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**M&As and Innovation: A New Approach to  
Classifying Technology**

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# M&As and Innovation: A New Approach to Classifying Technology\*

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## Abstract

A large literature considers the interplay between mergers and acquisitions (M&A) by multinationals and innovation, typically measured as patents. One theme that emerges is that technological similarity plays a role in which M&As occur. The challenge then becomes how to measure technological similarity. Typically, this is done by using either firms' sectors or the technological classifications of their patents. The first is a coarse measure of business activity and overlooks supply chains. The second may incorrectly match technical features with no overlapping business relation. In contrast, we offer an alternative based on a machine learning approach using patent technology descriptors. This decants over 600 technological codes into 21 technical business areas (TBAs). Similarity in this more parsimonious measure is highly related to the probability of a given M&A occurring. This provides a more intuitive approach to understanding the literature's findings.

**JEL classification:** F23; G34; O30

**Keywords:** Mergers and Acquisitions; Technological Similarity; Multinationals; Patents.

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# 1 Introduction

Innovation is a cornerstone of economic progress, driving advancements in productivity, economic growth, and technological capabilities. It enables firms to create new products, improve processes, and expand into emerging markets. However, the pathways through which innovation proliferates are multifaceted, with mergers and acquisitions (M&As) standing out as a prominent mode of innovation propagation. M&A activity, particularly as a form of foreign direct investment (FDI), has the potential to integrate technological capabilities, consolidate resources, and foster innovation across organizational and geographical boundaries.

The relationship between M&A activity and innovation is highly complex and context-dependent. While some studies suggest that M&As promote innovation by fostering synergies and expanding technological capabilities, others argue that they may stifle innovation by reducing competition or redirecting resources. This duality highlights the need for a nuanced understanding of how M&As influence innovation dynamics. Several factors contribute to the heterogeneity observed in the M&A-innovation relationship. In addition to critical factors such as the intensity of competition within the market and firm-specific characteristics such as size and absorptive capacity, the technological similarity between the target and acquirer is also a key factor. If technological capabilities are too disjoint, then the M&A may not yield positive innovation synergies. Similarly, if there is excessive overlap, the M&A may lead to redundancies or resource inefficiencies. To examine these possibilities, it is necessary to have a taxonomy of what a given firm's technological profile looks like in order to compare these between targets and acquirers.

In the literature, two primary taxonomies have been used. The first uses tra-

ditional sector-based classifications, i.e. if firms are in the same industry they are similar. This approach, however, is potentially too coarse to capture the overlaps of interest. The second uses the technical classifications, such as the U.S. Patent and Trademark Office’s Cooperative Patent Classification (CPC) system, in firms’ patent portfolios. Although certainly more detailed than an industry taxonomy, since CPC classes focus on the scientific content rather than business applications of an invention, it too can miss important relationships. With these limitations in mind, in this paper we instead use the novel classification of firms proposed by [Cheng et al. \(2023\)](#) which allocates firms to technological business areas (TBAs). This text-based approach integrates both technological advancements and their associated business applications, thus bridging the gap between the two main approaches in a way that includes the strengths of both. We then use the TBA classification to analyze patterns in M&A deals and their impact on both the probability of a deal occurring and the resulting acquisition stake.

The TBA framework builds upon the CPC system, but expands its utility by identifying clusters of patents frequently associated within business contexts. These clusters are determined through a natural language processing (NLP) technique, such as latent Dirichlet allocation (LDA), which groups related CPCs into coherent topics. These topics, representing TBAs, align not only on technological similarities but also on underlying business synergies. In contrast, traditional sectors or classifications often segment patents based solely on technical fields, such as chemicals or electronics, without considering how these innovations interact within broader business ecosystems. TBAs then bridge this gap, reflecting both technological and business realities. For example, patents in seemingly unrelated CPC categories like image processing and vehicle systems may cluster in a sin-

gle TBA due to their shared applications in driver-assistance systems. Therefore, the TBA framework offers a novel lens through which the M&A-innovation nexus can be analyzed, bridging the gap between technological capabilities and market dynamics.

Overall, our approach yields three key outcomes. First, the most coherent set of TBAs is one with 21 groups. This is far more compact than the 134 active three-digit CPC codes, providing a more tractable (and arguably policy-relevant) way of discussing technologies. Second, although the number of patents in each TBA continues to grow, some (such as Digital and Wireless Communication Systems, Electrical Connectivity and Control Systems, and Data Processing) grow markedly faster than others. Third, the similarity of target and acquirer technologies has moved from being concentrated within-sectors to a more dispersed pattern. In other words, rather than deals with higher technological overlap being concentrated on those where the target and acquirer are in the same industry, we see more and more overlap in cross-industry deals. Finally, our estimates suggest that the greater the TBA similarity between the target and acquirer, the more likely a deal between them and the greater the subsequent share of the target that is acquired.

The paper is structured as follows. Section 2 reviews the literature on M&A and innovation. Section 3 describes the data and methodology, with our analysis found in Section 4. Section 5 concludes.

## 2 Review of the Literature

Innovation and technological advancement are often seen as critical drivers of economic performance. The development of new processes and products is pivotal

in explaining growth across sectors and regions. Furthermore, the spread of innovation, or the lack thereof, significantly contributes to inequality. One key way innovation propagates is via multinational enterprises (MNEs), which act as conduits for innovation across borders (Bilir and Morales, 2020). With mergers and acquisitions (M&A) as the primary mode of foreign direct investment (FDI), this raises an important question: what is the relationship between M&A and innovation?<sup>1</sup> The existing literature lacks a definitive answer.<sup>2</sup>

We believe that this lack of consensus stems from three main sources. First, the relationship between M&A and innovation must be clearly defined. Does innovation drive M&A, or does M&A stimulate innovation? Further, does this question pertain to the acquirer, the target, or the post-merger entity? If different studies consider different questions, then it is no shock that the results vary.

Second, innovation itself is challenging to measure. Inputs like R&D spending provide clear metrics but may underestimate impacts if efficiencies are gained post-merger. Outputs, such as patent counts or forward citations, are common proxies but can be misleading due to differences in patenting behavior across industries and countries (Hall et al., 2012; de Rassenfosse et al., 2021; Hagedoorn and Cloudt, 2003; Griliches, 1998). Thus again, clarity on precisely what is being examined is paramount.

Third, even with precise definitions, theory often predicts ambiguous or heterogeneous effects. For instance, the impact of M&A on innovation can depend on

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<sup>1</sup>As discussed in Davies et al. (2018), FDI can take place via M&A or greenfield investment. Although there are more greenfield investment projects globally, approximately 80% of the value of FDI flows is attributed to M&A.

<sup>2</sup>For other reviews of the literature, see Suo et al. (2023) or Dezi et al. (2018). Surveys by Bergek and Group (2014) and Castellani and Zanfei (2006) also discuss cross-border acquisitions and innovation.

market competition (Ahn, 2002; Gilbert, 2006) and technological overlap between acquirer and target. Additional factors, such as market size and regulatory differences, further complicate the analysis (Miyagiwa and Wan, 2016; Peneder and Wörter, 2014; Tingvall and Poldahl, 2006).

This complexity, combined with challenges such as endogeneity in acquisition decisions, explains why the literature offers no straightforward conclusions. In light of this, this we organize our discussion of the literature into categories: pre-deal innovation driving M&A activity, post-deal impacts on innovation, and heterogeneity across acquirers, targets, and industries. It also highlights the importance of factors such as absorptive capacity and technological synergies (Cohen and Levinthal, 1990, 1989).

Studies examining how innovation influences M&A activity often highlight technological motives as a reason behind a deal. For example, firms lagging in innovation may acquire others to leapfrog ahead technologically (Blonigen and Taylor, 2000; Higgins and Rodriguez, 2006; Bena and Li, 2014).<sup>3</sup> Conversely, innovative firms are more likely to become acquisition targets, as their R&D activities increase their attractiveness (Guadalupe et al., 2012; Wu and Chung, 2019).

It is important to note, however, that just because a target has technology does not necessarily mean that the acquirer can benefit from it. For that to occur, the acquirer must possess sufficient absorptive capacity, that is, the ability of the acquirer to put its newly-acquired technologies to use (see Cohen and Levinthal, 1990 and Cohen and Levinthal, 1989). For example, Bena and Li (2014) find that CPC-based similarity between potential targets and acquirers tends to increase the

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<sup>3</sup>See Nocke and Yeaple (2007) and Nocke and Yeaple (2008) for theoretical treatment of the technological acquisition motive for M&As, including the importance of absorptive capacity.

probability of a deal. [Hall \(1987\)](#), [Frey and Hussinger \(2006\)](#), and [Guadalupe et al. \(2012\)](#), and [Davis and Madura \(2015\)](#) all obtain a similar prediction. [Bertrand and Zuniga \(2006\)](#), meanwhile, find that the effect depends very much on the industry. This work then highlights the need to carefully measure technological overlap and is where our work contributes.

In contrast to the reasonably robust result that innovation spurs M&As, the results regarding the impact of a deal on subsequent innovation is far more mixed. Starting with the work focusing on the acquirer, it is not difficult to find studies which suggest that M&As increase parent firm innovation through synergies or cost reductions ([Stiebale, 2013](#); [Desyllas and Hughes, 2010](#)). At the same time, however, others report declines in R&D intensity post-acquisition, particularly when there is insufficient technological overlap ([Hitt et al., 1991](#); [Cloodt et al., 2006](#)). The quality of innovation may also change; for instance, the number of patents may increase, but their average quality may decline ([Valentini, 2012](#); [Valentini and Di Guardo, 2012](#)).

For targets, the impact of M&A is similarly ambiguous. Some studies find that innovation decreases due to reallocation of R&D activities to the acquirer ([Stiebale and Reize, 2011](#); [Stiebale, 2016](#)). At the same time, others report increases, particularly when the deal crosses national borders ([Guadalupe et al., 2012](#); [Arnold and Javorcik, 2009](#); [Girma et al., 2012](#)). Finally, one can consider the impact of M&A activity on the joint innovation by the newly-paired firms (acquirer plus target). Once again, examples where innovation falls ([Ornaghi, 2009](#); [Haucap et al., 2019](#)) and or increases ([Bena and Li, 2014](#)) can be found.

One possible explanation for such variation is that a deal can impact rival firms as changes in competition and innovation levels in the merged entity may



alter market dynamics (Haucap et al., 2019; Valentini, 2016). This can then feed-back into changes in R&D within the newly-paired firms. Alternatively, and again the focus of our contribution is that the degree of technological synergies may determine whether innovation increases or decreases (Cloodt et al., 2006; Ornaghi, 2009; Makri et al., 2010; Bose et al., 2023). Hussinger (2012) provides one particularly interesting take on technological similarity but suggesting that the impact may be influenced by the ability of the inventors in the target to integrate with the existing research fields of the acquirer.

In any case, the link between M&As and innovation remains a complex and context-dependent topic. In particular, if one wishes to focus on the similarity of firms’ technological profiles, it is necessary to use a meaningful taxonomy to describe their capabilities. In the next section, we introduce our proposed approach and the data we use.

## 3 Data and Methodology

For our analysis, we require two types of information, one on M&A activity and one on the innovation activities of firms. Together, these can be used to construct our TBA taxonomy and then target-acquirer technological similarity. We begin by describing our data.

### 3.1 M&A and Patents

The Zephyr database has approximately 3 million observations in the period 1997–2020 with 2,169,892 unique deals<sup>4</sup> This difference is due to the fact that a single

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<sup>4</sup>The Zephyr database can be found at <https://login.bvdinfo.com/R0/ZephyrNeo>.

deal can involve more than just two firms, generating more than one observation per deal. The status of the deal is characterized as “Announced”, “Completed”, “Completed Assumed”, “Pending”, “Postponed”, “Rumour”, “Unconditional”, and “Withdrawn”. We retain only the deals that are completed or completed assumed. Moreover, we keep only the deals for which there is information on the country and sector of both the targets and acquirers. This selection corresponds to 964,123 observations and 625,446 deals.

To match deals with firm technologies, we match data on acquisitions with the COR&DIP data.<sup>5</sup> In particular, for the top 2,000 corporate R&D performers worldwide, the 2023 edition of the COR&DIP database links the R&D activity with IP assets (patents and trademarks). It relies on the 2021 EU Industrial R&D Investment Scoreboard data produced by the EC-JRC, covering the top 2,000 corporate R&D investors worldwide, and on the EPO-PATSTAT database. We can then map the patenting information for the 2,000 firms in the Scoreboard to roughly 700,000 entities, some of which are involved in a Zephyr-observed deal.

