of firm-to-firm linkages in the spread of new technologies. We find that firms with pre-existing supply chain linkages to pioneer firms before technologies emerged see faster technology diffusion, with external buyers and innovation partners being the most important types of linkages for technology diffusion.

4.1 Empirical specification

In this sub-section we outline the baseline empirical specifications for examining the concentration of technology hiring in pioneer firms and how it dissipates over time, and the role of pre-existing supply chain linkages to pioneer firms in technology diffusion. For every specification within this section, we aggregate the matched dataset of establishments to the firm level as we have supply chain linkages data only at the firm level, resulting in a final firm-technology-year panel dataset.[13]

4.1.1 Concentration of technology hiring in pioneer locations over time

Following our definition of pioneer firms in Section 2.3.1, we define the dummy variable $Pioneer^T_{i,\ t}$ as taking the value of 1 if firm i is a pioneer firm for technology T in year t, and 0 otherwise. For each technology T, firm i and year t, we run the following regression with firm, technology and year fixed effects:

$$Y^T_{i,\ t} = \alpha + \beta_1 Pioneer^T_{i,\ t} + \beta_2 (Pioneer * \textit{years since emergence})^T_{i,\ t} + \mu_T + \theta_t + \delta_i + \epsilon^T_{i,\ t} \quad (6)$$

where$Y^T_{i,\ t}$ measures technology diffusion, proxied by the normalized share of technology-related job postings. Apart from the dummy $Pioneer^T_{i,\ t}$, we also interact the variable with the number of years since a technology emerged to test for the persistence of this hiring concentration in pioneer firms.

4.1.2 The role of supply chain linkages to pioneer firms

We proceed by estimating a series of specifications that allow us to examine the role played by *ex ante* firm-to-firm linkages to pioneer firms in technology diffusion. In particular, we examine whether being linked to pioneer firms prior to the technology's emergence i.e., whether being a supplier, buyer, innovation partner, or affiliate of a pioneer firm, results in faster diffusion of technology jobs after the technology emerges.

Table 5 shows that in total 43% of entities in the Lightcast-FactSet matched dataset are connected to at least one firm in a pioneer city for at least one technology through supply chain relationships in the two years before the technology's emergence. Pioneer firms for

[13] Unlike the firm-level data from Factset, the establishment-level data derived from Lightcast does not contain sufficient information on exact location, industry and foundation year, which is needed to identify pioneers.

Machine Learning, in particular, have the highest share of connected firms through the supply chain network, shown by Table 6.

Table 5. Pioneer supply chain linkages summary statistics

Global			US		
Matched Firm Type	Number	Percentage	Matched Firm Type	Number	Percentage
Total	107981	100%	Total	43534	100%
Pioneer firm	24261	22.5%	Pioneer firm	24261	56%
Supplier	7806	7.2%	Supplier	4846	20.0%
Buyer	6202	5.7%	Buyer	4020	16.6%
Affiliate	18709	17.3%	Affiliate	18240	75.2%
Innovation partner	4815	4.5%	Innovation partner	3052	12.6%
Competitor	9109	8.4%	Competitor	6169	25.4%

Notes: The table on the left displays the number and percentage of firms in the pioneer cities, and the suppliers, buyers, affiliates, innovation partners and competitors that are linked to them, as a result of matching the Lightcast data with FactSet, across 17 countries from 2014 to 2022. The table on the right lists the same variables for the US alone.

Table 6. Percentage of all firms linked to a pioneer firm by technology and network

	Single linkage				Multiple linkages		
Technology	Buyers	Suppliers	Affiliates	Innovation partners	2 linkages	3 linkages	4 linkages
Autonomous Cars	0.55%	0.21%	0.13%	0.13%	0.11%	0.03%	0.00%
Bispecific Monoclal Antibody	0.64%	0.33%	0.42%	0.59%	0.27%	0.18%	0.03%
Cloud Computing	0.53%	1.25%	0.62%	0.72%	0.36%	0.22%	0.03%
Computer Vision	0.81%	1.68%	1.03%	0.99%	0.55%	0.33%	0.08%
3D Printing	0.44%	0.68%	0.15%	0.45%	0.24%	0.12%	0.01%
Extremely High Frequency	1.00%	1.36%	0.45%	0.88%	0.53%	0.29%	0.04%
Fingerprint Sensor	0.78%	1.76%	0.92%	0.99%	0.51%	0.33%	0.07%
Fracking	0.07%	0.10%	0.06%	0.04%	0.03%	0.00%	0.00%
Hybrid Vehicle\Electric Car	0.20%	0.03%	0.02%	0.01%	0.01%	0.00%	0.00%
Machine Learning\AI	1.17%	2.52%	1.64%	1.29%	0.73%	0.46%	0.06%
Mobile Payment	0.61%	0.99%	0.49%	0.63%	0.35%	0.22%	0.04%
Smart Devices	0.40%	0.66%	0.47%	0.42%	0.24%	0.13%	0.02%
Social Networking	0.44%	0.85%	0.41%	0.49%	0.25%	0.16%	0.02%
Virtual Reality	1.02%	2.25%	1.20%	1.32%	0.69%	0.43%	0.09%
Wireless Charging	0.84%	1.36%	0.39%	0.97%	0.51%	0.31%	0.05%

Notes: The table displays the percentage of firms that are linked to a pioneer firm for each technology that emerged since 2005 through supply chain relations. Percentage is calculated over the total number of firms (107,981). Multiple linkages are allowed since firms can have multiple networks with pioneer firms at the same time and for the same technology (e.g., buyer and supplier; supplier, buyer and innovation partner; etc.).

Since the Factset dataset begins only in 2003, we restrict the supply chain analysis to 15 technologies that emerged since 2005, and use the 2 years prior to the year of emergence of each technology to capture pre-existing firm-to-firm linkages.[14] Similarly to the pioneer

[14]The resulting 15 technologies are: Social Networking, Cloud Computing, Smart Devices, Machine Learn-

regressions, we control for firm, year and technology fixed effects. We consider several alternative specifications, including first the dummy variables for buyer, supplier, affiliate and partner individually, and then testing them jointly in various combinations. For example, for the pioneer and buyer's regression, we have the following equation:

$$\begin{aligned} Y_{i,\ t}^{T} &= \alpha + \beta_1 Pioneer_{i,\ t}^{T} + \beta_2 (Pioneer * \textit{years since emergence})_{i,\ t}^{T} \\ &\quad + \gamma_1 Buyer_{i,\ t}^{T} + \gamma_2 (Buyer * \textit{years since emergence})_{i,\ t}^{T} \\ &\quad + \mu_T + \theta_t + \delta_i + \epsilon_{i,\ t}^{T} \end{aligned} \tag{7}$$

where $Buyer_{i,\ t}^{T}$ takes the value of 1 if the firm was initially a buyer of a pioneer firm for technology t and 0 otherwise. All the remaining variables have the meaning defined above. We adopt similar specifications for the other types of pre-existing linkages individually, as well as a specification that considers all types of linkages at the same time.

