Cross-Technology Innovation Trends and Evidence with Patent and Funding Data

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Abstract

Since at least Schumpeter's theory of "new combinations," innovation has often been viewed as the synthesis of disparate knowledge areas. Recent works have investigated cross-sector innovation, where the disparity between combined technologies may be substantial. However, even within one sector, such as technology, leveraging combinations of ideas, software, and hardware from different technological sub-fields can yield innovative results. We analyze two large datasets—2.3 million patents and nearly 34,000 venture capital investments—in order to provide new evidence for and analyze the trends of "cross-technology" innovation. Notably, we test the hypothesis that for a number of emerging technologies, cross-technology innovation is growing more rapidly than innovation isolated within single technological categories. Our study provides supporting evidence for existing theory on entrepreneurship and innovation, yet it also prompts questions about the rates at which cross-technology innovation is occurring, particularly for emerging technologies.

Keywords: cross-technology innovation, emerging technologies, patent analysis, venture capital

1. Introduction

Innovation is fundamental to entrepreneurship, venture formation, corporate renewal, and economic growth [10, 15, 26, 48, 54]. Accordingly, understanding the conditions in which innovation occurs can yield important insights for a variety of market participants.

A popular definition of innovation is "new combinations" of existing ideas, products, and resources [50]. Schumpeter credits Jean-Baptiste Say as describing entrepreneurship as a process "to combine the productive factors, to bring them together" [51]. Lunvdall [39] places a heavy emphasis on the role of knowledge in innovation, viewing innovation as "...on-going processes of learning, searching and exploring, which result in new products, new techniques, new forms of organization and new markets." Others, such as Kline and Rosenberg [34], go further and describe a linear process of innovation that proceeds from knowledge gathering (R&D), to industrial development and production, and then marketing of the new innovation. Manimala [42] seeks to broaden Schumpeter's view, characterizing entrepreneurial innovation as "...anything new undertaken by an entrepreneur that enhances the competitive advantage of his/her enterprise." Schumpeter's definition of innovation has been critiqued by those such as Solo [53] and Ruttan [49], who note that Schumpeter fails to make strong connections between innovation and invention or to precisely account for the source of knowledge or inventions to be combined. Despite legitimate criticisms, the Schumpeterian view of innovation has influenced a number of similar definitions of innovation and entrepreneurship [14, 21, 45], and we assume this combinatorial perspective in what follows.

The factors that combine to form innovation may be "distant" from each other according to various metrics. For example, Bergendahl and Magnusson [7] found that generation of patents occurred more frequently when a corporation's employees collaborated with external parties than when they collaborated with colleagues in other departments of the same firm. Fitjar et al. [20] reported an optimal "Goldilocks" organizational distance for spurring firm-level innovation, in the context of a Norwegian innovation network.

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In particular, cross-industry innovation, wherein combined factors originate in different industries, has been a popular subject of both recent research and practical application (e.g., Nike's shock absorbers were adapted from Formula One racing technology) [6, 17, 18, 19, 22, 62]. We refer the reader to the detailed systematic literature review on cross-industry innovation of Mahnken [41], and also highlight the recent work of Mahnken and Moehrle [40], which identifies a growing trend in *multi*-cross-industry innovation patents in the USA.

A notion that is related to cross-industry innovation, yet which uses a slightly different metric to measure distance, is cross-technology innovation. Cross-technology innovation measures distance between combining factors based on their technological differences rather than the industries or firms in which these ideas or products originate. Although we are not the first to use the term cross-technology innovation nor the first to disambiguate it from cross-industry and cross-sector innovation [2, 23], we believe that the technological distance metric is less studied in the innovation and entrepreneurship literature. Nonetheless, in an era where many of the most successful new entrants to the market may be termed "technology companies," we feel it is helpful to differentiate combining factors along technological rather than sectorial lines in order to observe collaborative and combinatorial innovation more clearly.

At the outset, it is useful to untangle the related ideas of cross-technology innovation and technology convergence. Technology convergence, as discussed in works like Caviggioli [11], Jeong et al. [31], and Kose and Sakata [36], generally signifies two or more technologies fusing into one. Notably, the recent work of Eilers et al. [16] differentiates in particular between one-way and two-way technology convergence and uses the example of four application technologies in the field of UV LEDs to show how technology convergence and technology fusion offer enormous innovation potential. On the other hand, our working notion of cross-technology innovation focuses on two distinct technology areas yielding new, overlapping innovations; for instance, artificial intelligence and quantum computing may spawn an entirely new area of innovation that does not deter from distinct, growing trends in AI and quantum. Nonetheless, it is entirely possible that rising cross-technology innovation actually indicates a convergence where the greatest amount of innovation going forward occurs within the overlap of two or more fields.

Two quantities are immediately of interest when considering the notion of cross-technology innovation. One is the prevalence of cross-technology innovation, and the second is its time derivative—namely, the rate at which cross-technology innovation is increasing or decreasing. By attempting to measure these quantities, we can draw conclusions about the current and future relevance of cross-technology innovation and in turn whether this notion will remain of interest to the scholarly community.

In this paper, we collect evidence of and measure trends in cross-technology innovation using two distinct data sources. The first data source we consider is Google Patents, which provides rich information on millions of U.S. and worldwide patents. The second data source we study is venture funding data collected from PitchBook Data, Inc., a firm that aims to collect and standardize all information on venture capital investments. For both of these data sources, as suggested by the prior paragraph, we ask two research questions:

1. Does the data suggest that cross-technology innovation is occurring?
2. Does the data suggest that the rate of cross-technology innovation is increasing?