Table 1: Number of deals involving patents

|        |      | Acquirer |        |         |
|--------|------|----------|--------|---------|
|        | Pats | No       | Yes    | Tot.    |
| Target | No   | 606,829  | 20,765 | 615,719 |
|        | Yes  | 13,656   | 1,641  | 15,117  |
|        | Tot. | 609,111  | 22,374 |         |

Table 1 organizes deals into four categories, reflecting whether the target and acquirer own patents (Yes) or not (No).<sup>6</sup> The majority of deals (606,829) in-

<sup>5</sup>The EC-JRC-OECD COR&DIP’s database which results from the collaboration between the European Commission, Joint Research Centre Directorate B (Fair & Sustainable Economy) and the OECD STI Directorate.

<sup>6</sup>The row and column totals do not exactly match the final number of deals as there can be

volve entities that do not own patents, highlighting the prevalence of non-patent-intensive transactions. This is perhaps not a surprise given that most firms do not patent. It is also worth noting that the number of deals between patent-holding acquirers and non-patenting targets outweighs the reverse by 50%. Although it does not in itself negate the idea of technological leap-frogging via acquisition, it does suggest that this approach may necessitate acquirer absorptive capacity (Blonigen and Taylor, 2000; Higgins and Rodriguez, 2006; Bena and Li, 2014).

In order to discuss similarity, however, it is necessary to link both target and acquirer to patenting, hence we focus on the 1,641 deals where this is the case.

### 3.2 Constructing TBAs

The core idea behind the technological business area classification lies in identifying meaningful connections within patent data, specifically among the 4-digit CPCs associated with patents filed by the same assignee. To achieve this, an assignee’s patent filing portfolio is thought of as a “document” consisting of the collection of CPCs under which the assignee filed patents during a defined period. Each CPC in this context represents a “word” within the document. By applying topic modeling techniques, such as latent Dirichlet allocation (LDA), we can uncover underlying “topics” which we call Technological Business Areas (TBAs).

Ownership changes resulting from M&A activity during a given period inherently influence the definition of topics because they affect the patents that would enter a given assignee’s document. As a result, relying on these topic definitions to analyze and compare TBA coverage between an acquirer and a target could lead to inaccurate conclusions. To mitigate this issue, we derive TBAs using patent

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more than one target or/and more than one acquirer in a deal.

data from the 1995–2005 period as training data. More specifically, to prepare the training dataset, we exclude firms whose patent filings are limited to a single CPC subclass, as well as subclasses with an average of less than one filing per year. We then apply LDA to identify TBAs as “topics” derived from the patent portfolios of all assignees in the training dataset.

There is no commonly accepted way to choose the number of topics in a topic model. One way is to rely on “topic coherence” metrics. We use a probabilistic topic coherence measure.

Probabilistic coherence uses the concepts of co-occurrence and statistical independence to rank topics. Essentially, we fit several topic models across a range of topics (5 models spanning 5 to 25 topics). Then calculate the probabilistic coherence for each topic in each model. Finally, average the probabilistic coherence across all topics in a model. Probabilistic coherence averages differences in conditional probabilities across the top  $M$  most probable CPC classes (e.g., top 10 CPC codes) in a TBA (topic). Let  $(x_{i,k})$  correspond to the  $i$ -th most probable CPC (word) in TBA (topic)  $k$ , such that  $x_{1,k}$  is the most probable CPC,  $x_{2,k}$  is the second most probable, and so on. Then define:

$$x_{i,k} = \begin{cases} 1 & \text{if the } i\text{-th most probable CPC appears in a randomly selected firm's patent portfolio,} \\ 0 & \text{otherwise.} \end{cases}$$

which results in the probabilistic coherence for the TBA  $k$  then:

$$C(k, M) = \frac{1}{\sum_{j=1}^{M-1} (M-j)} \sum_{i=1}^{M-1} \sum_{j=i+1}^M [P(x_{j,k} = 1 \mid x_{i,k} = 1) - P(x_{j,k} = 1)],$$

where  $P(x_{j,k} = 1 \mid x_{i,k} = 1)$  is the fraction of documents (firms' patent portfolios) containing CPC  $i$  that also contain CPC  $j$ , and  $P(x_{j,k} = 1)$  is the fraction of all documents containing CPC  $j$ . Words are thus allocated to a given topic in order to maximize this coherence. When this is jointly done across the topics (so that each word satisfying the  $M$  criteria is probabilistically allocated to the  $K$  topics), we can then obtain the average coherence across topics.  $\frac{1}{\sum_{j=1}^{M-1} (M-j)}$  is a normalization factor and serves to normalize the coherence calculation, so that the resulting coherence value is appropriately scaled based on the number of document pairs considered in the calculation.

There is no commonly accepted way to choose the number of topics in a topic model. The most straightforward way is to plot the average coherence across values of  $K$  and choose the one with the highest average. Figure 1 visualizes the relationship between the number of topics ( $K$ ) and the coherence score. The trend in the graph helps identify the optimal number of topics by balancing coherence (higher values indicate better interpretability) and model complexity. In our training data, the optimal  $K$  is 21, i.e. 21 topics, with a corresponding coherence score of 0.33.

To define the 21 TBAs, we use the top 5 most probable CPC in each TBA. While a detailed description of the technological business areas (including their CPCs) is found in Appendix A, they are:

- **TBA 1:** Mineral Extraction & Processing

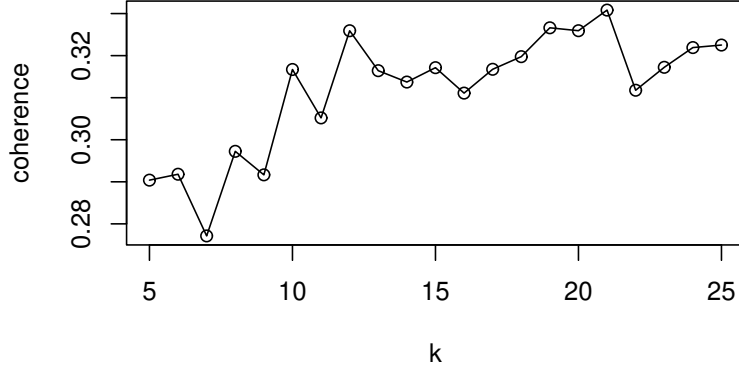


Figure 1: Average coherence per LDA model

- **TBA 2:** Household and Commercial Appliances
- **TBA 3:** Advanced Materials and Manufacturing Processes (Tires and Braking Systems)
- **TBA 4:** Bio-pharmaceuticals and Therapeutic Technologies
- **TBA 5:** Integrated Medical Systems
- **TBA 6:** Biotech Enhanced Functional Polymers
- **TBA 7:** Next-Gen Engine Technologies
- **TBA 8:** Computing and Data Infrastructure Solutions
- **TBA 9:** Multimedia and Display Systems
- **TBA 10:** Integrated Optic Devices
- **TBA 11:** Energy-Efficient Electronics and Display Technologies

- **TBA 12:** Vehicle Safety and Comfort Systems
- **TBA 13:** Next-Gen Semiconductors
- **TBA 14:** Mechanical Power Transmission Systems for Vehicles and Machinery
- **TBA 15:** Electronics
- **TBA 16:** Personal Care and Agricultural Chemicals
- **TBA 17:** Digital and Wireless Communication Systems
- **TBA 18:** Electrical Connectivity and Control Systems
- **TBA 19:** Data Processing
- **TBA 20:** Packaging and Material Processing Solutions
- **TBA 21:** Document Processing and Transaction Systems

Note that this group of 21 is distilled from the approximately 650 4-digit CPC codes used to construct them. Furthermore, they are relatively easier to interpret than the CPC codes. Likewise, and as we discuss next, they transcend sectoral classifications. Therefore, they provide an intuitive way of talking about the technological crossovers that can occur between businesses.

Using the TBAs and associated probabilities generated from our training data, we are finally able to fractionally assign each patent portfolio across the 21 TBAs. Intuitively, this works by examining the CPC codes (words) within each portfolio (document) and comparing them to the distribution of CPCs in each TBA (topic). For each TBA, the LDA model estimates how likely that portfolio is to have been

generated by that topic, based on how well the CPCs in the portfolio match the characteristic CPC distribution of the topic. The relative weights, which must sum to one, are assigned to each TBA in a portfolio and reflect these comparative likelihoods. Finally, for any two firms, we can construct the cosine similarity in their TBA portfolio. We discuss the patterns this process leads to in our next section.

## 4 Results

Table 2 reports a detailed breakdown of the average number of patents across TBAs over our sample (2006–2021, i.e. after the training data). Average numbers of patents vary significantly across TBAs, with some showing robust growth (e.g., TBA 2: Household and Commercial Appliances, or TBA 18: Electrical Connectivity and Control Systems) and others where the growth is relatively sluggish (e.g., TBA 3: Advanced Materials and Manufacturing Processes (Tires and Braking Systems) and TBA 8: Multimedia and Display Systems). As a different approach to these numbers, Figure 2 plots the evolution of patent stocks by TBA from 2006 to 2021. This makes the steep growth in TBAs linked to digital communication and engine technologies – TBAs 17 (Digital and Wireless Communication Systems), 18 (Electrical Connectivity and Control Systems), 19 (Data Processing) and 7 (Next-Gen Engine Technologies) especially clear. TBAs with less dramatic growth potentially represent mature TBAs.

Figure 3 presents a comparative analysis of M&A activity involving firms that own patents, classified by 2-digit NACE code. Each bar represents the total number of deals, while the inner shaded portion indicates the number of majority



Table 2: Average number of patents by TBA and year

|       | Technological Business Areas |      |      |      |      |      |       |       |       |      |      |
|-------|------------------------------|------|------|------|------|------|-------|-------|-------|------|------|
| year  | 1                            | 2    | 3    | 4    | 5    | 6    | 7     | 8     | 9     | 10   |      |
| 2006  | 5.63                         | 2.93 | 1.32 | 5.29 | 5.1  | 6.45 | 8.48  | 9.94  | 9.04  | 4.19 |      |
| 2007  | 5.84                         | 2.63 | 1.32 | 4.78 | 4.81 | 6.33 | 9.28  | 9.22  | 7.87  | 4.14 |      |
| 2008  | 6.08                         | 2.43 | 1.28 | 4.44 | 4.64 | 5.92 | 7.93  | 7.77  | 7.02  | 3.72 |      |
| 2009  | 6.34                         | 2.48 | 1.19 | 4.13 | 4.38 | 5.86 | 7.32  | 7.15  | 6.45  | 3.24 |      |
| 2010  | 6.66                         | 2.69 | 1.25 | 3.51 | 4.54 | 6.22 | 8.94  | 7.36  | 7.3   | 3.66 |      |
| 2011  | 7.6                          | 2.83 | 1.4  | 3.29 | 4.7  | 6.66 | 9.44  | 7.89  | 7.39  | 3.92 |      |
| 2012  | 9                            | 3.06 | 1.34 | 3.07 | 4.36 | 6.59 | 9.85  | 8.08  | 6.87  | 4.05 |      |
| 2013  | 8.82                         | 3.24 | 1.64 | 3.31 | 4.83 | 6.97 | 9.64  | 8.04  | 7.02  | 4.1  |      |
| 2014  | 8.28                         | 3.68 | 1.78 | 2.98 | 4.51 | 7.04 | 10.17 | 7.96  | 7.49  | 3.85 |      |
| 2015  | 6.79                         | 3.59 | 1.86 | 2.82 | 4.54 | 6.77 | 9.97  | 7.29  | 7.11  | 3.5  |      |
| 2016  | 7.06                         | 4.09 | 1.85 | 2.52 | 4.35 | 6.95 | 10.07 | 7.18  | 7.24  | 3.4  |      |
| 2017  | 6.64                         | 4.36 | 2.16 | 2.38 | 4.58 | 6.95 | 10.57 | 6.71  | 6.85  | 3.78 |      |
| 2018  | 5.94                         | 4.32 | 2.04 | 2.31 | 4.25 | 7.11 | 10.13 | 7.24  | 7.24  | 3.96 |      |
| 2019  | 5.54                         | 4.17 | 1.82 | 2.39 | 4.19 | 7.02 | 9.79  | 6.42  | 6.94  | 3.7  |      |
| 2020  | 4.83                         | 4.14 | 1.46 | 2.41 | 4.37 | 6.45 | 9.24  | 6.56  | 6.24  | 3.45 |      |
| 2021  | 4.76                         | 4.44 | 1.53 | 1.94 | 4.17 | 5.7  | 8.49  | 7.02  | 5.68  | 3.26 |      |
| Total | 6.59                         | 3.51 | 1.6  | 3.13 | 4.5  | 6.58 | 9.38  | 7.54  | 7.06  | 3.73 |      |
| year  | 11                           | 12   | 13   | 14   | 15   | 16   | 17    | 18    | 19    | 20   | 21   |
| 2006  | 6.03                         | 6.04 | 5.55 | 3.15 | 2.54 | 2.7  | 15.37 | 7.15  | 14.31 | 2.72 | 3.84 |
| 2007  | 4.99                         | 5.78 | 5.24 | 3.3  | 2.43 | 2.72 | 13.27 | 7.61  | 14.79 | 2.44 | 3.81 |
| 2008  | 4.65                         | 5.05 | 4.65 | 3.03 | 2.2  | 2.33 | 12.85 | 8.18  | 14.79 | 2.27 | 3.45 |
| 2009  | 5.29                         | 3.64 | 3.81 | 3.04 | 1.69 | 2.45 | 13.66 | 7.83  | 12.49 | 2.11 | 3.22 |
| 2010  | 6.62                         | 3.44 | 4.42 | 3.14 | 1.73 | 2.66 | 13.62 | 8.59  | 14.4  | 2.19 | 3.21 |
| 2011  | 7.11                         | 4.57 | 4.42 | 4.22 | 1.78 | 2.69 | 13.47 | 9.95  | 15.62 | 2.27 | 3.02 |
| 2012  | 7.25                         | 4.87 | 4.27 | 4.37 | 1.72 | 2.57 | 13.18 | 10.58 | 17.2  | 2.41 | 3.09 |
| 2013  | 6.94                         | 4.98 | 4.56 | 4.1  | 1.76 | 2.57 | 13.53 | 10.4  | 19    | 2.36 | 3.13 |
| 2014  | 6.66                         | 5.54 | 4.25 | 4.6  | 1.4  | 2.46 | 13.89 | 10.75 | 17.42 | 2.11 | 2.89 |
| 2015  | 6.13                         | 5.12 | 3.95 | 4.24 | 1.24 | 2.44 | 13.27 | 10.64 | 16.39 | 2.03 | 2.64 |
| 2016  | 6.39                         | 6.59 | 4    | 4.04 | 1.28 | 2.29 | 12.36 | 12.26 | 16.09 | 1.96 | 2.44 |
| 2017  | 6.55                         | 7.42 | 4.16 | 4.05 | 1.22 | 2.24 | 11.07 | 13.01 | 15.98 | 2.04 | 2.24 |
| 2018  | 7.26                         | 6.77 | 4.56 | 3.84 | 1.33 | 2.27 | 11.26 | 13.56 | 17.41 | 1.95 | 2.35 |
| 2019  | 6.95                         | 7    | 4.05 | 3.56 | 1.33 | 2.43 | 11.25 | 13.5  | 17.36 | 1.69 | 2.3  |
| 2020  | 7.79                         | 5.94 | 4.19 | 3.19 | 1.34 | 2.33 | 11.77 | 12.23 | 16.77 | 1.67 | 1.91 |
| 2021  | 7.96                         | 6.61 | 4.81 | 3.64 | 1.32 | 2.4  | 11.62 | 11.38 | 16.1  | 1.54 | 2.08 |
| Total | 6.61                         | 5.66 | 4.41 | 3.74 | 1.61 | 2.46 | 12.74 | 10.69 | 16.11 | 2    | 2.79 |