4.2 Results

4.2.1 Diffusion from pioneer firms

Table 7 reveals that pioneer firms see a statistically significantly higher normalized share of job postings for the technology for which they are pioneers, as shown by the positive and significant coefficients of the pioneer dummy variable in columns (1) and (2). Moreover, in column (2) we observe that this higher share of postings for the technology declines over time, indicative of the spread of technology hiring to firms in different industries and locations.

ing/AI, Hybrid Vehicle Electric Car, Virtual Reality, Autonomous Cars, Computer Vision, 3D Printing, Mobile Payment, Fracking, Extremely High Frequency, Bispecific Monoclonal Antibody, Wireless Charging, Fingerprint Censor.

Table 7. Pioneer firms and technology diffusion

	Dep variable: Normalized share of technology-related job adverts	
	(1)	(2)
Pioneer	3.131***	4.630***
	(0.226)	(0.398)
Pioneer $\times$ years since emergence		-0.202***
		(0.036)
Technology FE	Yes	Yes
Year FE	Yes	Yes
Firms FE	Yes	Yes
Adjusted R-squared	0.040	0.041
Observations	10,072,709	10,072,709

Notes: Standard errors clustered at the firm level in parentheses. The normalized shared is calculated by Normalized share$_{i,\tau,t} = \frac{share\ jobs\ exposed_{i,\tau,t}}{share\ jobs\ exposed_{\tau,t}}$. The normalized share is capped at the 99^{th} percentile of non-zero observations. The specification excludes observations before the year of emergence of a technology.

4.2.2 Faster diffusion for firms with supply chain linkages

We now present the results relating to the role of various types of pre-existing linkages to pioneer firms in shaping the spread of new technologies. The results in columns (2) to (4) of Table 8 show that firms that were buyers, suppliers or innovation partners of pioneers before the technologies emerged subsequently observe greater hiring related to these technologies after their emergence. There is less evidence of a decline in the importance of these linkages over time, as reflected by the weak significance of the negative coefficients of the linkage dummies interacted with years since emergence. The results in column (5) examine the extent to which there is also greater diffusion among firms that were affiliates of pioneer firms. In this case the coefficient of interest is also positive but not statistically significant.

Since the same entity can simultaneously have different types of pre-existing linkages with pioneer firms, in column (6) we include simultaneously all these linkage variables. The results reveal that the diffusion of new technologies occurs mainly through buyers and innovation partners of pioneer firms. The coefficients associated with these variables remain positive and statistically significant. In contrast, the coefficient on suppliers of pioneers is now close to zero and no longer statistically significant. Overall, these results suggest that, when accounting for a wide range of pre-existing firm-to-firm linkages, the diffusion of new technologies through global value chains is mainly observed among buyers and innovation partners of pioneer firms.

Table 8. Supply chain linkages and their role in technology diffusion

	Dep variable: Normalized share of technology-related job adverts					
	(1)	(2)	(3)	(4)	(5)	(6)
Pioneer	4.630***	4.468***	4.574***	4.474***	3.928***	3.893***
	(0.398)	(0.395)	(0.396)	(0.395)	(0.774)	(0.775)
Pioneer $\times$ years since emergence	-0.202***	-0.191***	-0.199***	-0.193***	-0.186***	-0.184**
	(0.036)	(0.036)	(0.036)	(0.036)	(0.072)	(0.072)
Linkages of pioneer firms						
Buyer		1.878***				1.490***
		(0.300)				(0.319)
Supplier			0.702***			0.074
			(0.173)			(0.170)
Innovation partner				1.658***		1.056***
				(0.275)		(0.291)
Affiliate					0.791	0.564
					(0.771)	(0.770)
Linkages of pioneer firms over time						
Buyer $\times$ years since emergence		-0.052*				-0.053*
		(0.029)				(0.030)
Supplier $\times$ years since emergence			-0.006			0.025
			(0.018)			(0.018)
Innovation partner $\times$ years since emergence				-0.037		-0.018
				(0.026)		(0.027)
Affiliate $\times$ years since emergence					-0.014	-0.001
					(0.072)	(0.072)
Technology FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firms FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.041	0.041	0.041	0.041	0.041	0.041
Observations	10,072,709	10,072,709	10,072,709	10,072,709	10,072,709	10,072,709

Notes: Standard errors clustered at the firm level in parentheses.The normalized share is capped at the 99^{th} percentile of non-zero observations. *** p<0.01, ** p<0.05, * p<0.1

4.2.3 Diffusion through supply chain linkages controlling for distance

A key question from the results above is whether firms that are more geographically proximate to pioneer firms are more likely to have supply chain linkages. To test whether the results are driven by distance, for each firm-technology pair we also consider the distance to pioneer firms for that technology as an additional control, given the negative and significant distance coefficients in 2.3.2. Results from Table 9 show not only negative and significant coefficients on distance across all specifications, but also consistent linkage coefficients with similar significance level to those in the baseline, with buyer and innovation partner linkages remaining the most important. This suggest that firm-to-firm linkages matter above and beyond the role of distance.

Table 9. Diffusion through supply chain linkages controlling for distance

	Dep variable: Normalized share of tech-related job adverts					
	(1)	(2)	(3)	(4)	(5)	(6)
Pioneer	4.496***	4.336***	4.440***	4.341***	3.800***	3.769***
	(0.398)	(0.395)	(0.396)	(0.395)	(0.777)	(0.777)
Pioneer × years since emergence	-0.204***	-0.193***	-0.201***	-0.196***	-0.189***	-0.187***
	(0.036)	(0.036)	(0.036)	(0.036)	(0.072)	(0.072)
Nearest distance from pioneer city, logs	-0.071***	-0.070***	-0.071***	-0.071***	-0.071***	-0.070***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Linkages of pioneer firms						
Buyer		1.869***				1.480***
		(0.300)				(0.319)
Supplier			0.701***			0.074
			(0.173)			(0.170)
Innovation partner				1.656***		1.056***
				(0.275)		(0.291)
Affiliate					0.783	0.557
					(0.774)	(0.773)
Linkages of pioneer firms over time						
Buyer × years since emergence		-0.053*				-0.054*
		(0.029)				(0.030)
Supplier × years since emergence			-0.006			0.024
			(0.018)			(0.018)
Innovation partner × years since emergence				-0.037		-0.018
				(0.026)		(0.027)
Affiliate × years since emergence					-0.014	-0.001
					(0.072)	(0.072)
Technology FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firms FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.041	0.041	0.041	0.041	0.041	0.041
Observations	9,834,969	9,834,969	9,834,969	9,834,969	9,834,969	9,834,969

Notes: Standard errors clustered at the firm level in parentheses.The normalized share is capped at the 99^{th} percentile of non-zero observations. *** p<0.01, ** p<0.05, * p<0.1

4.2.4 Linkages within and outside firm boundaries

We also examine whether the patterns of technology hiring documented in the previous section are mainly driven by linkages within or outside firm boundaries. In particular, we separate buyers, suppliers and innovation partners that belong to the same ultimate owner as the pioneer firms (defined as those within the firm boundary), from those whose ultimate owner differs from the pioneer's (defined as those outside the firm boundary). Only under 1 percent of our linked firms are within the firm boundary, while the vast majority are outside the firm boundary. The results shown in Table 10 reveal that the role of firm-to-firm linkages is driven by effects for firms outside the firm boundary, while linkages within the firm boundary are not statistically significant.