Analyses of both data sets suggest that not only is cross-technology innovation significant, but that it appears to be occurring at increasing rates. We conclude with limitations of our preliminary study and suggestions for future work.

2. Discretization and selection of technology categories

In order to ascertain which innovations are "cross-technology," it is first necessary to delineate a collection of technologies that are sufficiently distanced from one another. Since we are interested in relatively recent innovation, we do not consider technologies that have largely already matured. Rather, we are dually motivated by recent trends in digital transformation, as well as emerging technologies that could be considered part of the proposed "Fourth Industrial Revolution" [52]. Digital transformation has been studied extensively, e.g., in the context of how it affects innovation and entrepreneurship [47, 57, 60]; the reader is referred to Nadkarni and Prügl [46] for a helpful review. A common theme is that emerging technologies, e.g., those dependent on the present digital era, are in the midst of having profound impact on our society, perhaps more so than mature technologies or those outside the digital realm. Accordingly, in this preliminary study, we select the technologies listed in the Category column of Table 1. Although guided by the notion of selecting emerging technologies, the concepts of digital transformation and the Fourth Industrial Revolution, and conversations with entrepreneurs and investors, we stress that other technologies and technology categories could be considered within the framework of our analysis. Methodologically, we note that all these technologies were selected before querying any data sources, and we did not alter the categories or keywords after beginning data collection. Our overarching goal is not to prescribe any particular set of technologies nor to claim such a set is comprehensive; rather, the broader intent of our study is to demonstrate a methodology for evaluating, given a collection of reasonably differentiated technologies, cross-technology innovation among these categories.

Table 1: Keywords associated with each technology category studied in the paper.

Category	Keywords
AI/ML	AI, artificial intelligence, machine learning, deep learning, neural network
Additive Manufacturing and Advanced Robotics	additive manufacturing, 3D printing, drone delivery, drone, robotics
Smart Cities and Urban Mobility	smart city, autonomous vehicle, self-driving car, connected vehicle
Advanced Life Sciences	synthetic biology, CRISPR, Cas9, gene editing, genetic modification, personalized medicine
Blockchain	blockchain, token, cryptocurrency, distributed ledger, Bitcoin
Telecommunications with 5G	5G network, software defined virtualization, network slicing, edge computing

3. Patent data analysis

We first investigate cross-technology innovation by considering U.S. and worldwide patents that fall within one or more of the technology categories outlined in the previous section. All data is obtained from Google Patents, which is a publicly available service containing information on over 120 million patents from 105 patent offices around the world [27]. Our queries using Google Patents search the title, abstract, full-text description, and claims of each patent document. Patents with only non-English text were automatically translated to English by Google Patents, which allowed us to conduct our keyword searches (though obviously such translation is imperfect). Published patent applications as well as patent grants and utility patents are included in search results. Hits were taken into account regardless of the frequency with which each keyword occurred. Continuation-in-part patent applications, common in the U.S., were treated as separate documents, since oftentimes such continuations are only broadly connected to their predecessors. We chose to use the full global dataset of Google Patents, rather than selecting a particular country, in an effort to mitigate biases or trends that are unique to a particular nation's innovation ecosystem (nonetheless, we suspect Google Patents' coverage is best for U.S. patents).

Patent analyses are certainly not new within the entrepreneurship and innovation literature. Authors have leveraged patent analysis to investigate innovation within individual firms [32], particular industries or technologies [4, 38], or entire nations [1, 28, 29, 33]. Kogan et al. [35] combined stock market and patent data to build a model for assigning economic importance to different innovations. Notably, Geum et al. [24] used patent analysis to investigate overlaps between categories of information technology and categories of biomedical technology. Caviggioli [11] considered how technologies may "fuse" or merge over time by considering the emergence of patents with multiple disparate IPC subclasses (our study, instead, considers full-text search for keywords within patents). Patent analysis has also been used for the forecasting of innovation and emerging technologies [12, 37, 55].

We stress that patents are so frequently studied in this literature because theoretical and empirical studies have deeply linked patents to the dynamics of innovation. For instance, Golden [25] investigated how changes in government policies about patents influenced innovation. Argente et al. [5] identify several trends relating

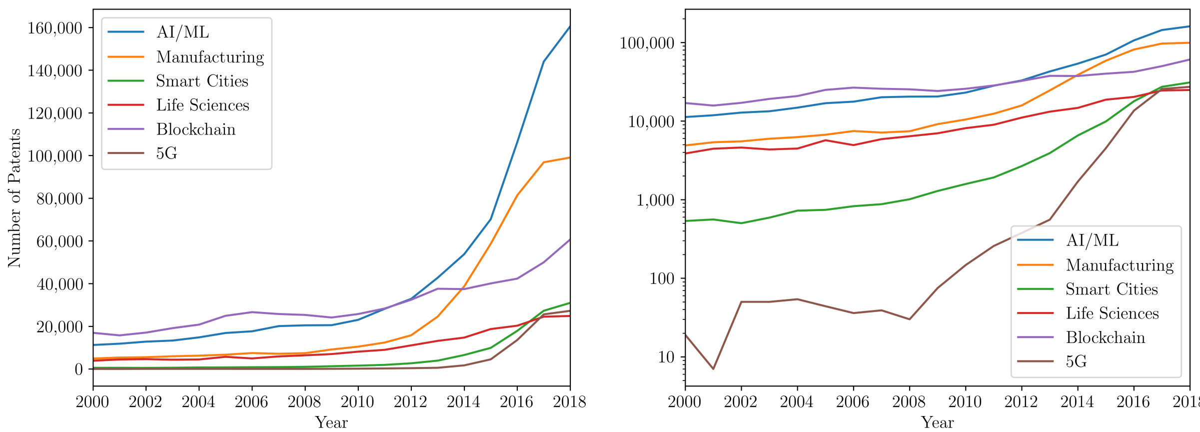

Figure 1: *(Left)* Approximate number of patents found for each technology category, from the year 2000 through 2018. *(Right)* The same data plotted with a logarithmic scale on the vertical axis. Data source: Google Patents.