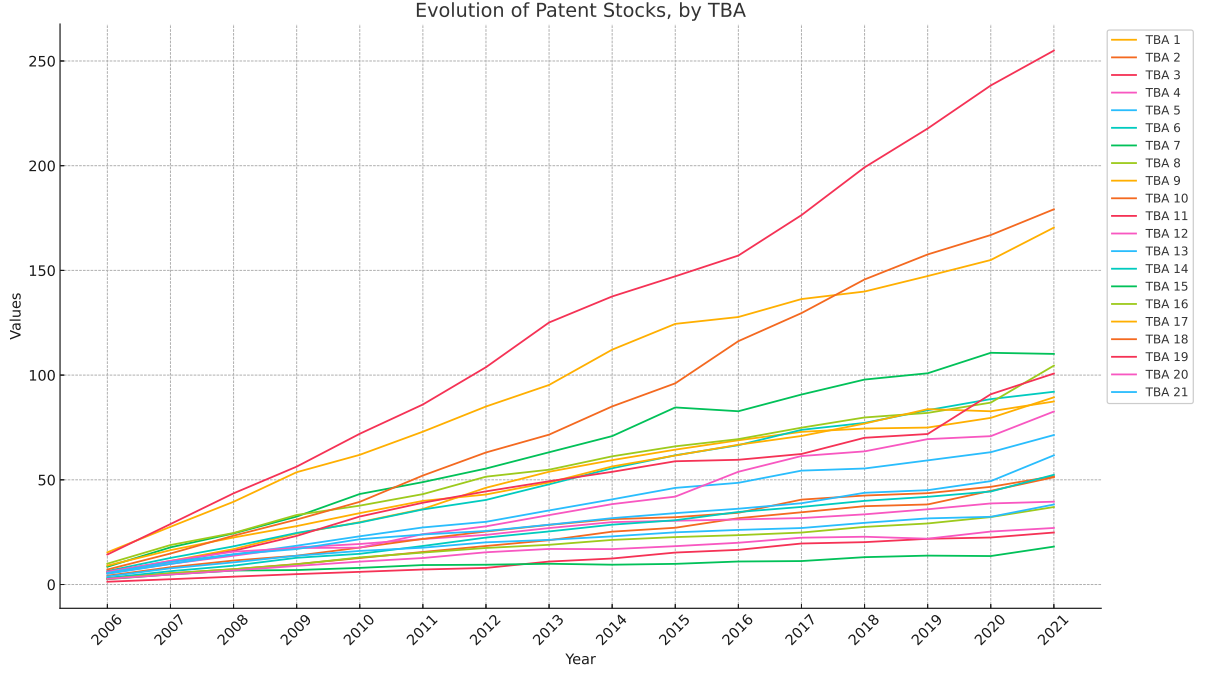


Figure 2: Innovation trends

acquisitions. This visualization allows to assess the relative frequency of deals involving patent-holding firms across different industries, as well as the proportion of transactions classified as acquisitions within each sector. Certain sectors exhibit significantly higher levels of M&A activity than others. Notably, technology-intensive industries, such as NACE 26 (Manufacture of Computer, Electronic, and Optical Products) and NACE 21 (Pharmaceuticals), report the highest number of deals involving patenting firms. This trend aligns with the expectation that firms in R&D-driven sectors are more likely to engage in M&A as a means of acquiring innovative assets and expanding technological capabilities. Some industries exhibit a relatively high share of acquisitions within their total deal activity, suggesting that firms in these sectors are actively acquiring patent-owning companies rather than engaging in other forms of transactions (e.g., capital increase or minority

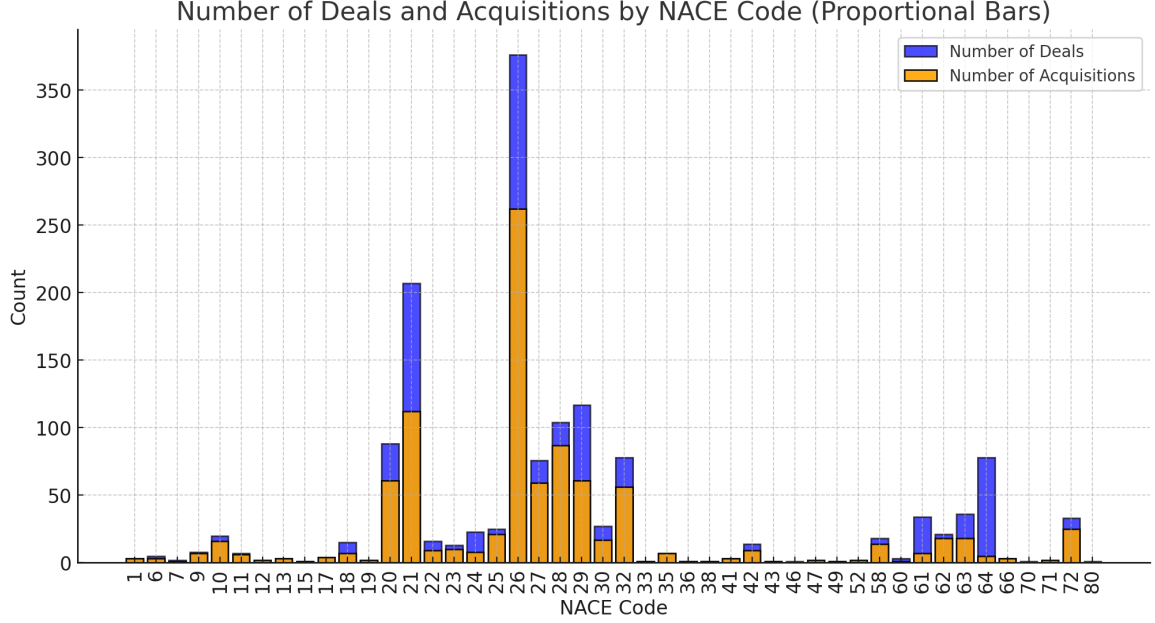


Figure 3: N. of deals and acquisitions, by sector (2006–2021 totals)

stakes). For example, in ICT-related industries (NACE 61 - Telecommunications, NACE 62 - Software Development), a large portion of deals involve acquisitions, reflecting the role of knowledge transfer and intellectual property consolidation in this sector. Certain sectors with traditionally lower patent intensity, such as manufacturing (NACE 24 - Basic Metals, NACE 25 - Fabricated Metal Products), still exhibit a noteworthy number of transactions. This suggests that even in capital-intensive industries, firms recognize the value of acquiring patented technologies to enhance competitiveness.

Figure 4 presents the relationship between the acquired stake and the number of deals across different acquirer sectors. High-tech industries like electronics (26) and software (62) exhibit both frequent transactions and substantial acquired stakes, highlighting a strategy of technology-driven consolidation. Other industries, particularly Civil Engineering (42) and Financial Services (64), display lower average

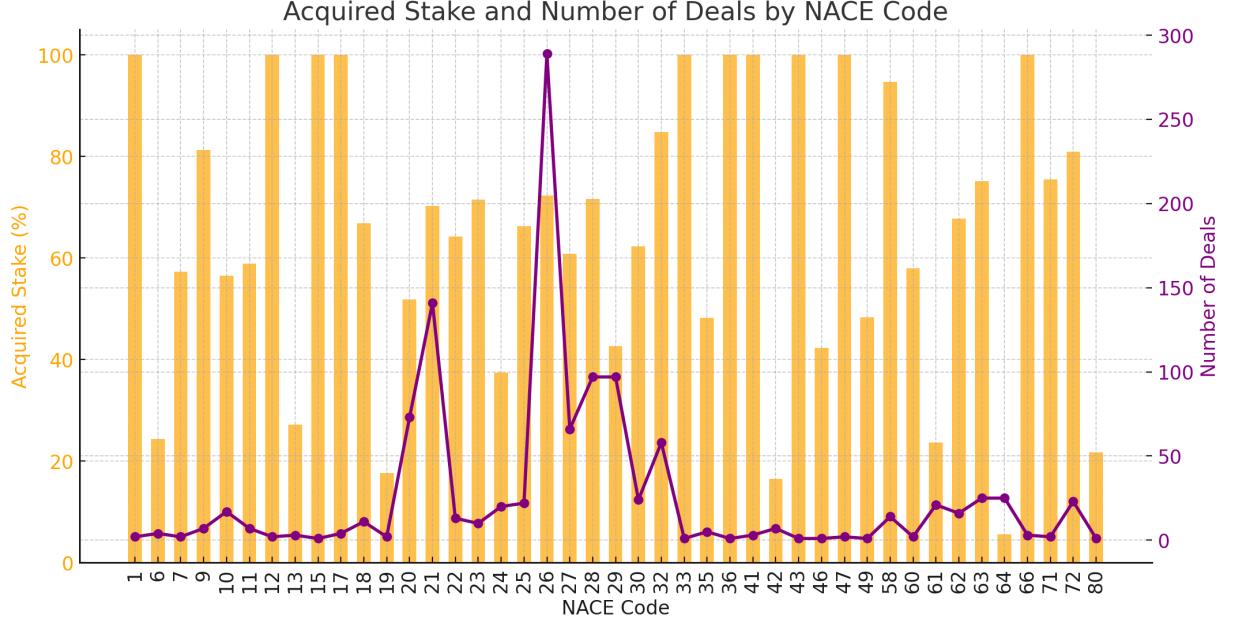


Figure 4: Average acquired stake (%) and n. of deals, by acquirer sector

acquired stakes. Indeed, banks, venture capital (VC) firms, and investment funds typically acquire minority stakes in target companies to diversify portfolios and mitigate financial risk. The construction and infrastructure sector often operates through joint ventures and consortia, where multiple stakeholders share risks and financing, making full takeovers less common.