Table 10. Diffusion through supply chain linkages within and outside firm boundaries

	Dep variable: Normalized share of technology-related job adverts				
	(1)	(2)	(3)	(4)	(5)
Pioneer	4.630***	4.448***	4.533***	4.453***	4.362***
	(0.398)	(0.394)	(0.391)	(0.394)	(0.390)
Pioneer × years since emergence	-0.202***	-0.190***	-0.196***	-0.193***	-0.187***
	(0.036)	(0.036)	(0.035)	(0.036)	(0.035)
Linkages of pioneer firms					
Buyer within org.		3.201			0.158
		(3.630)			(3.841)
Buyer outside org.		1.868***			1.470***
		(0.299)			(0.319)
Supplier within org.			6.733		4.383
			(4.736)		(6.414)
Supplier outside org.			0.686***		0.076
			(0.171)		(0.170)
Innovation partner within org.				4.241	2.141
				(2.874)	(3.455)
Innovation partner outside org.				1.617***	1.023***
				(0.274)	(0.292)
Linkages of pioneer firms over time					
Buyer within org. × years since emergence		0.146			0.217
		(0.266)			(0.266)
Buyer outside org.× years since emergence		-0.054*			-0.054*
		(0.029)			(0.030)
Supplier within org. × years since emergence			-0.376		-0.404
			(0.307)		(0.488)
Supplier outside org. × years since emergence			-0.003		0.025
			(0.018)		(0.018)
Innovation partner within org. × years since emergence				-0.019	0.089
				(0.190)	(0.299)
Innovation partner outside org. × years since emergence				-0.034	-0.015
				(0.026)	(0.027)
Technology FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Firms FE	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.041	0.041	0.041	0.041	0.041
Observations	10,072,709	10,072,709	10,072,709	10,072,709	10,072,709

Notes: Standard errors clustered at the firm level in parentheses. The normalized share is capped at the 99^{th} percentile of non-zero observations. *** p<0.01, ** p<0.05, * p<0.1

4.2.5 Considering multiple linkages

Our analysis so far has focused on firms with a single type of linkage, whether as buyers, suppliers, innovation partners, or affiliates of a pioneer firm. Next, we expand the scope to examine firms with multiple linkages - i.e. firms that are both a supplier and a buyer, or an innovation partner and a supplier, or an innovation partner and a supplier of a pioneer firm. Based on our findings that results are driven primarily by external linkages, this section focuses on firms with external linkages. The estimates in columns (1)-(5) of Table 11 indicate that all linkages combinations considered are positively associated with the normalized share of tech-related job postings. We further observe that the combinations of buyers-suppliers, supplier and innovation partner, and innovation partners-buyers display positive and significant coefficients when controlling for other linkage combinations.

Table 11. Technology diffusion and multiple supply chain linkages outside firm boundaries

	Dep variable: Normalized share of technology-related job adverts					
	(1)	(2)	(3)	(4)	(5)	(6)
Pioneer	4.630***	4.479***	4.501***	4.476***	4.487***	4.427***
	(0.398)	(0.393)	(0.394)	(0.395)	(0.394)	(0.393)
Pioneer × years since emergence	-0.202***	-0.193***	-0.195***	-0.194***	-0.194***	-0.191***
	(0.036)	(0.035)	(0.035)	(0.036)	(0.035)	(0.035)
Linkages of pioneer firms outside firm boundary						
Buyer and supplier		2.311***				1.257*
		(0.475)				(0.763)
Supplier and innovation partner			1.947***			1.029**
			(0.371)			(0.442)
Innovation partner and buyer				2.350***		1.402*
				(0.457)		(0.728)
Innovation partner and buyer and supplier					2.717***	-0.713
					(0.581)	(1.272)
Linkages of pioneer firms outside firm boundary over time						
Buyer and supplier × years since emerg.		-0.055				-0.073
		(0.048)				(0.065)
Supplier and innovation partner × years since emerg.			-0.032			-0.006
			(0.037)			(0.041)
Innovation partner and buyer× years since emerg.				-0.040		-0.015
				(0.046)		(0.072)
Innovation partner and buyer and supplier × years since emerg.					-0.043	0.051
					(0.060)	(0.122)
Technology FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firms FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.041	0.041	0.041	0.041	0.041	0.041
Observations	10,072,709	10,072,709	10,072,709	10,072,709	10,072,709	10,072,709

Notes: Standard errors clustered at the firm level in parentheses.The normalized share is capped at the 99^{th} percentile of non-zero observations. *** p<0.01, ** p<0.05, * p<0.1

4.3 Robustness checks

4.3.1 Studying international linkages only

A central objective of the analysis above was to document the role of pre-existing firm-to-firm linkages to pioneer firms in shaping the cross-country spread of new technologies. Given that almost 40% of matched firms in our dataset are based in the US, and that all identified pioneer cities are also within the US, one potential concern about the baseline results is whether they are driven by firm-to-firm linkages within the US (and not by international linkages). In this section, we first explore whether there is a differential effect for firms within and outside the US.

We take the baseline specifications defined above and add further interaction terms with a US dummy for each supplier, buyer, innovation partner and affiliate indicator. Consider the pioneer and buyer's regression again, for example, we now adopt the following specification:

$$\begin{aligned} Y_{i,\ t}^{T} &= \alpha + \beta_1 Pioneer_{i,\ t}^{T} + \beta_2 (Pioneer * years)_{i,\ t}^{T} \\ &\quad + \gamma_1 Buyer_{i,\ t}^{T} + \gamma_2 (Buyer * years)_{i,\ t}^{T} \\ &\quad + \lambda_1 US * Buyer_{i,\ t}^{T} + \lambda_2 (US * Buyer * years)_{i,\ t}^{T} \\ &\quad + \mu_T + \theta_t + \delta_i + \epsilon_{i,\ t}^{T} \end{aligned} \tag{8}$$

We also adopt analogous specifications for the other types of linkages. The results from these specifications are reported in Table 12. Overall, we do not observe a differential effect for supply-chain-linked firms within the US relative to those in other countries. Once we add these interaction terms, the coefficients for buyers and innovation partners remain positive and statistically significant in Column (5) as before, while the coefficients on the interaction terms are not statistically significant. This evidence therefore suggests that our results are not driven solely by firm-to-firm linkages within the US, but hold equally for the impacts of linkages across borders.