patent and innovation dynamics, including a positive association between firms' patent filings and product innovation. Archibugi and Planta [3] offer a thorough review of connecting patents, innovation dynamics, and technological change. Mansfield's well-known article [43] gives an empirical study that seeks to connect patents and U.S. patent protection to the rate of development of inventions and innovation. On the other hand, works like Boldrin and Levine [8] firmly argue that patent systems have no beneficial effect on—or are actively detrimental to—innovation. Nonetheless, the consensus view in the literature appears to be that patents, while an imperfect proxy, give some measure of insight into actual innovation occurring within a firm, society, or state.

To perform our analysis, we first identified a set of keywords associated with each technology category, as mentioned above. These keywords are listed in Table 1. We note that these keywords were manually selected by the authors and may result in both false positives (e.g., a musical device patent that mentions the word "drone") and false negatives (e.g., an AI patent that only uses the term "generative adversarial network"). Future work can focus on developing a formal taxonomy for these technology categories. Nonetheless, filtering using the present set of keywords, we obtain a total of 2.3 million patents.

Using this collection of patents, Fig. 1 demonstrates the overall trends for each of the technology categories from 2000 to 2018. Since patent applications are published for public view several months after they have been filed (e.g., in the United States, patent applications are automatically published for the public to view 18 months after their earliest priority date), we did not include 2019 and 2020 data in our analysis. In fact, we initially performed our analysis on data through the end of 2020, but we found that patent counts from 2018 to 2020 were significantly smaller than expected. We conjecture that this is due to a lag in including recent patents within the Google Patents index, particularly for foreign patents, along with the delayed publishing period we noted. Accordingly, we restricted our analysis to end at 2018. In this time range, all technology categories were observed to experience significant growth. These results suggest the disproportionate importance of these technologies in current innovation practice.

Fig. 2 emphasizes the importance and rise of cross-technology innovation across the categories of Table 1. Both subfigures display the number of patents identified that have keywords belonging to one or multiple technology categories. The left and right subfigures perform the same analysis for years 2012 and 2017, respectively. There are many more patents in each of the technology categories individually in 2017 (along the diagonal). However, there are also instances where there are disproportionately more cross-technology patents (off-diagonal entries). For example, the number of total AI/ML and total Manufacturing patents increased by an average factor of 5.23, while the number of overlapping AI/ML+Manufacturing patents increased by a factor of 10.32 in that same time.

3.1. Statistical analysis

To assess these initial findings more rigorously, we consider the following statistical tests:

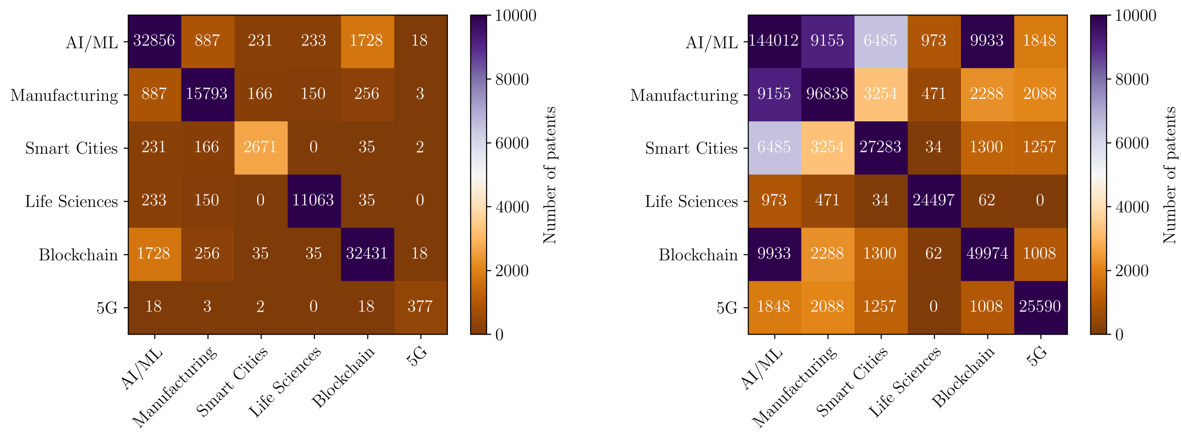

Figure 2: Approximate number of patents that fall within one or multiple technology categories, according to the methodology described in Section 3. Colors range from brown (few) to purple (many). *(Left)* Results for 2012. *(Right)* Results for 2017. Data source: Google Patents.

1. Have the technologies identified in Table 1 experienced statistically significant acceleration in patent generation within the studied time period?
2. For each pair of technologies, has cross-technology innovation become statistically significantly more or less prevalent within the same time period?