#### 4.1 TBA similarity between acquirers and targets

Of 625,446 deals, only 0.3% have information on patents for both the acquirer and the target. For these deals, we are able to calculate cosine similarity. The heatmap in Figure 5 represents the average cosine similarity of deals for the different sector combinations. The acquirer sector is on the horizontal axis while that of the target is on the vertical axis. Both are based on their 2-digit NACE codes. The intensity of the color indicates the degree of similarity in TBAs of the acquirers and targets.

Setting aside the intensity of similarity, there is a visible clustering of colored cells along the diagonal, suggesting that deals are more likely to occur between acquirers and targets that belong to the same (or closely related) sector. In particular, there are a number of mergers where both the target and acquirer are in manufacturing sectors.

Now turning to the similarity, certain deal clusters have very high similarity values (dark purple cells). In particular, three patterns emerge. First, the diagonal again tends to be darker, something that is not a surprise since one would normally expect technological similarity within industries. This extends to near-diagonal deals with sectors 21–28 and 61–62 reflecting potential industry-specific synergies (e.g., manufacturing, IT, and communication sectors). A second cluster of darker cells is found where the acquirer is in manufacturing and the target is in sector 71 (Architectural and Engineering Activities; Technical Testing and Analysis) or 72 (Scientific Research and Development). Given the range of topics these two industries work on, this is again somewhat anticipated.

The sectors Manufacture of Chemicals and Chemical Products (20), Manufacture of Computer, Electronic, and Optical Products (26), Manufacture of Machinery and Equipment (28), and Financial Services (64) exhibit the highest diversification in acquisition strategies, engaging in M&A deals across a broad range of sectors. This indicates that firms in these sectors actively pursue cross-sector acquisitions, leveraging M&A to integrate complementary technologies, expand innovation capabilities, and enhance market positioning beyond their core industries.

The two heatmaps in Figure 6 repeat this exercise but do so for the years 2006 (left) and 2019 (right). This allows us to examine the evolution of the M&A -

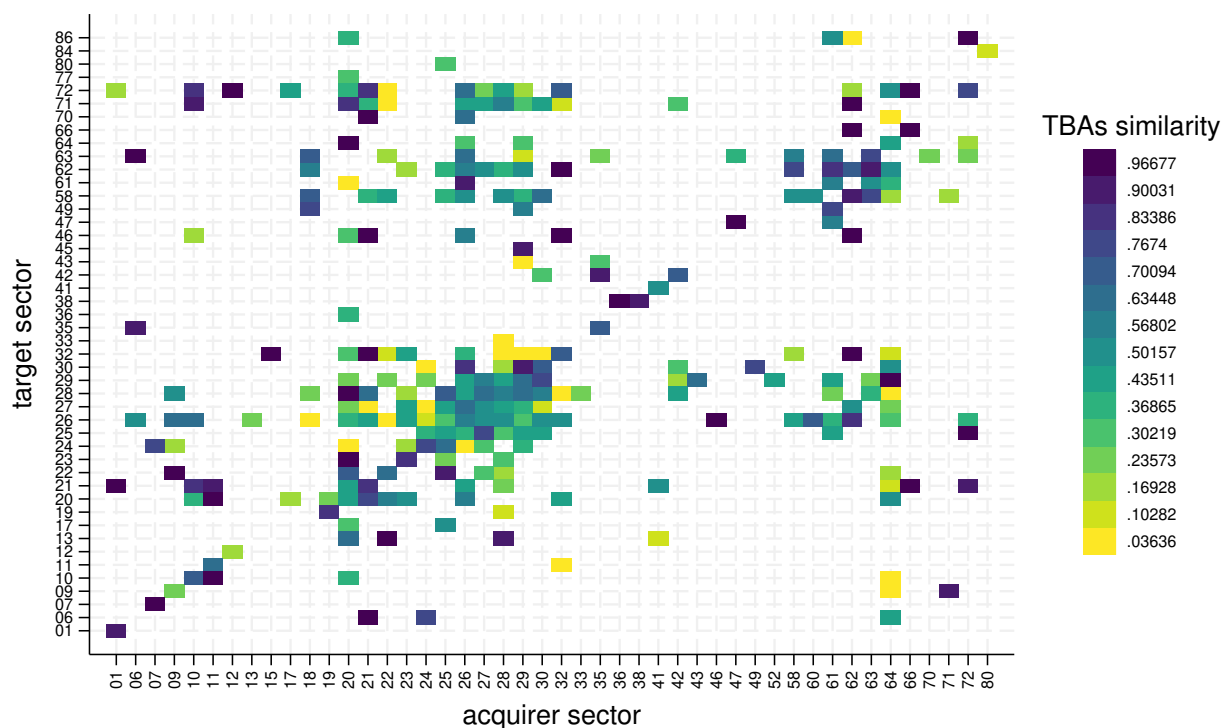


Figure 5: TBA similarity between targets and acquirers, by sector (2006–2021 average)

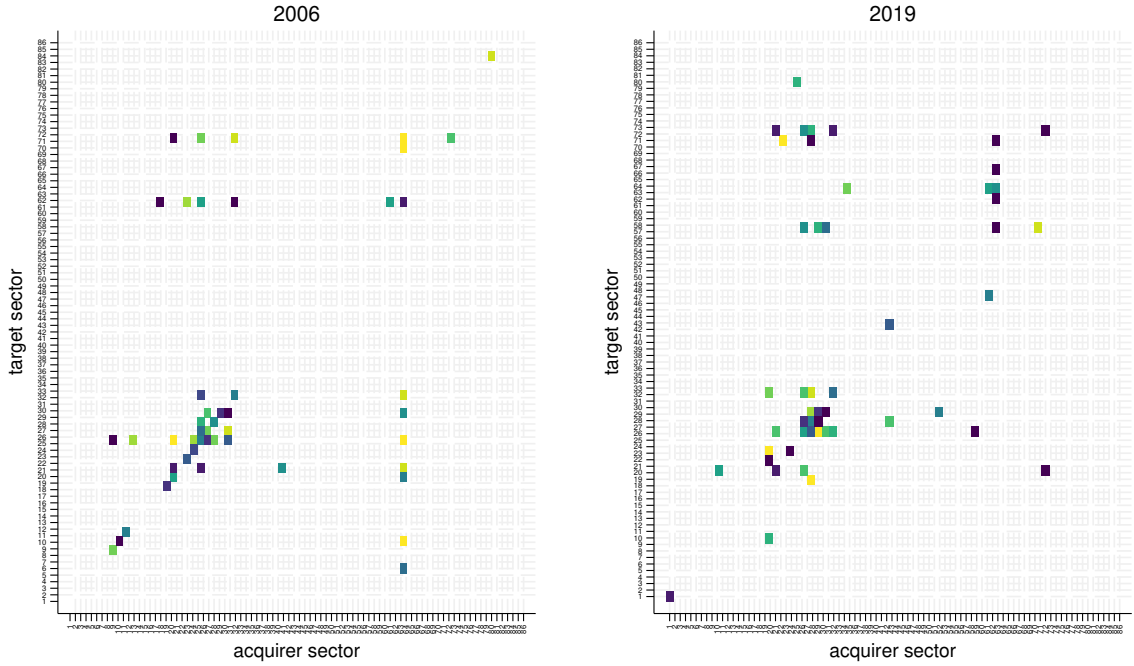


Figure 6: TBA similarity between targets and acquirers, by sector (2006 vs 2019)

technological similarity nexus. Two differences are immediately apparent. First, in comparison to 2006, where within-sector deals are of greater importance, the deals of 2019 are somewhat more dispersed. This suggests a tendency to more cross-sector M&As.

Figure 7 shows a general increase in TBAs similarity from 2006 to 2020, with fluctuations in certain years. This suggests a shift towards more aligned acquisitions, particularly after 2012, indicating a strategic focus on acquiring firms with closer technological-business profiles over time.

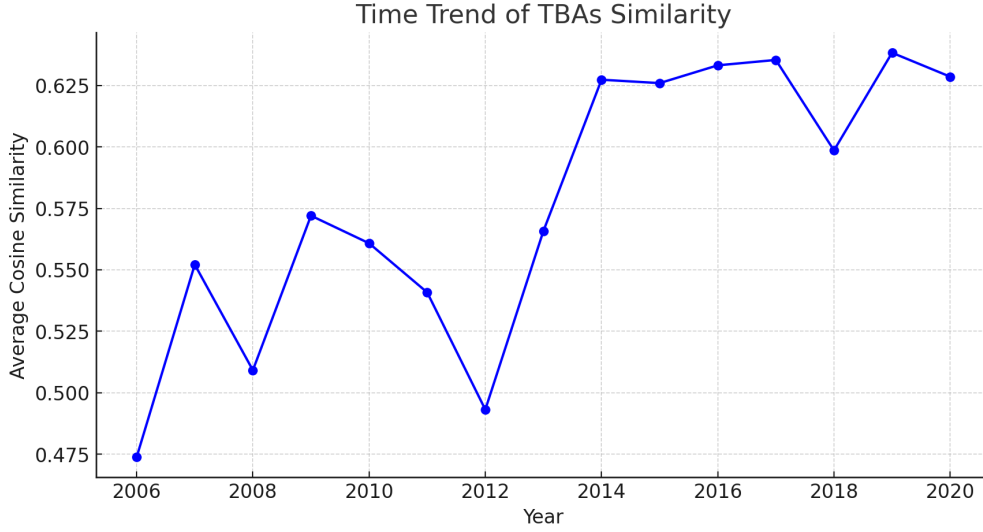


Figure 7: TBAs similarity over time

## 4.2 Regression analysis

This section presents the results of the regression analysis conducted to examine the relationship between TBA similarity (cosine similarity) and two acquisition outcomes: the probability of acquisition and, conditional on a deal occurring, the acquired stake.

Beginning with the probability of acquisition, we take those deals where we can construct TBA similarity and expand the dataset so that, for each of our targets, we have a pairwise observation between it and each acquirer. We then code the binary outcome variable so that it is one for the actual target-acquirer pair and zero otherwise. We then estimate this outcome controlling for TBA similarity, the logged stock of patents for each firm, controls for their region and sector, and a set of year dummies.<sup>7</sup> Note that our dataset only includes firms where we observe them as either a target and/or an acquirer. Thus the estimates must be interpreted

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<sup>7</sup>Note that we treat the panel as a cross section, thus the year dummies control for the year of the deal.



as the relation between TBA similarity and the probability of a given match being made conditional on *some* match being made. We estimate this probability using both probit and logit models.

The results from this estimation are presented in Table 3. First and foremost, the coefficient for TBAs similarity is positive and statistically significant at the 1% level in both models. This indicates that firms with higher technological-business affinity are more likely to engage in acquisitions. This result supports the hypothesis that firms are more likely to acquire targets that operate in similar or complementary TBAs.

The patent stock of the acquirer is also positively associated with the likelihood of acquisition, with coefficients of 0.094 (probit) and 0.374 (logit), both significant at the 1% level. This suggests that firms with larger patent portfolios are more active in acquiring other firms, possibly to consolidate their technological position or expand their innovation capabilities. In contrast, the patent stock of the target has a negative, although marginally significant, effect on the likelihood of acquisition. This may indicate that targets with larger patent portfolios are more established and less willing to be acquired or – because their larger patent portfolios – can demand higher acquisition prices.

Finally, the geographic and sectoral controls reveal some heterogeneity in acquisition likelihood. For example, targets based in the EU and the US are less likely to be acquired compared to those in China, while acquirers from certain sectors (e.g., sector 05-09 which make up Section B: Mining and Quarrying of the NACE classification) are less likely to engage in acquisitions. These results suggest that regional and sectoral factors play a role in shaping acquisition dynamics.

The second-stage OLS regression (Table 4) investigates the factors influencing

the percentage of the target’s stake acquired in the deal.<sup>8</sup> The results suggest that the greater the TBA similarity, the greater the acquired stake. In column (1), a one-unit increase in TBA similarity is associated with a 10.95 percentage point increase in the acquired stake, highlighting the importance of technological compatibility in determining the level of control an acquirer seeks in a transaction. Intuitively, this would indicate that going from no overlap in TBAs to complete overlap would increase the acquired stake by enough to go from no ownership to above 10% – the common statutory threshold for corporate control. In column (2), we introduce dummy variables for target region and sector as well as year dummies. This slightly reduces the magnitude of the TBA similarity effect but maintains its significance. Finally, column (3) uses a Heckman two-step procedure and includes the Inverse Mills Ratio (IMR) from the above probit results to control for selection bias pertaining to the match between this specific target-acquirer pair. This does not impact the TBA estimate, however, as Table 5 shows, there is a strong degree of correlation between the IMR and TBA similarity. As with any situation where the IMR is correlated with a control variable, this can inflate standard error. Give the results of 4, however, we still obtain strong indications of significance.