Table 12. Firm-to-firm linkages within and outside the US

	Dep variable: Normalized share of technology-related job adverts					
	(1)	(2)	(3)	(4)	(5)	(6)
Pioneer	4.630***	4.487***	4.569***	4.486***	3.920***	3.903***
	(0.398)	(0.394)	(0.394)	(0.394)	(0.852)	(0.853)
Pioneer × years since emergence	-0.202***	-0.192***	-0.200***	-0.195***	-0.177**	-0.177**
	(0.036)	(0.035)	(0.035)	(0.036)	(0.079)	(0.079)
Linkages of pioneer firms						
Buyer		2.312***				1.857***
		(0.568)				(0.622)
Buyer × US		-0.637				-0.544
		(0.666)				(0.723)
Supplier			0.610**			-0.098
			(0.242)			(0.303)
Supplier × US			0.159			0.281
			(0.335)			(0.364)
Innovation partner				1.833***		1.245**
				(0.434)		(0.496)
Innovation partner × US				-0.260		-0.286
				(0.557)		(0.613)
Affiliate					0.600	0.500
					(0.674)	(0.679)
Affiliate × US					0.203	0.076
					(1.103)	(1.105)
Linkages of pioneer firms over time						
Buyer × years since emergence		-0.061				-0.041
		(0.048)				(0.054)
Buyer × years since emergence × US		0.015				-0.015
		(0.059)				(0.064)
Supplier × years since emergence			-0.029			0.009
			(0.023)			(0.028)
Supplier × years since emergence × US			0.036			0.023
			(0.034)			(0.036)
Innovation partner × years since emergence				-0.072**		-0.051
				(0.033)		(0.041)
Innovation partner × years since emergence × US				0.053		0.049
				(0.048)		(0.054)
Affiliate × years since emergence					0.111*	0.118*
					(0.065)	(0.065)
Affiliate × years since emergence × US					-0.135	-0.131
					(0.104)	(0.104)
Technology FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firms FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.041	0.041	0.041	0.041	0.041	0.041
Observations	10,072,709	10,072,709	10,072,709	10,072,709	10,072,709	10,072,709

Notes: Standard errors clustered at the firm level in parentheses.The normalized share is capped at the 99^{th} percentile of non-zero observations. *** p<0.01, ** p<0.05, * p<0.1

4.3.2 Excluding pioneers from Silicon Valley

Another potential concern about the results from the baseline analysis is that these pioneers might exhibit specific features, both with regard to their innovative capacity and the network to which they belong. For example, one might be concerned that a few leading technology firms in Silicon Valley might be driving the overall patterns observed in the data, and that the results for these firms might not extend to those of other innovative regions or technologies. To address this concern, in Table 13 we exclude pioneer firms located within Silicon Valley from our linkage sample. We observe that the empirical results remain similar to those in the baseline analysis, suggesting that our findings apply more broadly to other pioneer regions as well. In particular, the coefficients on pre-existing buyers and innovation partners of pioneers in Column (5) remain positive and statistically significant. The main qualitative difference relative to the baseline analysis is that the coefficient on affiliates in Column (5) is now also positive and statistically significant.

Table 13. Firm-to-firm linkages excluding Silicon Valley pioneers

	Dep variable: Normalized share of technology-related job adverts					
	(1)	(2)	(3)	(4)	(5)	(6)
Pioneer	4.269***	4.135***	4.223***	4.140***	2.761***	2.743***
	(0.420)	(0.417)	(0.418)	(0.418)	(0.482)	(0.483)
Pioneer × years since emergence	-0.177***	-0.168***	-0.175***	-0.170***	-0.093*	-0.093*
	(0.038)	(0.038)	(0.038)	(0.038)	(0.050)	(0.050)
Linkages of pioneer firms						
Buyer		1.921***				1.539***
		(0.299)				(0.319)
Supplier			0.690***			0.065
			(0.168)			(0.166)
Innovation partner				1.654***		1.038***
				(0.268)		(0.284)
Affiliate					1.722***	1.523***
					(0.519)	(0.519)
Linkages of pioneer firms over time						
Buyer × years since emergence		-0.052*				-0.052*
		(0.029)				(0.030)
Supplier × years since emergence			-0.003			0.027
			(0.018)			(0.018)
Innovation partner × years since emergence				-0.037		-0.019
				(0.026)		(0.026)
Affiliate × years since emergence					-0.092*	-0.081
					(0.053)	(0.053)
Technology FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firms FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.040	0.040	0.040	0.040	0.040	0.040
Observations	10,057,442	10,057,442	10,057,442	10,057,442	10,057,442	10,057,442

Notes: Standard errors clustered at the firm level in parentheses. The normalized share is capped at the 99^{th} percentile of non-zero observations. *** p<0.01, ** p<0.05, * p<0.1

4.3.3 Interacting linkages with affiliates of pioneer firms

The results above show no significant effect for firms affiliated with pioneer firms. This lack of significance is evident both in the baseline regression (Table 8) and when controlling for distance (Table 9). To further understand this null affiliate estimate, we also interact all other linkage variables with an affiliate dummy. Consistent with earlier results, all linkage effects lose significance when interacted with the affiliate dummy, as shown in Table 14. This further solidifies the evidence that it is linkages outside the firm boundary that are important for the spread of new technologies.

Table 14. Single linkage interacted with affiliate dummy

	Dep variable: Normalized share of technology-related job adverts				
	(1)	(2)	(3)	(4)	(5)
Pioneer	4.630***	3.883***	3.908***	3.923***	3.878***
	(0.398)	(0.774)	(0.775)	(0.776)	(0.775)
Pioneer × years since emergence	-0.202***	-0.185**	-0.187***	-0.188***	-0.185***
	(0.036)	(0.072)	(0.072)	(0.072)	(0.072)
Linkages of pioneer firms					
Buyer		1.731***			1.416***
		(0.291)			(0.311)
Buyer × affiliate		1.855			0.297
		(1.693)			(2.337)
Supplier			0.545***		-0.027
			(0.156)		(0.161)
Supplier × affiliate			3.222*		2.765
			(1.809)		(2.041)
Innovation partner				1.517***	1.031***
				(0.258)	(0.273)
Innovation partner × affiliate				1.632	-0.439
				(1.594)	(2.234)
Linkages of pioneer firms over time					
Buyer × years since emergence		-0.048			-0.051*
		(0.029)			(0.030)
Buyer × years since emergence × affiliate		-0.069			0.044
		(0.137)			(0.179)
Supplier × years since emergence			0.003		0.031*
			(0.017)		(0.018)
Supplier × years since emergence × affiliate			-0.189		-0.205
			(0.156)		(0.163)
Innovation partner × years since emergence				-0.030	-0.017
				(0.026)	(0.026)
Innovation partner × years since emergence × affiliate				-0.092	0.018
				(0.129)	(0.169)
Technology FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Firms FE	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.041	0.041	0.041	0.041	0.041
Observations	10,072,709	10,072,709	10,072,709	10,072,709	10,072,709

Notes: Standard errors clustered at the firm level in parentheses.The normalized share is capped at the 99^{th} percentile of non-zero observations. *** p<0.01, ** p<0.05, * p<0.1

4.3.4 Interacting linkages with distance

While we have controlled for distance separately in Table 9, as an additional robustness check, we now also include both the linkage dummies and their interaction with distance and time. Table 15 shows the linkage coefficients and the linkage dummies interacted with both distance and the emergence year for each technology. In line with our previous findings, the coefficients for all linkage types (except for affiliates) remain positive and statistically significant across all specifications in Columns (2) to (5). These findings prevail in column (6) when controlling for other types of linkages, with the exception of innovation partners, whose coefficient remains positive, but loses precision. Meanwhile, there is no differential effect of linkages for firms by distance to the pioneer location in columns (2) to (6), except for suppliers, which now see a positive linkage effect that is diminishing with distance.