The intent of the first hypothesis is to test whether we have selected reasonable emerging technologies, as opposed to mature or underdeveloped technologies. The second hypothesis examines the time derivative of cross-technology innovation. We note that the absolute prevalence of cross-technology innovation is already indicated by Fig. 2: generally, this type of innovation appears to occur less than innovation within a specific technology category, though it appears to be occurring at an increasing rate. Accordingly, we focus on the changing rate of cross-technology innovation for our statistical analysis.

Positive or negative acceleration is defined as a non-constant velocity; accordingly, the null hypothesis for the first statistical test is that a technology's patent count curve is fit by a linear function (including a constant function, which is a linear function with zero slope). To evaluate this hypothesis, we use ordinary least squares regression with the data from 2000–2018. We compute the R^2 coefficient of the regression as a measure of goodness-of-fit; generally, a value below 0.8 indicates a weak fit, while a value from 0.9–1.0 indicates a very strong fit. The diagonal entries of Fig. 3 (Left) show that for most categories, we are able to reject the null hypothesis and conclude that the technology categories experience acceleration during the considered time period. The biggest exception to this trend is the "Blockchain" category. We suspect that since the keyword "token" in included in the definition of the category, many non-blockchain patents (e.g., those published before 2010) are included in our dataset, which obscures what is likely a recent nonlinear rise in blockchain patents. Nonetheless, our analysis suggests that overall, the technological areas we consider are not yet mature and are demonstrating accelerating innovation.

The second statistical test is conducted similarly, and results appear in the entries of Fig. 3 (Left). For each pair of technologies, we perform linear regression and evaluate the R^2 coefficient. Red cells indicate statistically significant nonlinearity in a trend, while green cells do not indicate significant positive or negative acceleration. We emphasize that these results should be interpreted alongside Fig. 2; for example, cross-technology patents may be increasing noticeably for a given pair, but perhaps at a merely linear rate.

Moreover, we can show that not only are the majority of technologies and cross-technology pairs increasing, but they are doing so at an exponential rate. We consider this by taking the natural logarithm of patent counts (replacing 0 values by 0.1 so that the logarithm is well-defined) and performing linear regression on the result. Fig. 3 (Right) shows the resulting R^2 coefficients. Both life sciences and blockchain—the two categories that were most likely linear—have stronger R^2 coefficients using the exponential fit, so we conclude they are more likely to be exponentially than linearly increasing. Similarly, the majority of cross-technology pairs appear to demonstrate moderate to very strong fits using an exponential curve. We conclude that

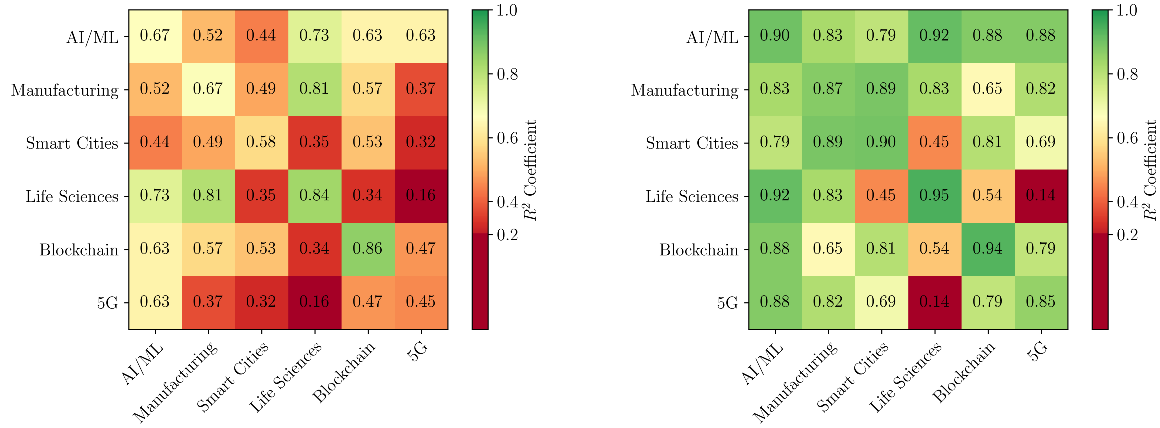

Figure 3: R^2 coefficients for regression tests of each combination of categories from 2000–2018. Colors range from red (not linear) to green (likely linear). *(Left)* Fitting to linear models. *(Right)* Fitting to exponential models. Data source: Google Patents.

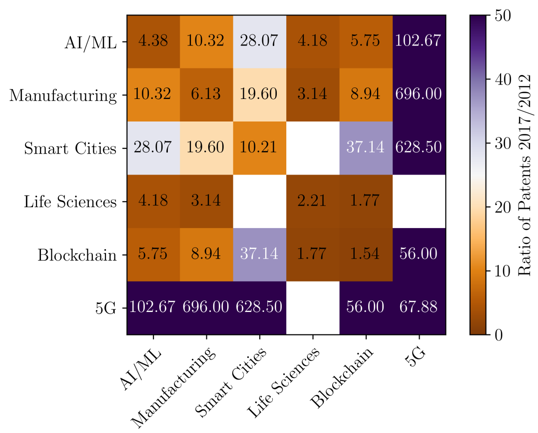

Figure 4: The ratio of number of patents in 2017 to the number of patents in 2012 for each technology category and cross-technology pair. Undefined ratios are indicated by cells with white backgrounds. Data source: Google Patents.

the majority of cross-technology pairs, as well as the individual technological categories, are demonstrating exponential growth in patent generation.