In addition to the TBA, the estimates also indicate that the greater the initial ownership share, the smaller the acquired stake. This result is intuitive given the upward bound of 100% on the acquired stake. Finally, in league with the above results, the estimates suggest that acquirers with bigger patent stocks buy bigger stakes while targets with bigger patent stocks tend to result in deals with lower stakes.

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<sup>8</sup>Note that this restricts the sample to the deals which actually occurred. Further, limited information on acquisition stake further reduces the number of usable observations.

Overall, the results confirm that technological similarity between acquirer and target, as measured by TBA similarity, is a key driver of acquisition decisions and ownership structure. The findings suggest that firms strategically acquire targets with closely related technological business areas to enhance knowledge integration and innovation potential. Additionally, acquirers tend to favor targets with moderate patent stock levels, avoiding those with overly large portfolios, which may reflect concerns over integration challenges or competition within the same technological space.

These findings have important implications for both academic research and policy. For researchers, the results suggest that technological alignment should be a key consideration in studies of mergers and acquisitions, particularly in innovation-intensive industries. For policymakers, the results highlight the potential benefits of fostering technological alignment between firms, as it may facilitate more efficient and successful acquisitions that promote innovation and competition.

## 5 Conclusions

Mergers and acquisitions are unlikely to be random pairings of firms but rather arise from a belief that a joint entity is more profitable than two separate ones. One key source of those synergies is the possibility that the technology embodied in the target will interact with that of the acquirer. This suggests a link between innovation and M&As. At the same time, an M&A may affect subsequent innovation. Further, both of these may well hinge on the overlap in the technological portfolios of the two deal-makers. To analyze that, however, requires the use of a taxonomy that describes a firm's technological know-how. While existing methods

based on industry codes or CPC technology codes drawn from patents are certainly useful, they lack precision and the ability to meaningfully map the importance of cross-technology spillovers for economic outcomes.

With this in mind, we develop a new taxonomy that classifies patent portfolios using the latent Dirichlet allocation, a text-based topic modeling techniques which brings together both the business focus of an industry classification and the technology focus of the CPC approach. This yields a set of 21 classifications which are both easier to work with and more interpretable than the CPC method. Further, these classifications reflect a growing role for cross-industry innovations. The findings align with the broader literature suggesting that the success of M&As in driving innovation depends on achieving a balance between leveraging synergies and avoiding redundancy. While some degree of overlap between acquirer and target fosters integration and knowledge transfer, excessive overlap can stifle R&D efforts.

By using TBAs, this study offers a more robust methodology to address the limitations of traditional metrics and to capture the economic and industrial relevance of innovation. In particular, we identify shifts in technological priorities, such as a move towards digital and green technologies, as evidenced by the growth of TBAs focused on communication systems and energy efficiency. Furthermore, regression analysis points to TBA similarity as an important factor in which firms are paired under a deal and how great the subsequent acquisition stake is. Although such patterns are not unique to our TBA taxonomy, their relative intuitiveness brings a simplicity to a topic where conflicting terminology has clouded a complex topic. Thus, these findings underscore the diversification and evolving focus of the global innovation landscape. As such, we hope that this analysis and proposed

taxonomy serves as a foundation for further investigation into the patterns driving innovation.

## References

- AHN, S. (2002). Competition, innovation and productivity growth: A review of theory and evidence. *OECD Economics Department Working Papers*, (No. 317).
- ARNOLD, J. M. A. AND B. S. JAVORCIK (2009). Gifted kids or pushy parents? foreign acquisitions and plant performance in indonesia. *Journal of International Economics*, 79(1):42–53.
- BENA, J. AND K. LI (2014). Corporate innovations and mergers and acquisitions. *The Journal of Finance*, 69(5):1923–1960.
- BERGEK, B. C., ANNA AND K. R. GROUP (2014). The impact of environmental policy instruments on innovation: A review of energy and automotive industry studies. *Econlogical Economics*, 106:112–123.
- BERTRAND, O. AND P. ZUNIGA (2006). R&D and M&A: Are cross-border M&A different? An investigation on OECD countries. *International Journal of Industrial Organization*, 24(2):401–423.
- BILIR, L. K. AND E. MORALES (2020). Innovation in the global firm. *Journal of Political Economy*, 128(4):1566–1625.
- BLONIGEN, B. A. AND C. T. TAYLOR (2000). R&d intensity and acquisitions in high-technology industries: Evidence from the us electronic and electrical equipment industries. *Journal of Industrial Economics*, 48(1):47–70.
- BOSE, U., W. D. GREGORI, AND M. MARTINEZ CILLERO (2023). Does green transition promote green innovation and technological acquisitions? *JRC Working Papers in Economics and Finance*, (2023/4).
- CASTELLANI, D. AND A. ZANFEI (2006). *Multinational Firms, Innovation and Productivity*. Edward Elgar Publishing, Northampton, MA.
- CHENG, Z., G. Z. JIN, M. LECCESE, D. LEE, AND L. WAGMAN (2023). M&a and innovation: A new classification of patents. *AEA Papers and Proceedings*, 113:288–93.
- CLOODT, M., J. HAGEDOORN, AND H. VAN KRANENBURG (2006). Mergers and acquisitions: Their effect on the innovative performance of companies in high-tech industries. *Research Policy*, 35:642–654.

- COHEN, W. M. AND D. A. LEVINTHAL (1989). Innovation and learning: The two faces of r&d. *Economic Journal*, 99:569–596.
- COHEN, W. M. AND D. A. LEVINTHAL (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly*, 35(1):128–152.
- DAVIES, R. B., R. DESBORDES, AND A. RAY (2018). Greenfield versus merger and acquisition fdi: Same wine, different bottles? *Canadian Journal of Economics*, 51(4):1151–1190.
- DAVIS, S. M. AND J. MADURA (2015). Growth options and acquisition likelihood in high tech. *Journal of High Technology Management Research*, 26:1–13.
- DE RASSENFOSSE, G., W. E. GRIFFITHS, A. B. JAFFE, AND E. WEBSTER (2021). Low-quality patents in the eye of the beholder: Evidence from multiple examiners. *The Journal of Law, Economics, and Organization*, 37(3):607–636.
- DESYLLAS, P. AND A. HUGHES (2010). Do high technology acquirers become more innovative? *Research Policy*, 39(8):1105–1121.
- DEZI, L., E. BATTISTI, A. FERRARIS, AND A. PAP (2018). The link between mergers and acquisitions and innovation: A systematic literature review. *Management Research Review*, 41(6):716–752.
- FREY, R. AND K. HUSSINGER (2006). The role of technology in m&as: a firm-level comparison of cross-border and domestic deals. *ZEW discussion paper*, (No. 06-069).
- GILBERT, R. (2006). Looking for mr. schumpeter: Where are we in the competition-innovation debate? *Innovation Policy and the Economy*, 6:159–215.
- GIRMA, S., Y. GONG, H. GÖRG, AND S. LANCHEROS (2012). Foreign ownership structure, technology upgrading and exports: Evidence from chinese firms. *Kiel Working Paper*, (No. 1793).
- GRILICHES, Z. (1998). Patent statistics as economic indicators: A survey. In Z. Griliches, editor, *R&D and Productivity: The Econometric Evidence*, pages 287–343. University of Chicago Press, Chicago.
- GUADALUPE, M., O. KUZMINA, AND C. THOMAS (2012). Innovation and foreign ownership. *American Economic Review*, 102(7):3594–3627.

- HAGEDOORN, J. AND M. CLOODT (2003). Measuring innovative performance: is there an advantage in using multiple indicators? *Research Policy*, 32(8):1365–1379.
- HALL, B. H. (1987). The effect of takeover activity on corporate research and development. In A. J. Auerback, editor, *Corporate Takeovers: Causes and Consequences*. University of Chicago Press, Chicago.
- HALL, B. H., C. HELMERS, M. ROGERS, AND V. SENA (2012). The choice between formal and informal intellectual property: A literature review. Working Paper 17983, National Bureau of Economic Research.
- HAUCAP, J., A. RASCH, AND J. STIEBALE (2019). How mergers affect innovation: Theory and evidence. *International Journal of Industrial Organization*, 63:283–325.
- HIGGINS, M. J. AND D. RODRIGUEZ (2006). The outsourcing of r&d through acquisitions in the pharmaceutical industry. *Journal of Financial Economics*, 80:351–383.
- HITT, M. A., R. E. HOSKISSON, R. D. IRELAND, AND J. S. H. HARRISON (1991). Effects of acquisitions on r&d inputs and outputs. *The Academy of Management Journal*, 34(3):693–706.
- HUSSINGER, K. (2012). Absorptive capacity and post-acquisition inventor productivity. *Journal of Technology Transfer*, 37:490–507.
- MAKRI, M., M. A. HITT, AND P. J. LANE (2010). Complementary technologies, knowledge relatedness, and invention outcomes in high technology mergers and acquisitions. *Strategic Management Journal*, 31:602–628.
- MIYAGIWA, K. AND Y. WAN (2016). Innovation and the merger paradox. *Economics Letter*, 147:5–7.
- NOCKE, V. AND S. R. YEAPLE (2007). Cross-border mergers and acquisitions vs. green-field foreign direct investment: the role of firm heterogeneity. *Journal of International Economics*, 72(2):529–557.
- NOCKE, V. AND S. R. YEAPLE (2008). An assignment theory of foreign direct investment. *Review of Economic Studies*, 75(2):529–557.
- ORNAGHI, C. (2009). Mergers and innovation in big pharma. *International Journal of Industrial Organization*, 27(1):70–79.



- PENEDER, M. AND M. WÖRTER (2014). Competition, r&d and innovation: testing the inverted-u in a simultaneous system. *Journal of Evolutionary Economics*, 24(3):653–687.
- STIEBALE, J. (2013). The impact of cross-border mergers and acquisitions on the acquirers' r&d — firm-level evidence. *International Journal of Industrial Organization*, 31:307–321.
- STIEBALE, J. (2016). Cross-border m&as and innovative activity of acquiring and target firms. *Journal of International Economics*, 99:1–15.
- STIEBALE, J. AND F. REIZE (2011). The impact of FDI through mergers and acquisitions on innovation in target firms. *International Journal of Industrial Organization*, 29:155–167.
- SUO, L., K. YANG, AND H. JI (2023). The impact of technological mergers and acquisitions on enterprise innovation: A review. *Sustainability*, 15.
- TINGVALL, P. G. AND A. POLDAHL (2006). Is there really an inverted u-shaped relation between competition and r&d? *Economics of Innovation and New Technology*, 15(2):101–118.
- VALENTINI, G. (2012). Measuring the effect of m&a on patenting quantity and quality. *Strategic Management Journal*, 33(3):231–346.
- VALENTINI, G. (2016). The impact of m&a on rivals' innovation strategy. *Long Range Planning*, 49:241–249.
- VALENTINI, G. AND M. C. DI GUARDO (2012). M&a and the profile of inventive activity. *Strategic Organization*, 10(4):384–405.
- WU, S.-Y. AND K. H. CHUNG (2019). Corporate innovation, likelihood to be acquired, and takeover premiums. *Journal of Banking & Finance*, 108(C).