Table 15. Interacting linkages with distance

	Dep variable: Normalized share of technology-related job adverts					
	(1)	(2)	(3)	(4)	(5)	(6)
Pioneer	4.723***	4.561***	4.596***	4.556***	3.822***	3.800***
	(0.412)	(0.402)	(0.402)	(0.402)	(0.921)	(0.921)
Pioneer × distance	-0.420**	-0.445**	-0.419**	-0.440**	-0.331	-0.363*
	(0.209)	(0.210)	(0.209)	(0.209)	(0.215)	(0.215)
Pioneer × distance × years since emergence	0.047**	0.049**	0.047**	0.048**	0.035*	0.037*
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Linkages of pioneer firms						
Buyer		2.132***				1.550**
		(0.626)				(0.702)
Supplier			1.581***			0.893**
			(0.477)			(0.442)
Innovation partner				1.926***		0.704
				(0.610)		(0.717)
Affiliate					1.023	0.761
					(0.975)	(0.970)
Linkages of pioneer firms in space						
Buyer × distance		-0.041				-0.011
		(0.094)				(0.104)
Supplier × distance			-0.139**			-0.130**
			(0.064)			(0.063)
Innovation partner × distance				-0.041		0.060
				(0.087)		(0.103)
Affiliate × distance					-0.109	-0.104
					(0.130)	(0.130)
Linkages of pioneer firms in space over time						
Buyer × distance × years since emergence		0.001				0.002
		(0.008)				(0.009)
Supplier × distance × years since emergence			0.001			0.001
			(0.006)			(0.006)
Innovation partner × distance × years since emergence				-0.003		-0.006
				(0.008)		(0.009)
Affiliate × distance × years since emergence					0.013	0.014
					(0.012)	(0.012)
Technology FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firms FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.041	0.041	0.041	0.041	0.041	0.041
Observations	9,834,969	9,834,969	9,834,969	9,834,969	9,834,969	9,834,969

Notes: Standard errors clustered at the firm level in parentheses. The normalized share is capped at the 99^{th} percentile of non-zero observations. *** p<0.01, ** p<0.05, * p<0.1. Distance refers to the distance to the nearest pioneer city, in logs.

4.3.5 Technologies that emerged after the Lightcast data start date

The analysis above considered technologies that emerged after 2005, such that their linkages could be identified through the Factset data. However, our Lightcast panel data of job postings begins from 2014 only. Therefore there are several technologies for which in the early years of emergence there is no data in Lightcast. Our coefficients on the years since emergence variables may be disproportionately stemming from the impacts during the later years after emergence. To consider whether this is the case, we also run a robustness check keeping only the technologies that emerged from 2014 onwards, for which there is Lightcast data for all the years directly after emergence. This results in a significantly diminished sample to only 3 very new technologies: machine learning, autonomous cars and extremely high frequency. The estimates based on this restricted sample are presented in Table 16. Power is lost in this sample and so coefficients on the linkages variables are weaker and only the buyer coefficient remains statistically significant. However, the results remain qualitatively similar to those in the baseline analysis, with pioneer locations seeing higher technology postings and this advantage diminishing over time. This suggests that the early years after emergence are similar to the later years in terms of the extent to which technologies diffuse from pioneer firms.

Table 16. Keeping technologies that emerged after 2014

	Dep variable: Normalized share					
	(1)	(2)	(3)	(4)	(5)	(6)
Pioneer	7.949***	7.949***	7.990***	7.974***	8.445***	8.442***
	(0.860)	(0.861)	(0.860)	(0.861)	(1.927)	(1.927)
Pioneer × since emergence	-0.732***	-0.755***	-0.744***	-0.753***	-0.939***	-0.945***
	(0.145)	(0.145)	(0.145)	(0.145)	(0.320)	(0.320)
Linkages of pioneer firms						
Buyer		0.942				1.106*
		(0.593)				(0.648)
Supplier			-0.434			-0.487
			(0.342)			(0.326)
Innovation partner				0.068		0.146
				(0.561)		(0.595)
Affiliate					-0.556	-0.535
					(1.823)	(1.823)
Linkages of pioneer firms over time						
Buyer × since emergence		0.228**				0.160*
		(0.089)				(0.095)
Supplier × since emergence			0.130**			0.035
			(0.053)			(0.044)
Innovation partner × since emergence				0.240**		0.137
				(0.096)		(0.098)
Affiliate × since emergence					0.236	0.207
					(0.304)	(0.304)
Technology FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firms FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.143	0.143	0.143	0.143	0.143	0.143
Observations	1,963,325	1,963,325	1,963,325	1,963,325	1,963,325	1,963,325

Notes: Standard errors clustered at the firm level in parentheses.The normalized share is capped at the 99^{th} percentile of non-zero observations. *** p<0.01, ** p<0.05, * p<0.1

5 Conclusion

Cross country differences in economic development are strongly influenced by the extent to which new technologies diffuse across nations. While it is often hypothesized that multinational corporations and international firm-to-firm relationships through global value chains play an important role in this process of international technology diffusion, understanding their role in the spread of new technologies has proved difficult because of the lack of detailed panel data on both the adoption of new technologies and various types of international-firm-to-firm linkages.

In this paper, we have assembled an unusually rich combination of granular information on online job postings with data on several types of international firm-to-firm linkages to study the role of multinational firms and global value chains in the cross-country diffusion of new technologies. Following a growing literature, we used the online job postings data to construct proxies for the spread of new technologies. We then examined the spread of 29 new technologies across 17 countries and 107,981 firms over the period 2014-2022. We combined this information with detailed panel data on international firm-to-firm linkages, which includes information on buyer-supplier relationships, innovation partner and affiliate. This made it possible to examine, for the first time, the role of these linkages in shaping the intensity and spread of technologies across countries, regions, and firms.

We first established the following stylized facts about the geographic and firm-to-firm diffusion of new technologies. First, we find that technology hiring has become more dispersed across countries and regions over time. Second, while technology hiring has disseminated more across firms over time, it remains highly clustered in multinational firms and their value chains. Third, the share of technology hiring is still significantly higher in richer countries. Fourth, there is evidence that proximity to invention sites (pioneer cities) contributes to accelerate technology diffusion across countries and regions.