Finally, we consider which type of innovation—single-technology or cross-technology innovation—has grown faster from 2012–2017, according to our patent dataset. We compute the elementwise ratios of the two matrices in Fig. 2 and plot the result in Fig. 4. We note that for cells that were 0 in 2012, there is not a well-defined ratio, which we indicate by marking them with a white background in the figure. The figure demonstrates that while many specific cross-technology pairs have not grown as quickly as their single-technology counterparts, there are instances where cross-technology pairs are producing patents at a similar or even faster rate. We note that this figure should be considered in conjunction with Fig. 3; i.e., emerging cross-technology pairs may be demonstrating accelerating growth that has simply not yet eclipsed single-technology patent publication.

4. Venture and funding data analysis

Cross-technology innovation can be seen not only through the increase in patent activities, but also through venture formation and funding events. We used PitchBook Data Inc.'s platform to analyze nearly 34,000 investment deals over the past several years within the spaces of the technology categories described in Section 2. We assessed the numbers of deals in various categories as well as the amount of funding invested into these various domains. Similar to our approach described above in Section 3, we considered how each of these domains has grown on their own, but more importantly, how crossovers between these technological categories have proliferated in the recent past. PitchBook's interface allows querying for companies that match certain keywords, joined by logical AND or OR operators; we used these operators and parenthetical groupings to form queries that select companies matching multiple domains according to Table 1.

We note that while PitchBook collects investment data from companies around the globe—approximately 3.4 million of them—the majority of those companies (1.8 million) are based in the United States [30]. While this may be due in part to increased investment activity within the U.S., it is also likely due to PitchBook's connections with American investment firms and a greater difficulty in obtaining data from overseas investments, e.g., in more closed economies. Thus, while our intent is to mitigate biases of any one economy, it is likely that the data we present skew somewhat towards the dynamics of investments and innovation in the U.S. Finally, we note that in querying from PitchBook, no distinction was made between parent companies and subsidiaries, as corporate ownership structures are often unclear and may not be public.

Fig. 5 demonstrates that all of the technology categories listed in Table 1 have experienced growth over the plotted time period (2010–2018). We note that, as with the patent data, recent data in PitchBook (2019–2021) appears to be incomplete—this is likely due to the fact that once a venture financing round is complete, it is oftentimes not immediately announced to the public, and therefore PitchBook is unable to collect funding data from more recent years. As such, we exclude those years for clarity of exposition. In the figure, the categories of artificial intelligence and advanced manufacturing seem to demonstrate the largest, most consistent growth in both number of deals and amounts invested.

Fig. 6 and Fig. 7 evaluate the metrics of number of deals and amounts invested, respectively, for companies that overlap multiple domains. Results are shown for 2012 (left) and 2017 (right). Labels in the figures are rounded to two decimal places; hence, some squares labeled "0.0" appear white (true zero) while others appear dark brown (between zero and 0.01). We observe substantial growth in several cells, particularly for businesses that relate to both artificial intelligence and advanced manufacturing. For example, comparing 2012 to 2017, the number of investment deals in companies involved in both artificial intelligence and advanced manufacturing increased by a factor of 11.56, whereas individually, those sectors increased only by factors of 8.68 and 5.91, respectively. Similarly, the number of investment deals overlapping advanced manufacturing and smart cities increased by a factor of 12.50, while all smart city deals combined increased only by a factor of 11.26. In several of these domains, such as advanced life sciences or 5G networking, corporate formation and investment deals seem to lag behind patent activities, particularly at the interfaces with other fields. This may reflect a general trend of the innovation cycle (patents leading venture funding by several years), or it is possible that many of these cross-technology patents are being developed within larger, established companies that are not actively raising capital.

4.1. Statistical analysis

To rigorously assess these initial findings, we conduct a similar set of statistical analyses as in Section 3. First, we consider regression tests for the two variables of interest (amount of capital invested, and number of investment deals) using both linear and exponential models. For the exponential tests, we replace values of 0 with values of 0.1 so that the natural logarithm is well-defined. The R^2 coefficients for the linear and exponential tests are shown in Fig. 8 and Fig. 9, respectively. The results in these figures present a slightly more mixed picture than the patent analysis in the previous section; while both capital invested and number of deals tend to agree more strongly with exponential models than linear models, there are certain pairs (such as Manufacturing + Life Sciences) that fit poorly in either model. This is due to the sparsity of data for those pairs (e.g., Manufacturing + Life Sciences only records five total deals across just two years from 2000–2017). For categories and pairs with more robust data, the regression analysis more strongly suggests exponential fits, which are corroborated by the patent results of Section 3.