Table 3: Probability of Acquisition

| Variable               | Probit Coefficient (SE) | Logit Coefficient (SE) |
|------------------------|-------------------------|------------------------|
| TBA Similarity         | 0.999*** (0.018)        | 3.965*** (0.074)       |
| Acq. Patent Stock      | 0.094*** (0.003)        | 0.374*** (0.013)       |
| Target Patent Stock    | -0.0087* (0.0045)       | -0.031* (0.018)        |
| <i>Acquirer Region</i> |                         |                        |
| EU                     | -0.038 (0.026)          | -0.191* (0.107)        |
| East Asia              | -0.024 (0.026)          | -0.138 (0.109)         |
| US                     | -0.040 (0.026)          | -0.204* (0.107)        |
| Other                  | -0.078** (0.036)        | -0.353*** (0.145)      |
| <i>Target Region</i>   |                         |                        |
| EU                     | -0.055** (0.026)        | -0.225** (0.104)       |
| East Asia              | 0.039 (0.028)           | 0.133 (0.110)          |
| US                     | -0.085*** (0.026)       | -0.333*** (0.104)      |
| Other                  | -0.124*** (0.039)       | -0.487*** (0.156)      |
| <i>Acq. Sector</i>     |                         |                        |
| B                      | -0.362** (0.157)        | -1.416** (0.635)       |
| C                      | -0.204 (0.144)          | -0.786 (0.581)         |
| D                      | -0.318* (0.169)         | -1.239* (0.692)        |
| E                      | -0.211 (0.220)          | -0.749 (0.914)         |
| F                      | -0.200 (0.155)          | -0.789 (0.627)         |
| G                      | -0.448** (0.197)        | -1.767** (0.818)       |
| H                      | -0.218 (0.200)          | -0.847 (0.818)         |
| I                      | -0.322** (0.146)        | -1.255** (0.588)       |
| J                      | 0.142 (0.146)           | 0.494 (0.589)          |
| K                      | -0.399*** (0.149)       | -1.576*** (0.602)      |
| L                      | -0.104 (0.280)          | -0.464 (1.157)         |
| <i>Target sector</i>   |                         |                        |
| B                      | 0.443* (0.242)          | 1.683 (1.031)          |
| C                      | 0.216 (0.234)           | 0.797 (1.003)          |
| D                      | 0.061 (0.258)           | 0.190 (1.098)          |
| E                      | 0.197 (0.272)           | 0.748 (1.157)          |
| F                      | 0.022 (0.252)           | -0.018 (1.072)         |
| G                      | 0.147 (0.244)           | 0.565 (1.040)          |
| H                      | 0.475* (0.269)          | 1.860* (1.120)         |
| I                      | 0.180 (0.234)           | 0.645 (1.005)          |
| J                      | 0.246 (0.251)           | 0.917 (1.063)          |
| K                      | 0.256 (0.235)           | 0.990 (1.004)          |
| L                      | 0.216 (0.276)           | 0.741 (1.157)          |
| M                      | 0.239 (0.336)           | 0.822 (1.417)          |
| N                      | 0.255 (0.266)           | 0.908 (1.121)          |
| Year Dummies           | Yes                     | Yes                    |
| Obs.                   | 44,434,740              | 44,434,740             |
| Pseudo R-sq            | 0.1023                  | 0.1020                 |

Notes: Robust standard errors. \*/\*\*/\*\* indicates significance at the 10%/5%/1% level.

Table 4: Acquisition Stake

| Variable            | (1)               | (2)               | (3)               |
|---------------------|-------------------|-------------------|-------------------|
| TBA Similarity      | 10.949*** (2.942) | 6.564** (2.732)   | 42.785** (18.524) |
| Initial Share       | -0.934*** (0.025) | -0.760*** (0.034) | -0.761*** (0.034) |
| Acq. Patent Stock   | 2.460*** (0.495)  | 1.478** (0.485)   | 4.936*** (1.874)  |
| Target Patent Stock | -6.011*** (0.701) | -5.139*** (0.684) | -5.358*** (0.696) |
| IMR                 |                   |                   | 39.021** (19.565) |
| <i>Dummies for:</i> |                   |                   |                   |
| Target Geography    | No                | Yes               | Yes               |
| Target Sector       | No                | Yes               | Yes               |
| Year                | No                | Yes               | Yes               |
| Obs.                | 957               | 957               | 957               |
| R-squared           | 0.4745            | 0.5926            | 0.5962            |

*Notes:* Robust standard errors. \*/\*\*/\*\* indicates significance at the 10%/5%/1% level.

Table 5: Pairwise Correlations

|                  | Acquired % | Initial %  | Acq Pat Stock | Target Pat Stock | TBA Similarity | IMR        |
|------------------|------------|------------|---------------|------------------|----------------|------------|
| Acquired %       | 1.0000     | -0.5663*** | 0.2214***     | -0.3451***       | -0.0059        | 0.1119***  |
| Initial %        | -0.5663*** | 1.0000     | -0.0296       | 0.0997***        | 0.1366***      | -0.1388*** |
| Acq. Pat Stock   | 0.2214***  | -0.0296    | 1.0000        | 0.0305           | -0.0738***     | -0.3502*** |
| Target Pat Stock | -0.3451*** | 0.0997***  | 0.0305        | 1.0000           | 0.0907***      | -0.1948*** |
| TBA Similarity   | -0.0059    | 0.1366***  | -0.0738***    | 0.0907***        | 1.0000         | -0.8053*** |
| IMR              | 0.1119***  | -0.1388*** | -0.3502***    | -0.1948***       | -0.8053***     | 1.0000     |

*Notes:* Robust standard errors. \*/\*\*/\*\* indicates a significant correlation at the 10%/5%/1% level.

## 6 Appendix

### Definition of technological business areas

#### TBA 1: Mineral Extraction & Processing

*Description of the top CPCs*

E21B: Earth or Rock Drilling; Mining

This class encompasses technologies related to the drilling and extraction of minerals, oil, gas, and other subterranean resources. It includes drilling equipment, mining machinery, and methods for efficient resource extraction.

F01D: Internal Combustion Engines; Engine Accessories

Focuses on the design, construction, and optimization of internal combustion engines and their ancillary components. This includes engines used in various machinery, power generation, and transportation.

B01D: Separation

Pertains to processes and apparatuses for separating mixtures into their constituent components. This is crucial in both resource extraction and processing industries to purify and refine materials.

F05D: Ventilation; Air-Conditioning; Refrigeration

Covers technologies related to controlling air quality, temperature, and humidity in industrial settings. Effective ventilation and climate control are vital for maintaining safe and efficient working environments.

C22C: Ferrous Metal Alloys; Ferroalloys; Processes for Their Manufacture

Involves the production and processing of ferrous alloys, including steel and other iron-based materials. This class covers both the alloy compositions and the manufacturing processes essential for creating durable and high-strength materials.

Collectively, these CPC classes represent key technologies in the extraction, processing, and machinery used within heavy industries.

#### TBA 2: Household and Commercial Appliances

*Description of the top CPCs*

F25D: Refrigerators; Cold Rooms; Ice-Boxes; Cooling or Freezing Apparatus Not Covered by Other Subclasses; Combined Cooling and Heating Appliances; Accessories Thereof

This class covers the design and operation of refrigeration appliances, including domestic and commercial refrigerators, freezers, and cold storage rooms. It also includes ice-making machines and accessories related to these appliances.

F25B: Refrigeration Machines, Plants, or Systems; Combined Heating and Refrigeration Systems; Heat Pump Systems; Pumping Liquefied or Solidified Gases  
Focuses on the mechanical and thermodynamic systems used in refrigeration and heat pumps. It includes the components and methods for cooling and heating through refrigeration cycles.

D06F: Laundry Drying; Washing; Cleaning; Dry-Cleaning; Ironing; Pressing; Finishing

Pertains to laundry appliances and processes, including washing machines, dryers, ironing devices, and related technologies for fabric care.

F24F: Air-Conditioning; Air-Humidification; Ventilation; Use of Air Currents for Screening

Encompasses technologies for conditioning indoor air, including heating, cooling, humidifying, dehumidifying, and ventilating spaces to maintain desired environmental conditions.

A47L: Domestic Washing or Cleaning; Suction Cleaners in General

Covers domestic cleaning appliances, such as vacuum cleaners, dishwashers, and floor cleaning devices. It includes both manual and automated cleaning technologies.

Collectively, these CPCs pertain to household and commercial appliances that manage environmental conditions or perform cleaning tasks.

### **TBA 3: Advanced Materials and Manufacturing Processes (Tires and Braking Systems)**

*Description of the top 5 CPCs*

B29C: Shaping or Joining of Plastics; Shaping of Substances in a Plastic State, in General; After-Treatment of the Shaped Products

This class covers methods and apparatus for processing plastics and other materials in a plastic state. It includes molding, extruding, and joining techniques used to shape materials into desired forms.

B29D: Producing Particular Articles from Plastics or from Substances in a Plastic State

Focuses on the manufacturing of specific articles made from plastics or rubber, such as tires, belts, and hoses. It involves specialized processes tailored to produce these items.

B60C: Vehicle Tyres; Tyre Inflation; Tyre Changing; Connecting Valves to Inflatable Elastic Bodies in General

Pertains to the design, construction, manufacturing, and maintenance of vehicle tires. It includes tire structures, tread patterns, inflation systems, and tools or methods for changing tires.

B60T: Vehicle Brake Control Systems or Parts Thereof; Brake Control Systems or Parts Thereof, in General

Covers technologies related to vehicle braking systems, including mechanical, hydraulic, pneumatic, and electronic brake control systems and their components..

Y10T: Technical Subjects Covered by Former USPC Cross-Reference Art Collections [XRACs] and Digests

This class includes various specialized or interdisciplinary technologies that were previously classified under the United States Patent Classification system's cross-reference collections. It often encompasses niche or legacy technologies relevant to multiple fields.

Collectively, these CPC classes are interconnected through their focus on automotive technology and manufacturing processes, particularly relating to vehicle tires, braking systems, and the shaping of materials used in these components. The focus is on:

- Automotive Component Manufacturing: Specifically, the design, production, and improvement of vehicle tires and braking systems.
- Materials Processing and Shaping Technologies: Utilizing advanced shaping and joining techniques (B29C, B29D) to produce automotive components.

- Integration of Advanced Materials: Employing new materials (plastics, composites, rubber compounds) to enhance the performance and safety of tires and brakes.
- Innovation in Vehicle Safety and Performance: Developing technologies that contribute to safer, more efficient, and higher-performing vehicles.

## TBA 4: Biopharmaceuticals and Therapeutic Technologies

### *Description of the top 5 CPCs*

A61P: Therapeutic Activity of Chemical Compounds or Medicinal Preparations

This class categorizes inventions based on the specific therapeutic use of chemical compounds or medicinal preparations. It addresses the treatment, prophylaxis, or diagnosis of diseases and medical conditions.

A61K: Preparations for Medical, Dental, or Toilet Purposes

This class covers the formulation and delivery of medicinal preparations. It includes pharmaceutical compositions, dosage forms, drug delivery systems, and methods for preparing medicinal compounds..

C07D: Heterocyclic Compounds

Focuses on the synthesis and chemical properties of heterocyclic compounds—organic compounds featuring rings with at least one atom other than carbon (e.g., nitrogen, oxygen, sulfur). Many pharmaceuticals are based on heterocyclic structures due to their biological activity.

C07K: Peptides

Relates to the synthesis and manipulation of peptides, which are short chains of amino acids. This includes both natural and synthetic peptides, including proteins and antibodies used in therapeutics.

C12N: Microorganisms or Enzymes; Compositions Thereof

Encompasses biotechnological methods and products, including genetic engineering, recombinant DNA technology, and the use of microorganisms or enzymes in industrial processes.

Collectively, these CPC classes represent the *intersection of chemistry, biology, and medicine*, specifically focusing on:



- Drug Discovery and Development: From small molecules (C07D) to biologics like peptides and proteins (C07K).
- Pharmaceutical Formulations and Delivery Systems: Developing effective ways to deliver these compounds to patients (A61K).
- Therapeutic Applications: Targeting specific diseases and medical conditions (A61P).
- Biotechnology and Genetic Engineering: Utilizing microorganisms and enzymes in the production and development of drugs (C12N).

## **TBA 5: Integrated Medical Systems**

### *Description of the top 5 CPCs*

#### A61B: Diagnosis; Surgery; Identification

This class covers technologies and devices used in the diagnostic processes, surgical procedures, and identification methods. It includes instruments and methods for examining, diagnosing, and treating medical conditions.

#### A61F: Filters Implantable into Blood; Prostheses; Orthopedic Appliances

Focuses on implantable medical devices such as prostheses and orthopedic appliances. This includes devices that replace or support body parts and filters used in medical treatments.

#### A61M: Devices for Introducing Media into the Body

Encompasses medical devices designed to introduce substances (such as medications, nutrients, or fluids) into the body. This includes a variety of delivery systems and administration devices.

#### A61N: Therapeutic or Diagnostic Methods, Apparatus, or Compositions

Covers methods and apparatuses for therapy and diagnosis, as well as therapeutic compositions. This class includes innovative treatment methods and the compositions used in therapies.

#### A61L: Medical or Veterinary Science; Hygiene

Relates to hygiene and sterilization technologies within medical and veterinary contexts. It includes devices and methods that maintain cleanliness and prevent infections.

These classes all integral components of the medical and healthcare technology sector. They encompass a wide range of technologies related to diagnosis, surgery, therapeutic devices, drug delivery systems, and hygiene.

## **TBA 6: Biotech Enhanced Functional Polymers**

### *Description of the top 5 CPCs*

#### C08L: Compositions of Macromolecular Compounds

This class encompasses inventions related to the composition and formulation of macromolecules, including polymers, plastics, rubber, and other large molecular structures. It covers both synthetic and natural polymers.

#### C08G: Compositions of Macromolecular Compounds; Biochemistry, Microbiology or Other Biotechnology

Focuses on the biotechnological aspects of polymer chemistry, including the use of biological processes and organisms to create or modify polymers. This includes biopolymers, enzymatic polymerization, and genetically engineered polymers.