We have then explicitly examined the role of different types of firm-to-firm linkages in the cross-country diffusion of new technologies. The results point to a dual trend. On the one hand, there is a strong technological advantage for firms located in pioneer cities in the US, as revealed by the fact that technology postings tend to be concentrated in these firms for several years. However, we also document that the technology advantage of these firms tends to diminish over time. On the other hand, we provide evidence that firm-to-firm linkages play an important role in the international diffusion of technologies. In particular, the results reveal that buyers and innovation partners of pioneer firms experience the most significant technological benefits. In contrast, being an affiliate of a pioneer firm does not emerge as a statistically significant driver of the diffusion of new technologies across countries. Once we control for firm ownership, we find that external firm relationships drive the positive results.

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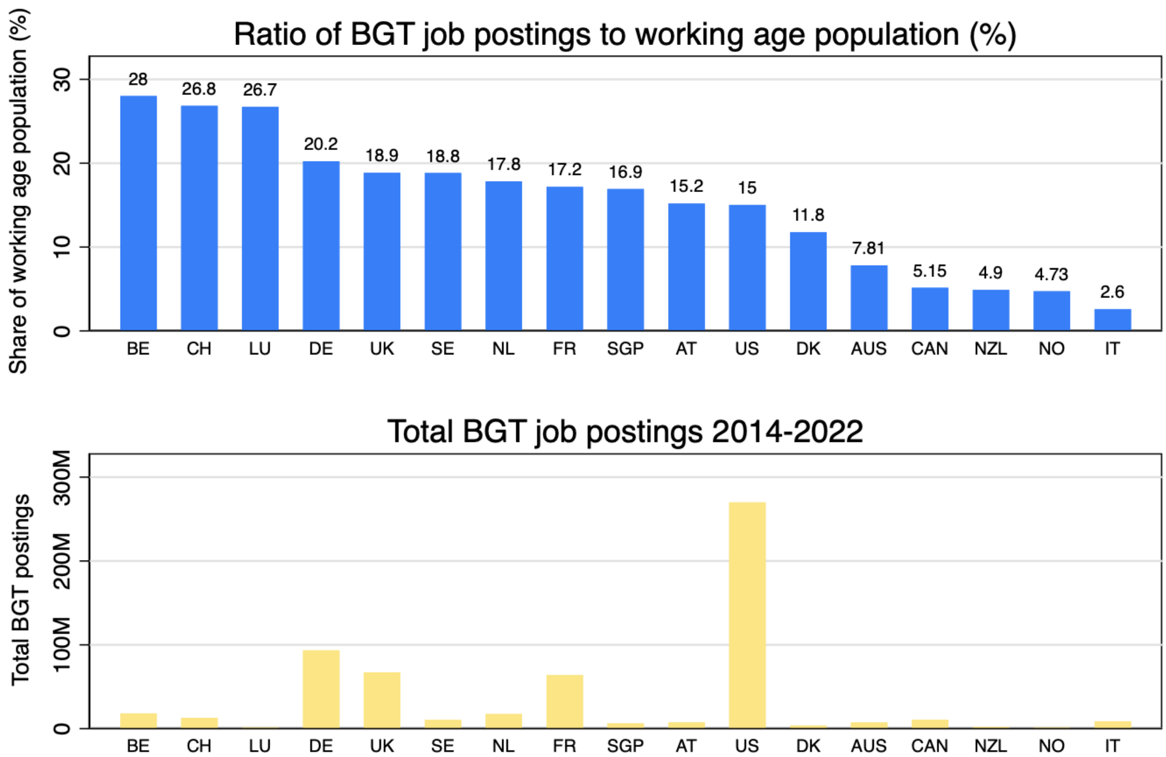
6 Appendix

A1 Lightcast data coverage

Figure A1. Lightcast job adverts data as a share of working age population by country



Note: The bottom figure shows the total number of Lightcast online job postings for 17 countries from 2014 to 2022: Belgium, Switzerland, Luxembourg, Germany, United Kingdom, Sweden, the Netherlands, France, Singapore, Austria, United States, Denmark, Australia, Canada, New Zealand, Norway and Italy. The top panel shows the ratio of Lightcast job postings to the working age population (extracted from the International Labour Organisation) for each country.

Table A1. Lightcast job adverts by country, from 2014 to 2022

Country	Code	Start quarter	Technology postings	Total postings
Austria	AT	2014Q1	266951	5946319
Australia	AUS	2014Q1	417346	5261358
Belgium	BE	2014Q1	928509	18379669
Canada	CAN	2014Q1	833773	9027658
Switzerland	CH	2016Q1	752679	13112599
Germany	DE	2014Q1	2921739	82051043
Denmark	DK	2014Q1	192309	3591168
France	FR	2014Q1	3108584	54427353
Italy	IT	2014Q1	256944	10129354
Luxembourg	LU	2014Q1	97669	860942
The Netherlands	NL	2014Q1	827063	13713021
Norway	NO	2014Q1	38947	1015097
New Zealand	NZL	2014Q1	69767	1136948
Sweden	SE	2014Q1	223996	5191277
Singapore	SGP	2014Q1	1034600	3419776
United Kingdom	UK	2014Q1	4855523	40936420
United States	US	2014Q1	23646858	225977968

Note: This table aggregates the number of technology-related job postings and total Lightcast job adverts by country from 2014 to 2022.

A2 Additional Data Processing

To assess the relevance of disruptive technologies in the labor market, we conduct a textual analysis of job adverts provided by Lightcast, following the method used by Bloom at al. (2021). The Lightcast dataset offers broad coverage of job postings across countries. However, due to its multilingual nature, we have to match the keywords/bigrams in each country's official language. This involves translating the Lightcast scripts and the technical bigrams in different languages to English for cross-country comparison. Our data cleaning involves identifying the number of job adverts mentioning disruptive technologies (we count a posting being 1 even if the keywords are mentioned multiple times), resulting in a unique dataset for each country. The information from each country is then disaggregated using available data on year, industry, region, and firm, allowing us to gain insights about the demand for specific technologies-related skills across different dimensions.

Furthermore, we adopted a standardized approach to aggregate the information of job postings at the geographic level to ensure consistency and comparability of data across 17 countries, given the heterogeneity of the geographical information. For European countries, we utilized the Nomenclature of Territorial Units for Statistics (NUTS) 2021 classification[15] to achieve a consistent unit of measurement. While in most European countries we aggregated the data at the NUTS1 level (major socio-economic regions), we had to use the NUTS0 level (country as a whole) or Switzerland, Denmark, Luxembourg, and Norway since these countries don't have a NUTS1 classification. On the other hand, for anglophone countries, we grouped them into states or provinces for the United States, Canada, Australia/New Zealand, ITLS1 for the United Kingdom, and at the country level for Singapore. Our approach thus ensures a standardized unit of measurement across countries and allows for meaningful comparison of data. Table A2 below lists the region level aggregation for each of the 17 Lightcast countries.