Similar to our patent analysis, we also consider the ratio of both investment-related variables between 2017 and 2012. Fig. 10 shows the results; cells are marked with a white background when the value in 2012 is zero (and hence the ratio is undefined). Although the patent analysis suggested the largest ratios for 5G-related technologies, the funding metrics suggest AI-related technology investments multiplied the most from 2012 to 2017. Moreover, there are more "large" ratios (e.g., as indicated by the color scales in

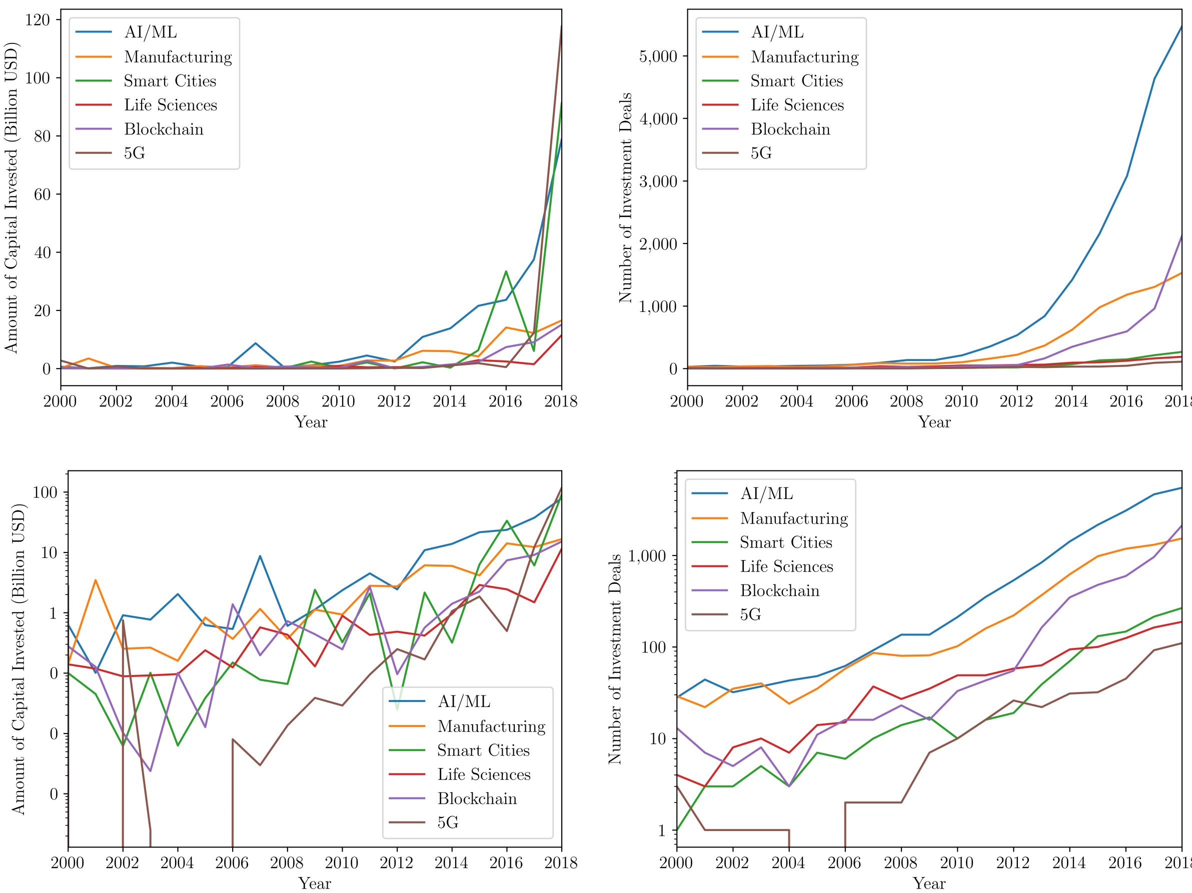

Figure 5: Investment in various technology categories over time according to PitchBook data, from the year 2010 to 2018. *(Top Left)* Capital invested. *(Top Right)* Number of investment deals. *(Bottom)* The same plots presented with logarithmic scaling on the vertical axis. Data source: PitchBook Data, Inc.

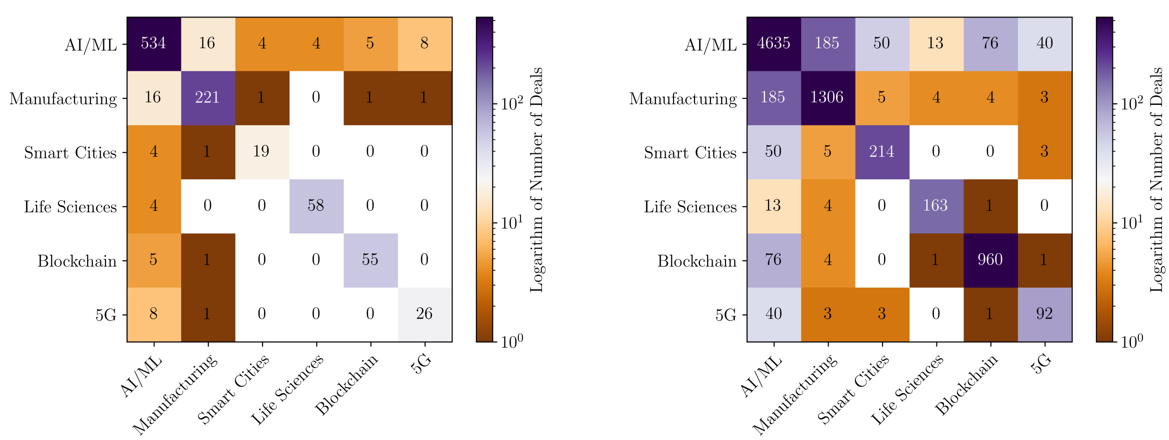

Figure 6: Number of investment deals in companies that overlap one or more technology categories. Raw numbers are labeled, and colors are determined by the logarithms of the values for clarity. *(Left)* Results for 2012. *(Right)* Results for 2017. Data source: PitchBook Data, Inc.