#### C08F: Thermoplastic Compositions

Deals with specific types of polymer compositions, particularly thermoplastics, which are polymers that become pliable or moldable above a specific temperature and solidify upon cooling. It includes formulations for enhanced mechanical, thermal, or chemical properties.

#### C07C: Heterocyclic Compounds

Covers the synthesis and use of heterocyclic compounds—organic compounds featuring rings containing at least one atom other than carbon (e.g., nitrogen, oxygen, sulfur). These compounds are often used as monomers, additives, or functional groups in polymer chemistry to impart specific properties.

#### Y10T: Technical Subjects Covered by Former USPC Cross-Reference Art Collections [XRACs] and Digests

Collectively, these CPC classes represent the *intersection of polymer chemistry, biotechnology, and specialized chemical synthesis*. They emphasize the development of advanced, functional, and sustainable polymer materials through both chemical and biological methodologies.

This technological area focuses on the research, development, and commercialization of advanced polymeric materials that are engineered through both chemical and biotechnological processes. It leverages the synthesis of specialized polymers, the incorporation of heterocyclic compounds for enhanced functionalities, and biotechnological methods to create sustainable and high-performance materials suitable for a wide range of applications.

## **TBA 7: Next-Gen Engine Technologies**

### *Description of the top 5 CPCs*

**Y02T: Technologies for Mitigation or Adaptation against Climate Change**

This class encompasses innovations specifically aimed at reducing greenhouse gas emissions, enhancing energy efficiency, and supporting climate adaptation strategies. It includes technologies that contribute to environmental sustainability across various sectors.

**F02M: Internal Combustion Engines Characterized by Fuel Used; Devices for Mixing Fuel with Air; Devices for Controlling Fuel Supply**

Focuses on internal combustion engines (ICEs), particularly the aspects related to fuel types, fuel-air mixing mechanisms, and fuel supply control systems. Innovations in this class aim to improve engine efficiency, reduce emissions, and accommodate alternative fuels.

**F02D: Air-Breathing Engines; Jet Engines**

Pertains to air-breathing engines, including jet engines used in aviation. This class covers the design, operation, and efficiency improvements of engines that rely on atmospheric oxygen for combustion.

**F02B: Steam or Other Vapor Engines**

Covers engines that operate using steam or other vapor-based mechanisms. While historically significant, modern innovations in this class focus on improving efficiency and integrating with renewable energy sources.

**Y10T: Technical Subjects Covered by Former USPC Cross-Reference Art Collections [XRACs] and Digests**

These CPC classes are interconnected through their focus on engine technologies and their implications for sustainability and climate change mitigation.

This technological area centers on the development, integration, and commercialization of advanced engine technologies that prioritize sustainability, energy efficiency, and reduced environmental impact. It encompasses a wide range of engine types—internal combustion, air-breathing (jet), and steam/vapor engines—while leveraging emerging and interdisciplinary innovations to create holistic power solutions.

## **TBA 8: Computing and Data Infrastructure Solutions**

### *Description of the top 5 CPCs*

**H01L: Semiconductor Devices; Electric Solid State Devices; Their Manufacture; Parts**

This class covers the design, fabrication, and characteristics of semiconductor and solid-state devices. It includes integrated circuits (ICs), transistors, diodes, sensors, and the manufacturing processes involved in producing these components.

**G11C: Information Storage Based on Relative Movement of Indicia and Readout by Head**

Focuses on magnetic and optical data storage technologies where data is stored based on the movement of a storage medium relative to a read/write head. This includes technologies like hard disk drives (HDDs), floppy disks, magnetic tapes, and optical discs (CDs, DVDs).

**G06F: Electric Digital Data Processing**

Encompasses a broad range of computer systems and data processing technologies. This includes hardware and software for general-purpose computing, data management, artificial intelligence, machine learning, and cybersecurity.

**H03K: Oscillators; Resonators; Filters; Frequency Multipliers**

Pertains to signal generation and processing technologies. This includes devices that generate oscillations (oscillators), filter signals (filters), and manipulate signal frequencies (frequency multipliers). These components are essential for communication systems, timing circuits, and signal integrity.

**G01R: Measuring Electric Variables**

Covers technologies related to measuring and monitoring electrical param-

eters. This includes devices and methods for measuring voltage, current, resistance, power, and other electrical variables.

These classes belong to electronics, computing, and data processing sectors. They encompass technologies related to semiconductor devices, data storage, digital processing, signal generation, and electrical measurement.

Together, they form a business technological area which focuses on the development and integration of semiconductor devices, data storage systems, digital processing units, signal generation components, and precise measurement tools to create comprehensive smart computing and data infrastructure solutions. It aims to deliver high-performance, scalable, and reliable systems tailored for various applications ranging from consumer electronics to enterprise-level data centers and emerging technologies like the Internet of Things (IoT) and artificial intelligence (AI).

## **TBA 9: Multimedia and Display Systems**

### *Description of the top 5 CPCs*

H04N: Pictorial Communication, e.g., Television Systems; Video Recording and Reproducing Systems; Digital Communication Systems

Encompasses technologies related to the capture, transmission, processing, and display of video and pictorial information.

G11B: Recording; Reproducing; Specifically, Magnetic Recording; Optical Recording

Focuses on data storage technologies, including both magnetic and optical methods for recording and reproducing information.

G02F: Optical Devices and Systems

Pertains to the design and implementation of optical components and systems used in various devices.

G09G: Electrical Signaling or Addressing; Specifically, Display Technologies  
Covers technologies related to display devices and methods for visualizing information electronically.

G06F: Electric Digital Data Processing

Involves technologies related to computer systems, including hardware and software for data processing.

Collectively, these CPC classes represent a comprehensive ecosystem for multimedia creation, storage, processing, transmission, and display. This technological business area combines advanced data processing, efficient storage solutions, sophisticated optical systems, high-fidelity video communication, and cutting-edge display technologies. This area focuses on creating seamless, high-quality multimedia experiences across various platforms and devices by leveraging the synergy between these interconnected technologies.

## **TBA 10: Integrated Optic Devices**

### *Description of the top 5 CPCs*

#### **G02B: Optical Elements, Systems, or Apparatus**

Covers optical devices such as lenses, prisms, mirrors, and other elements used to manipulate light, including systems for imaging, focusing, or filtering light. It also includes fiber optics and optical devices for various technical applications.

#### **G01N: Investigating or Analyzing Materials by Determining Their Chemical or Physical Properties**

This class pertains to devices and methods used to test and analyze materials, including chemical compositions, structures, and physical properties. Examples include spectrometry, chromatography, and other analytical techniques used in laboratories for materials testing.

#### **Y10T: Technical Subjects Covered by Former US Classification**

#### **H01S: Lasers, Devices Using Amplification of Stimulated Emission of Radiation**

Covers laser technologies, including methods and devices for generating, controlling, and applying laser light in various contexts. It includes laser diodes, solid-state lasers, and the modulation or amplification of light.

#### **C03C: Chemical Composition of Glasses, Glazes, or Vitreous Enamels**

This class is focused on the composition and properties of glass and ceramics, including their surface treatments and special properties (e.g., UV absorption, bioactivity). It also covers glass-ceramic compositions and methods for producing them.

This technological business area focuses on developing and manufacturing high-performance optical materials and photonic devices for applications in industries such as telecommunications, medical diagnostics, and advanced manufacturing. It combines expertise in optical systems (G02B), laser technologies (H01S), and surface treatment of glass and materials (C03C), along with material analysis techniques (G01N), to create innovative products that enhance light transmission, material durability, and precision sensing.

## **TBA 11: Energy-Efficient Electronics and Display Technologies**

### *Description of the top 5 CPCs*

Y02E: Reduction of Greenhouse Gas [GHG] Emissions Related to Energy Generation, Transmission, or Distribution

This class encompasses technologies aimed at mitigating greenhouse gas emissions, particularly through renewable energy sources such as solar, wind, and hydro energy, as well as through more efficient combustion technologies and energy transmission systems.

H01J: Electric Discharge Tubes or Discharge Lamps

Focuses on devices using electric discharge in gas-filled tubes or vacuum environments to generate light or radiation. This includes gas discharge lamps, cathode ray tubes, and plasma displays.

H01M: Processes or Means for the Direct Conversion of Chemical Energy into Electrical Energy

This class deals with batteries and electrochemical systems, such as primary and secondary batteries, fuel cells, and hybrid systems. It includes methods of manufacturing electrodes, electrolytes, and other battery components.

H10K: Organic Electric Solid-State Devices

Covers organic electronic devices, including organic light-emitting diodes (OLEDs), organic thin-film transistors (OTFTs), and organic solar cells. It includes the materials and methods used to create organic semiconductors and electroluminescent layers.

G09G: Arrangements or Circuits for Control of Indicating Devices Using Static Means to Present Variable Information

This class involves control circuits for displays, such as those using LED, OLED, and LCD technologies. It includes the control of pixels and matrix displays in electronic devices.

This area focuses on the intersection of renewable energy systems (Y02E), energy storage solutions (H01M), and energy-efficient electronic devices (H01J, H10K, G09G).

## **TBA 12: Vehicle Safety and Comfort Systems**

### *Description of the top 5 CPCs*

**B60R: Vehicles, Vehicle Fittings, or Vehicle Parts, Not Otherwise Provided for**

This class covers vehicle fittings and parts not otherwise categorized. It includes safety systems such as airbags, bumpers, pedestrian protection systems, and other structural elements designed to mitigate the impact of accidents.

**B62D: Motor Vehicles; Trailers**

Related to the structure and arrangement of motor vehicles and trailers, including body design, steering systems, and suspension systems. It focuses on vehicle stability and control, covering technologies related to the chassis, steering mechanisms, and crash mitigation systems.

**B60Y: Indexing Scheme Associated with Vehicle Adaptive Control Systems**  
Indexing scheme that relates to cross-cutting aspects of vehicle technology, such as autonomous driving, collision prediction, and adaptive cruise control systems.

**B60N: Seats Specially Adapted for Vehicles; Vehicle Passenger Accommodation**

Related to technologies focused on vehicle seating systems, such as adjustable, heated, or ventilated seats. It also covers safety and ergonomic features of vehicle seating.

**F16H: Gearing**

This class focuses on gearings and transmission systems for vehicles. It covers manual and automatic transmissions, as well as gear systems that control the transfer of power from the engine to the vehicle's wheels.



The common denominator among these classes is vehicle safety, control, and comfort systems. Each class involves critical components of modern vehicle design, focusing on safety features (B60R, B60N), control systems such as steering and gearing (B62D, F16H), and intelligent vehicle systems (B60Y). This business technological area focuses on developing integrated systems that enhance vehicle safety, driver assistance, and passenger comfort through a combination of advanced seating technologies, autonomous driving features, safety mechanisms, and efficient powertrain systems.

## **TBA 13: Next-Gen Semiconductors**

### *Description of the top 5 CPCs*

#### H01L: Semiconductor Devices

Processes and apparatus for the manufacture, treatment, and application of semiconductor or solid-state devices. This includes devices like integrated circuits, light-emitting diodes (LEDs), and photovoltaic cells, focusing on the materials and processes involved in producing these components.

#### G03F: Photomechanical Production of Textured or Patterned Surfaces

This class pertains to the photolithographic production of textured or patterned surfaces, such as those used in semiconductor manufacturing, printing plates, and optical components. It includes processes like photoresist coating and development, as well as apparatus used in photolithography.

#### C23C: Coating Metallic Material

Covers coating metallic materials by physical or chemical processes such as vapor deposition, sputtering, or ion implantation. It is widely used in industries for protective coatings, semiconductor manufacturing, and other surface treatment processes.

#### Y10S:

This section is a repository of cross-referenced technologies from various other subclasses in the U.S. Patent Classification system. It often includes specialized or niche technologies not easily categorized under the primary CPC classifications.

#### H01J: Electric Discharge Tubes or Devices

Includes electron tubes and discharge devices like cathode-ray tubes, X-ray

tubes, and gas-discharge lamps. It focuses on technologies where electricity interacts with gases or vacuum to generate light or other effects.

Key technological areas are Nanopatterning via Photolithography and Electron-Beam Lithography (G03F, H01J): Creating highly detailed patterns at the nanoscale for next-gen semiconductor devices; Advanced Thin-Film Deposition (C23C): Using PVD and CVD for precise coatings in electronics, improving performance and durability; Semiconductor Device Fabrication (H01L): Developing novel processes for manufacturing and refining semiconductors.