[15] For more info about the NUTS Classification, see: https://ec.europa.eu/eurostat/web/nuts

Table A2. Regional level equivalences across countries

BGT Countries	Region Level
Austria	NUTS1 - 2021
Belgium	NUTS1 - 2021
Switzerland	Country (NUTS0 - 2021)
GermanY	NUTS1 - 2021
Denmark	Country (NUTS0 - 2021)
France	NUTS1 - 2021
Italy	NUTS1 - 2021
Luxembourg	Country (NUTS0 - 2021)
Netherlands	NUTS1 - 2021
Norway	Country (NUTS0 - 2021)
Sweden	NUTS1 - 2021
United States	State and Capitol Territory
United Kingdom	NUTS1 / ITLS1
Australia/New Zealand	State and Capitol Territory
Canada	Provinces
Singapore	Country

A3 Technologies and Keywords

Table A3. Top Technical Bigram in Job Adverts and Earning Transcripts

Bigram	Technology	Job Posting	Earning Call
social media	Social Networking	9302561	9902
smart phone	Smart Devices	3568299	12067
saas	Cloud Computing	2552279	6807
mobile devices	Smart Devices	2409096	6858
machine learning	Machine Learning AI	2070152	5087
cloud based	Cloud Computing	1923934	7994
cloud computing	Cloud Computing	1242289	2176
cloud service	Cloud Computing	1153677	3878
live stream	Online Streaming	1149664	559
cloud platform	Cloud Computing	992014	2256
enterprise applications	Cloud Computing	987698	710
search engine	Search Engine	924375	1887
artificial intelligence	Machine Learning AI	862863	5471
social network	Social Networking	725431	0
cloud infrastructure	Cloud Computing	673007	1534
wifi	Wifi	659055	2279
cloud environments	Cloud Computing	649078	1389
cloud solution	Cloud Computing	616987	2404
paas	Cloud Computing	596042	273
public cloud	Cloud Computing	589913	2292
iaas	Cloud Computing	509521	142
cloud storage	Cloud Computing	473538	444
social networking	Social Networking	453572	507
video game	Electronic Gaming	438451	827
cloud security	Cloud Computing	402859	619
video conferencing	Online Streaming	383378	748
hybrid cloud	Cloud Computing	302718	1367
wireless networks	Wifi	300529	1164
deep learning	Machine Learning AI	295306	548
enterprise network	Cloud Computing	286231	336

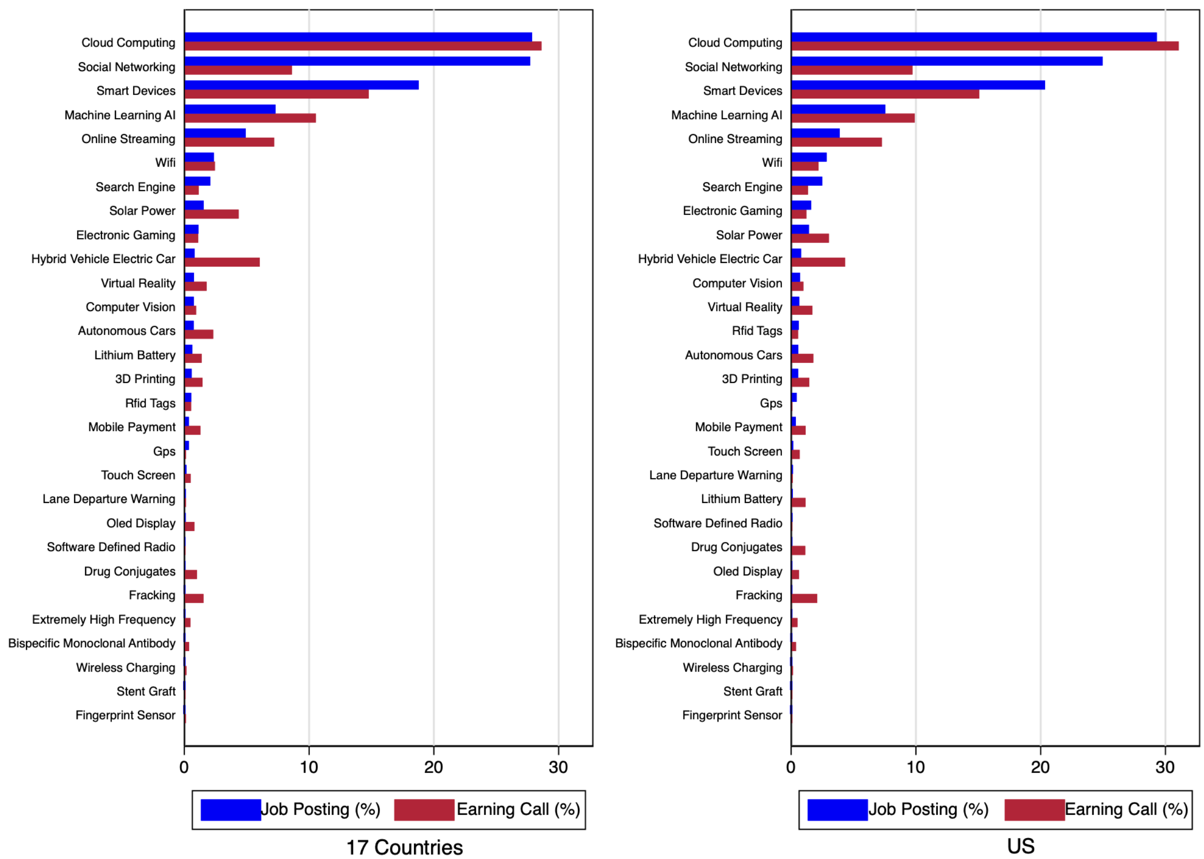
Note: This table presents the top 30 technical bigrams ordered by the number of job postings. The technical bigrams are adopted from those identified by Bloom et al. (2021) using patent citations and earnings calls transcripts.

Table A4. Total Job Postings Compared with Bloom et al. (2021)

Global Diffusion		**Bloom et al. (US only)**	
Technology	Job Posting	Technology	Job Posting
Social Networking	11004493	Cloud computing	3684901
Cloud Computing	10822170	Social Networking	3457390
Smart Devices	7026763	Smart devices	2376510
Machine Learning Ai	3187308	Machine Learning AI	679776
Online Streaming	2943758	Search Engine	535784
Wifi	982736	Online streaming	487731
Search Engine	767763	Wi-Fi	388844
Solar Power	675212	Electronic gaming	247201
Electronic Gaming	425334	Solar Power	201296
Hybrid Vehicle Electric Car	424437	Hybrid vehicle/Electric car	118550
Virtual Reality	356612	Touch Screen	109538
Autonomous Cars	334835	Rfid	80894
Computer Vision	312653	Computer vision	76350
D Printing	242706	GPS	65922
Lithium Battery	235658	Mobile payment	65482
Rfid Tags	203742	Virtual Reality	61102
Gps	132183	3d printing	57904
Mobile Payment	128069	Autonomous Cars	52974
Touch Screen	68299	Lane departure warning	32107
Oled Display	53467	Lithium battery	16926
Lane Departure Warning	36467	Software defined radio	14187
Software Defined Radio	33065	Drug conjugates	10603
Drug Conjugates	27928	Fracking	8966
Fracking	18360	Millimeter wave	6161
Extremely High Frequency	11274	Oled display	5528
Bispecific Monoclonal Antibody	9521	Bispecific monoclonal antibody	2702
Wireless Charging	4850	Wireless charging	1649
Stent Graft	2158	Stent graft	1270
Fingerprint Sensor	1436	Fingerprint sensor	711
Year coverage: 2014Q1 - 2022Q4.		Year coverage: 2007-2019.	