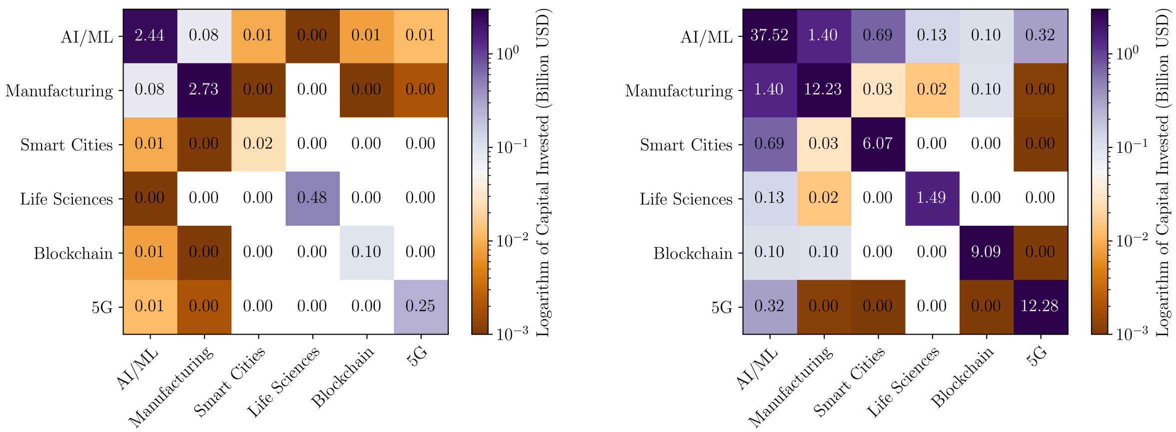

Figure 7: Amount of capital invested in companies (in billion USD). Raw numbers are labeled, and colors are determined by the logarithms of the values for clarity. *(Left)* Results for 2012. *(Right)* Results for 2017. Data source: PitchBook Data, Inc.

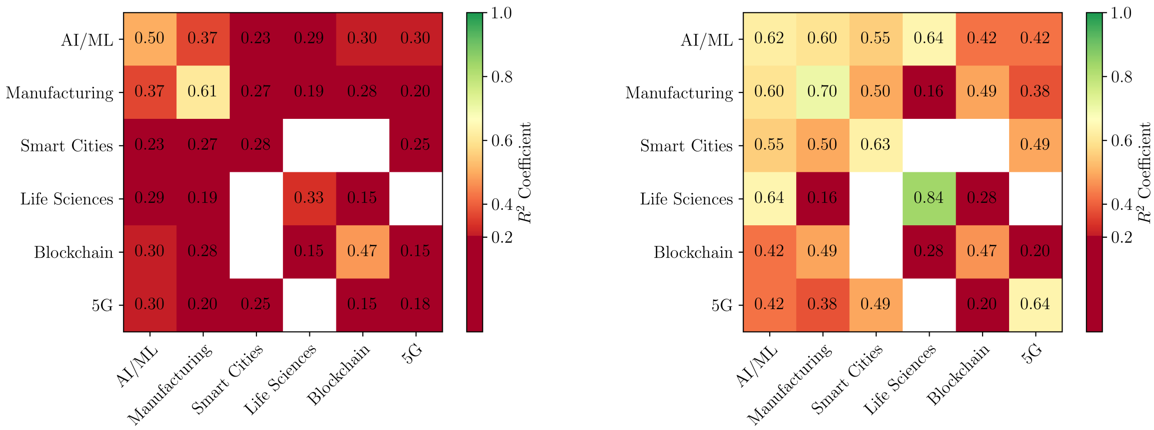

Figure 8: R^2 coefficients for linear model regression tests of each combination of categories from 2000–2018. Colors range from red (not linear) to green (likely linear). *(Left)* Capital invested. *(Right)* Number of deals. Data source: PitchBook Data, Inc.

the figures) for cross-technology pairs than for individual technology categories, which suggests that cross-technology companies had a relatively greater acceleration of investment activity than single-technology companies from 2012 to 2017.

5. Conclusions

This study presented evidence for and studied trends in cross-technology innovation using patent and venture funding data. Based on a curated set of technology categories and associated keywords, relevant patents and investment deals were identified using data from Google Patents and PitchBook Data, Inc. Considering the time period of 2000–2018, both datasets suggested exponential growth is occurring for each of the considered technology categories. For the majority of cross-technology pairs (particularly, pairs that had enough data to elucidate meaningful trends), patent and funding data generally agreed in supporting exponential models and rejecting linear models. In a number of instances, cross-technology innovation appeared to increase by a greater multiple than associated single technology categories from 2012 to 2017.

We reiterate that the technological categories and keywords we chose were selected before gathering any data and were not changed after data collection began. In spite of this, our hand-curated list of technologies and keywords revealed consistent numerical evidence for cross-technology innovation. While