This technological business area focuses on the development and commercialization of cutting-edge fabrication technologies for the semiconductor industry. It integrates photolithography, thin-film deposition, and electron-beam technologies to manufacture and pattern nanostructures on semiconductor materials. The area would serve sectors like microelectronics, telecommunications, and nanotechnology, offering advanced manufacturing solutions for integrated circuits, sensors, and high-performance electronics.

## **TBA 14: Mechanical Power Transmission Systems for Vehicles and Machinery**

### *Description of the top 5 CPCs*

Y10T: Technical Subjects Covered by Former USPC Cross-Reference Art Collections.

F16C: Shafts; Flexible Shafts; Elements of Crankshaft Mechanisms

This class covers technologies related to mechanical components like shafts, bearings, pivots, and other rotary bodies. These elements are crucial for transmitting mechanical motion and supporting various mechanical systems.

F16D: Couplings for Transmitting Rotation; Clutches; Brakes

This class pertains to mechanical couplings, clutches, and brakes that are used to transmit rotational power. It includes various designs of friction-based and fluid-based clutches, as well as braking systems for vehicles and machinery.

F16H: Gearing

Covers gearing systems, including all types of mechanical transmissions, gear-

boxes, and the associated components used for changing the speed and direction of mechanical power transmission.

B62D: Motor Vehicles; Trailers

This class relates to motor vehicles and trailers, focusing on their structural and mechanical design aspects, such as the arrangement of wheels, steering systems, and frame configurations.

The common denominator among these CPC classes is mechanical systems for power transmission and vehicle technologies. Each class deals with core mechanical components—such as shafts, clutches, gears, and vehicle structures—that are essential for transmitting power, controlling motion, and ensuring the functionality of vehicles and industrial machinery.

This technological business area focuses on developing mechanical systems that improve power transmission in vehicles and machinery. It includes innovations in gearboxes, clutches, shafts, and braking systems that can be applied to industries such as automotive, aerospace, and heavy machinery.

## **TBA 15: Electronics**

### *Description of the top 5 CPCs*

G11B: Information Storage Based on Relative Movement Between Record Carrier and Transducer

This class relates to data storage devices such as magnetic tapes, disks, and optical storage (e.g., CDs and DVDs) where data is read or written by physically moving a transducer relative to the storage medium. It also includes error correction, data management, and processing techniques for these systems.

Y10T: Technical Subjects Covered by Former USPC Cross-Reference Art Collections

H05K: Printed Circuits; Casings or Constructional Details of Electric Apparatus; Manufacture of Assemblages of Electrical Components

Printed circuit boards (PCBs) and methods for assembling electrical components onto them, as well as enclosures or structural features for electronic devices. It focuses on the fabrication and assembly of electronic hardware.

H04R: Loudspeakers, Microphones, Gramophone Pick-Ups, or Like Acoustic Electromechanical Transducers

Acoustic transducers like microphones and speakers. It covers their design, manufacturing, and any associated technologies for improving sound quality, such as noise reduction or enhanced signal processing.

B82Y: Specific Uses or Applications of Nanostructures

This class focuses on nanotechnology applications, including nanostructures used in electronics, materials science, and medicine. It includes the use of nanostructures for information processing (e.g., quantum computing), sensing, and various material enhancements.

The common theme across these CPC classes is their focus on advanced electronic devices and systems, ranging from traditional data storage, circuit manufacturing, and acoustic transducers, to cutting-edge nanotechnology. All these classes contribute to the development, assembly, and functionality of electronic components that underpin modern devices.

This technology business area focuses on the design, manufacturing, and application of micro- and nanoscale electronic components for modern electronics and communication devices. By integrating principles from traditional electronics (e.g., G11B, H05K) with advances in nanotechnology (B82Y), this area aims to improve Data Storage and Processing: Developing hybrid systems that integrate traditional memory and storage solutions (G11B) with nanotechnology-enhanced data storage and quantum computing capabilities (B82Y); enhance Audio Technologies: Using nanomaterials to enhance the performance of loudspeakers, microphones, and transducers (H04R), improving audio quality and device efficiency; innovate PCB and Electronic Assembly: Incorporating nanostructures into printed circuit boards (H05K) for better conductivity, smaller form factors, and enhanced durability.

## **TBA 16: Personal Care and Agricultural Chemicals**

*Description of the top 5 CPCs*

A61K: Preparations for Medical, Dental, or Toilet Purposes

Covers the preparation of pharmaceutical compounds, including cosmetics and similar toiletry preparations, but with a focus on their chemical proper-

ties and therapeutic uses. It includes medicinal compositions, drug delivery forms, and formulations for cosmetic purposes.

**A61Q: Specific Use of Cosmetics or Similar Toiletry Preparations**

This class pertains to the intended cosmetic or toiletry use of known compositions, such as preparations for hair care, skin care, make-up, oral care, and perfume formulations. It classifies products based on their specific use rather than their chemical composition.

**C11D: Detergent Compositions; Use of Single Substances as Detergents**

Focuses on detergent compositions used for cleaning purposes, including household cleaning products, industrial cleaners, and personal hygiene products.

**A23L: Foods, Foodstuffs, or Non-Alcoholic Beverages; Their Preparation or Treatment**

Includes techniques for preserving, enhancing flavor, and enriching food. This class also includes dietary supplements and food additives.

**A01N: Biocides, Pest Repellants, Plant Growth Regulators, or Preservatives for Plants or Animals**

This class involves biocides and pesticides, including disinfectants, herbicides, fungicides, and other agents designed to control pests or preserve plants and animals. It also includes compositions for preventing microbial growth or repelling insects.

This technological business area focuses on the development of formulations for pharmaceuticals, personal care products, household cleaning agents, foodstuffs, and agricultural treatments.

## **TBA 17: Digital and Wireless Communication Systems**

*Description of the top 5 CPCs*

**H04L: Transmission of Digital Information** Covers transmission of signals supplied in digital form, including telegraphic communication, data transmission, and methods for monitoring such transmissions. It also encompasses link adaptation techniques, power control, and handshaking procedures.

H04W: Wireless Communication Networks This class focuses on wireless communication systems, including network protocols and resource management for mobile devices. It covers aspects such as mobility management, resource allocation, and scheduling for wireless communications.

H04B: Transmission

This class deals with the physical layer of transmission systems, including those that use radio waves, sound waves, and other types of electromagnetic radiation. It addresses issues related to noise, interference, power control, and system fault detection.

H04M: Telephonic Communication

Covers communication systems for telephony, including both traditional wired and wireless systems. It also addresses mobile communication devices and systems that handle speech and data transmission.

H04Q: Selecting (Switches, Relays)

Includes switching systems for managing communication networks, specifically how to select and route signals between different points in a communication network. It covers the control and management of communication pathways, such as multiplexing and telecontrol systems.

Altogether, these classes relate to communication technologies, particularly focusing on the transmission, networking, and management of digital and wireless communications. This business area focuses on the development, integration, and optimization of advanced wireless communication systems. It leverages technologies related to digital transmission, wireless networks, telephonic systems, and communication switching to build more efficient, reliable, and scalable wireless infrastructure.

## **TBA 18: Electrical Connectivity and Control Systems**

*Description of the top 5 CPCs*

H01R: Electrically-conductive connections; Structural associations of a plurality of mutually-insulated electrical connecting elements; Coupling devices; Current collectors

This class pertains to devices and methods for creating electrical connections, including connectors, terminals, and coupling systems for electrical circuits.

These are used in a wide range of applications from household appliances to complex industrial machinery.

Y10T: Technical subjects covered by former USPC cross-reference art collections and digests

G01S: Radio direction-finding; Radio navigation; Determining distance, velocity, or position using radio waves; Radar; Lidar; Sonar

Covers technologies related to location and navigation systems using electromagnetic, radio, or acoustic waves. This includes radars, LiDAR systems, GPS, and other sensing systems used for detecting distance, position, and velocity.

H01H: Electric switches; Relays; Selectors; Emergency protective devices

This class involves electric switches and relays, which are devices used to make or break an electrical circuit. It includes mechanical switches, protective devices, and relays that operate based on inputs such as magnetic fields or temperature changes.

H05K: Printed circuits; Casings or constructional details of electric apparatus; Manufacture of assemblages of electrical components

Focuses on the design and construction of printed circuit boards (PCBs), as well as the casings and housings for electronic components. It includes technologies to reduce electromagnetic interference, manage heat, and optimize circuit layouts.

These CPC classes refer electronic systems and components, focusing on electrical connectivity, circuit design, sensing technologies, and control mechanisms. This technological business area focuses on the design, manufacturing, and integration of advanced electronic components, sensors, and connectivity solutions for modern applications in industries such as automotive, telecommunications, defense, and consumer electronics. It centers around the development of advanced electronic systems for controlling, connecting, and managing electronic devices and components.

## **TBA 19: Data Processing**

*Description of the top 5 CPCs*

G06F: Electric Digital Data Processing

This class involves digital computing or data processing systems, including general-purpose computers, algorithms, and data processing operations. It covers elements such as system architecture, data storage, data security, and user interfaces.

H04L: Transmission of Digital Information

Focuses on the transmission of digital information, including methods and systems for data communication over networks. It also encompasses cryptographic mechanisms for securing data and managing network security.

G06Q: Data Processing Systems for Administrative, Commercial, or Financial Purposes

This class covers information and communication technology (ICT) applied to administrative, commercial, financial, managerial, or supervisory functions. Examples include systems for managing business processes, financial transactions, or resource planning.

Y10S: Technical Subjects Covered by Former USPC Cross-Reference Art Collections (XRACs)

G06T: Image Data Processing or Generation

This class involves image data processing, covering methods of image enhancement, analysis, and generation. It includes technologies such as image recognition, medical imaging, and visual effects.

These CPC classes are all data-centric technologies that involve processing, transmission, and management of digital information. They also specialized data applications like image processing (G06T).

## **TBA 20: Packaging and Material Processing Solutions**

*Description of the top 5 CPCs*

Y10T: Technical Subjects Covered by Former USPC

B32B: Layered Products

Focuses on the manufacturing of composite and multi-layer materials. These are used in packaging and other applications requiring enhanced material properties like strength, flexibility, or insulation.



**B65D: Containers for Storage and Transport**

Relates to the design and production of containers such as bottles, boxes, and other packaging solutions, including those made from composite or molded plastics.

**B65H: Handling Thin or Filamentary Material**

Involves technologies for handling and processing thin materials, such as films, tapes, or sheets, used in packaging and material processing industries.

**B29C: Shaping or Joining of Plastics**

Encompasses plastic molding and shaping techniques, critical for creating plastic components used in packaging and composite materials.

A common denominator among these classes is material processing and packaging technologies, particularly focusing on the manufacturing and handling of composite or layered materials, as well as packaging, printing, and plastic shaping.

This technological business area focuses on the design and production of packaging solutions using advanced materials, such as composites, plastics, and printed materials. It involves Smart Packaging, innovative packaging solutions that incorporate layered materials for better durability, flexibility, and functionality (from B32B and B65D); Eco-Friendly Packaging, such as containers from biodegradable or recyclable materials, using novel production techniques (from B29C and B65D); Automation in Material Handling, systems to automate the handling and processing of thin, filamentary, or sheet materials for industries like printing, textiles, and packaging (from B65H).

## **TBA 21: Document Processing and Transaction Systems**

*Description of the top 5 CPCs*

**G03G: Electrography; Electrophotography; Magnetography**

This class involves technologies related to electrostatic printing methods such as photocopying, laser printing, and related imaging processes. It includes both the apparatus and the consumable materials used in these methods, such as toners and photoconductive layers.

**B41J: Typewriters; Selective Printing Mechanisms**

This class is concerned with inkjet and other selective printing mechanisms,

covering devices that print characters or images using ink droplets, laser beams, or other mechanisms. It includes inkjet printers, dot-matrix printers, and related technologies.

H04N: Pictorial Communication, e.g., Television

This class focuses on visual communication technologies, such as image transmission, processing, and display, including television and video recording. It covers systems and methods for capturing, transmitting, and reproducing images and videos.

G06K: Graphical Data Reading and Presentation of Data

This class pertains to automatic reading of data (e.g., barcodes, QR codes, or RFID tags) and the presentation of data on record carriers, including technologies like optical scanners, magnetic stripe readers, and RFID readers.

G07F: Coin-Freed or Like Apparatus

This class covers self-service machines such as vending machines, ATMs, and other devices that accept payment in the form of coins, bills, or electronic cards. It includes technologies for securely handling and processing payments and dispensing goods or services.

The common thread among these CPC classes is the integration of imaging and printing technologies (G03G, B41J, H04N) with data recognition and transaction processing systems (G06K, G07F). This technological business area focuses on the development of integrated systems that combine advanced imaging and printing technologies with data recognition and automated transaction capabilities.

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