Note: This table lists the number of job postings associated with each of the 29 technologies across the 17 countries our dataset covers from 2014Q1 to 2022Q4 (left) and for the US alone (right) from 2007 to 2019 as presented by Bloom at al. (2021). Comparing with tech postings in the US, both the top 4 and the last 4 technologies follow the same ranking.

Figure A2. Share of Job Postings and Earning Call Transcripts for the 29 Technologies, Global (left) vs the US (right)



Note: The bar graph plots highly similar shares of job postings and earning call transcripts aggregating all technology-related counts from 17 countries from 2014 to 2022, comparing to the shares within the US. Both graphs are ranked in descending order by the share of Lightcast postings.

A4 Lightcast-FactSet matching procedure

Prior to the matching process, we established four distinct variations of the company names present in both the FactSet and Lightcast datasets, taking into account any possible differences that could hinder company identification. Subsequently, we conducted an *exact* matching analysis using these different name variations in a predetermined order. Specifically, we first matched company names using Variation N°1, followed by Variation N°2, and so on. It's worth noting that we removed previously matched companies from the Lightcast dataset before moving on to the next variation to avoid matching the same company twice.

Table A5. **Variations of company names to conduct matching**

Variation	Description
1	Lower-case company name. No changes or deletion of any special character or symbol.
2	Lower-case company name. Punctuation marks and special symbols dropped.
3	Punctuation marks-free, lower-case company name. Company suffixes (Ltd., Corp., LLC, etc.) removed (whole word and abbreviation).
4	Punctuation marks-free, lower-case company name. International company suffixes (AG, B.V., Oy, etc.) removed (whole word and abbreviation).

Additionally, we also considered that a fuzzy matching was necessary even after conducting the exact matching because of variations in spelling or punctuation that could cause an exact match to fail, leading to an incomplete or inaccurate match. Thus, to ensure a more thorough and comprehensive analysis, a fuzzy matching was performed using company names with Variation N°2, utilizing the TF-IDF and Levenshtein distance methods to account for such variations in the text.

Once the results of the two matching processes were obtained and put together, we dropped the duplicated matches from the combined results based on entity characteristics from FactSet using the following criteria:

1. Keep the FactSet Entity that is incorporated in the same country as the Lightcast country, if there is only one of these among all of the possible FactSet ID values for the duplicated Lightcast firm-country pair.
2. For still unidentified duplicates, we keep the FactSet Entity of a duplicated company with the highest average annual sales (if info available).
3. For still unidentified duplicates, we keep the FactSet Entity of a duplicated company with the oldest founding year.
4. For still unidentified duplicates, we keep the FactSet Entity that is not a subsidiary.

5. If after all of these steps, we still couldn't identify the correct duplicate, we proceed to identify those duplicated Lightcast firm-country pairs that belong to the same entity from the relationship dataset (i.e., the parent company), and create an artificial affiliate that captures the duplicated entities within a country. For example, if there is a 'Google Germany' company name in Lightcast, and it has a match with 'Google Germany Ltd.' and 'Google Germany Inc.' in FactSet, we create the artificial affiliate as 'Google Germany' in FactSet, and keep that instead of 'Google Germany Ltd.' and 'Google Germany Inc.'.
6. We drop every duplicate we cannot identify using this criteria ($\approx 1\%$ of the dataset).

A5 Pioneer location and industry by technology

Table A6. Pioneer location and industry by technology

Technology	Pioneer Location	Pioneer Industry
3d printing	Riverside-San Bernardino-Ontario, CA	Industrial Machinery Manufacturing
bispecific monoclonal antibody	Boston-Cambridge-Newton, MA-NH	Pharmaceutical and Medicine Manufacturing
cloud computing	San Francisco-Oakland-Hayward, CA	Computer and Peripheral Equipment Manufacturing
computer vision	Boston-Cambridge-Newton, MA-NH	Navigational, Measuring, Electromedical, and Control Instruments Manufacturing
drug conjugates	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	Pharmaceutical and Medicine Manufacturing
electronic gaming	Las Vegas-Henderson-Paradise, NV	Motion Picture and Video Industries
extremely high frequency	Denver-Aurora-Lakewood, CO	Aerospace Product and Parts Manufacturing
fingerprint sensor	Reno, NV	Semiconductor and Other Electronic Component Manufacturing
fracking	Houston-The Woodlands-Sugar Land, TX	Utility System Construction
gps	Grand Rapids-Wyoming, MI	Communications Equipment Manufacturing
hybrid vehicle electric car	Santa Cruz-Watsonville, CA	Motor Vehicle Manufacturing
lithium battery	Atlanta-Sandy Springs-Roswell, GA	Medical Equipment and Supplies Manufacturing
machine learning ai	San Francisco-Oakland-Hayward, CA	Computing Infrastructure Providers, Data Processing, Web Hosting, and Related Services
mobile payment	San Jose-Sunnyvale-Santa Clara, CA	Computer Systems Design and Related Services
oled display	Trenton, NJ	Motor Vehicle Parts Manufacturing
online streaming	Portland-Vancouver-Hillsboro, OR-WA	Motion Picture and Video Industries
rfid tags	Detroit-Warren-Dearborn, MI	Motor Vehicle Parts Manufacturing
search engine	New York-Newark-Jersey City, NY-NJ-PA	Computer and Peripheral Equipment Manufacturing
smart devices	Dallas-Fort Worth-Arlington, TX	Computer and Peripheral Equipment Manufacturing
social networking	Boston-Cambridge-Newton, MA-NH	Motion Picture and Video Industries
software defined radio	Denver-Aurora-Lakewood, CO	Communications Equipment Manufacturing
solar power	Chicago-Naperville-Elgin, IL-IN-WI	Glass and Glass Product Manufacturing
stent graft	Minneapolis-St. Paul-Bloomington, MN-WI	Medical Equipment and Supplies Manufacturing
touch screen	Washington-Arlington-Alexandria, DC-VA-MD-WV	Audio and Video Equipment Manufacturing
virtual reality	Seattle-Tacoma-Bellevue, WA	Computer and Peripheral Equipment Manufacturing
wifi	Los Angeles-Long Beach-Anaheim, CA	Computer and Peripheral Equipment Manufacturing
wireless charging	Miami-Fort Lauderdale-West Palm Beach, FL	Computer and Peripheral Equipment Manufacturing
autonomous cars	Boston-Cambridge-Newton, MA-NH	Computing Infrastructure Providers, Data Processing, Web Hosting, and Related Services
lane departure warning	Chicago-Naperville-Elgin, IL-IN-WI	Motor Vehicle Manufacturing

Note: This table lists the pioneer location and pioneer industry for each of the 29 technologies, identified by Bloom et al. (2021). For technologies that have more than one pioneer location or industry, we list the first that appeared in the data for illustration.