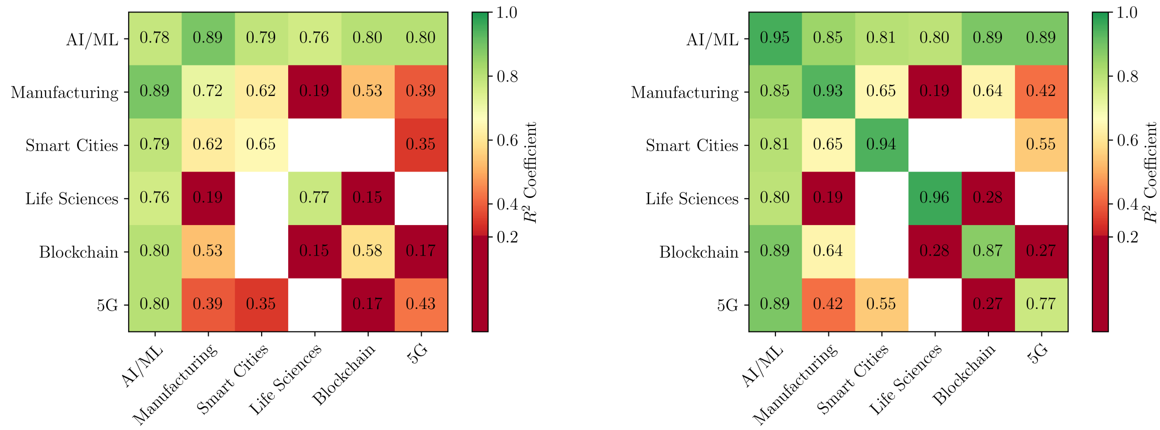

Figure 9: R^2 coefficients for exponential model regression tests of each combination of categories from 2000–2018. Colors range from red (not exponential) to green (likely exponential). *(Left)* Capital invested. *(Right)* Number of deals. Data source: PitchBook Data, Inc.

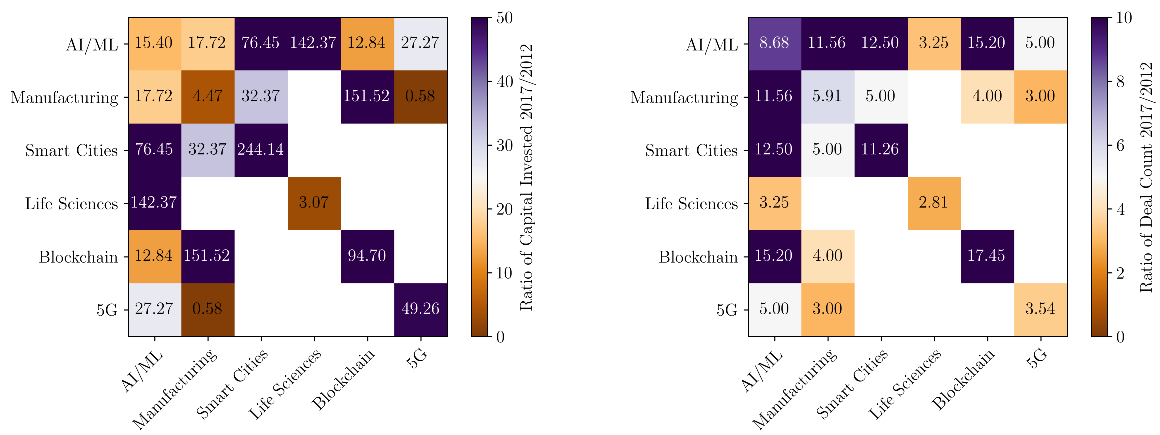

Figure 10: Ratio of values in 2017 to values in 2012 for both funding metrics. (Left) Amount of capital invested. (Right) Number of deals. Data source: PitchBook Data, Inc.

this in no way proves external validity nor generalization, we are optimistic that other categories would reveal similar trends, and our methodology generalizes regardless of the technologies or keywords being studied. Our study established no causal relationships among the variables studied, so certain trends in the data may be coincidental; however, we claim that since two disjoint datasets and several different technologies and technology pairs alll yielded highly similar results (when data was available), our results are legitimate evidence of the existence and rising rates of cross-technology innovation. As future work, for sake of comparison, we are interested in performing our same analyses on more mature technological areas to investigate, e.g., whether technologies must be emerging in order for cross-technology innovation to occur.

The current work suggests both theoretical and practical implications. On the side of theory, we believe the data help justify the consideration of cross-technology innovation being a distinct phenomenon from cross-industry innovation or technology convergence. While cross-technology innovation may rely on technologies developed for different industries, or may signify the first steps towards technological convergence, neither of these is a necessary condition for what we view as cross-technology innovation. Practically, few studies have assessed company-level venture investment data and combined such assessments with patent analysis; we believe it is interesting for practitioners to see these data sets generally corroborate one another. Moreover, we believe that further studies are possible based on the present work, as suggested below.

A limitation of this preliminary study is our selection of technology categories and keywords. Adding additional relevant keywords to each category would help identify more patents and investment deals related to the technological categories. Moreover, there are ample additional categories of technologies where innovation is occurring, and studying these would likely reveal additional insights. As future work, we are interested in replacing our manual selection strategy with a topic modeling approach, where categories and associated keywords can be automatically identified using natural language processing [58, 59, 44, 61]. We suspect that topic modeling would work well for our datasets given their large size and rich textual information.

Finally, given that we focused our study on emerging technologies, it is interesting to consider whether we can use these types of trend analysis to help identify the types of "general purpose technologies" suggested by Bresnahan and Trajtenberg [9] that become pervasive in driving technical progress or economic growth. For example, one could study whether the rise in both AI and AI-related technologies is proof of AI becoming a general-purpose technology or merely peaking in a hype cycle [56, 13]. Similarly, it would be interesting to investigate whether cross-technology innovation will lead to convergence [11] that results in forming such general-purpose technologies. Generally, with increasing trends of combining emerging technologies, we anticipate further research on cross-technology innovation in the entrepreneurship literature.

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