World Economy Brief

August 12, 2024 | Vol. 14 No. 25 | ISSN 2233-9140

The Impact of Digital Platform Mergers and Acquisitions on Corporate Innovation

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I. Introduction

The U.S. has been at the forefront of active discussions on whether mergers and acquisitions (M&As) by large U.S. digital platforms, collectively known as GAFAM (Google, Apple, Facebook, Amazon, Microsoft), constitute so-called "killer acquisitions." The term "killer acquisitions" gained attention when three economists and business scholars, Colleen Cunningham, Florian Ederer, and Song Ma, published a paper titled "Killer Acquisitions" in 2018 in the *Journal of Political Economy*, one of the most prestigious journals in the field of economics. According to their paper, a "killer acquisition" is defined as a merger in which an existing firm acquires an innovative company to discontinue the latter's innovative projects and preempt future market competition.

Such merger activities by large digital platforms, suspected of being killer acquisitions, have garnered significant attention because these are often approved by competition authorities without much resistance, as there was no apparent concern about hindering market competition at the time of the merger review. The "Investigation of Competition in Digital Markets" report highlighted Facebook's acquisition of Instagram in 2012 as a merger intended to neutralize an emerging competitor, and Google's acquisition of Waze as a move to eliminate an independent provider of mapping services. The report also pointed out that the dominance of one or two firms in key online markets such as social media, online search, and online advertising is the result of numerous acquisitions by market-dominant digital platforms over time.

This study examines how such killer acquisitions in the digital platform market have impacted innovation performance post-merger. This analysis focuses particularly on M&As among various types of corporate consolidations by digital platforms. It estimates factors influencing the probability of M&A by digital platforms and uses the technological similarity index between the acquiring digital platform and the acquired company as a key explanatory variable. Then, using the technological similarity index, the analysis categorizes the M&A cases involving digital platforms into "killer acquisitions" and "non-killer acquisitions" and compares innovation performance by type of acquisition.

II. Estimation Model and Data

The analysis methodology employed in this study is the event study analysis, also known as the dynamic difference-in-difference (dynamic DID) method. This methodology is well-suited for analyzing how the treatment effect changes over time, especially when the timing of event occurrence is staggered across observations.

One of the key considerations when applying this methodology is defining the pre-event window and post-event window, which are the periods before and after the occurrence of a specific event. In this study, we limit the analysis to a five-year period before and after the occurrence of the digital platform M&A events, including killer acquisitions, to assess their impact on innovation performance.

The estimation equation for this methodology is represented by the equation below.

$$y_{i,t} = \alpha + \sum_{d \neq -1} \beta_d I[year - M\&A\,year = d]_{i,t} + X_{i,t}\gamma + \delta_i + \zeta_t + \epsilon_{i,t}$$

In this equation, $I[A]$ denotes an indicator function (here the indicator function is $I[year - M\&A\,year = d]$), which takes the value of 1 if condition A is satisfied, and 0 otherwise. For example, if a digital platform acquires a particular startup in 2014, the indicator function $I[2014 - M\&A_{2014} = d]$ equals 1 for the year 2014 if $d = 0$. Similarly, $d < 0$ denotes the period before the M&A event and $d > 0$ represents the period after the M&A deal. The immediate pre-event period ($d = -1$) is excluded from the regression analysis to avoid issues of perfect collinearity.

Key terms in the estimation equation are as follows. The dependent variable, $y_{i,t}$, refers to the natural log values of the indicators used to measure the innovation performance of the digital platform i. These indicators include the number of patent applications, the number of patent citations, and the sum of the number of patent applications and patent citations. Next $X_{i,t}$ represents the matrix of other control variables that may affect the innovation performance of the digital platform. These variables are total assets of the digital platform, R&D expenditure, revenue, cash flow, operating profit before tax, and the technological similarity index with the acquired company. Finally, α represents the constant term, δ_i indicates firm fixed effects, ζ_t denotes year fixed effects, and $\epsilon_{i,t}$ represents the error term.

In addition, the COVID-19 pandemic, which began in 2020, might introduce bias in the estimates due to its impact on the dependent variables, apart from the influence of digital platform mergers on their innovation performance. Therefore, the analysis period is set from 1997 to 2019, excluding data from 2020 onwards. This period selection also adequately accounts for the truncation characteristics of patent data, where the number of patent applications or patent citations significantly decreases closer to recent years.

Table 1 shows the descriptive statistics of various variables used in the event study analysis. The average number of patent applications and patent citations of GAFAM, the major digital platforms in the United States recognized as leading global innovation, greatly exceeds the average values recorded by the acquired firms (target firms) of GAFAM. The technology similarity index between the digital platform and the acquired company, which is the variable employed to identify killer acquisitions in this study, was constructed by referencing the method of Jaffe (1986). Specifically, as shown in the equation below, the technology type vectors of the patents applied by the digital platform and the acquired company annually were constructed, and then the correlation between the two vectors was calculated.

$$Tech.Similarity_{i,j,t} = \frac{\frac{1}{c_t}\sum_{c_t}^{C_t}(f_{i,c_t}-\overline{f_{i,t}})(f_{j,c_t}-\overline{f_{j,t}})}{\sqrt{\frac{1}{c_t}\sum_{c_t}^{C_t}(f_{i,c_t}-\overline{f_{i,t}})^2\frac{1}{c_t}\sum_{c_t}^{C_t}(f_{j,c_t}-\overline{f_{j,t}})^2}}$$

In this context, f_{i,c_t} and f_{j,c_t} denote the proportion of patents in technology type c_t out of all patents filed by digital platform i and the target firm j in year t respectively. These represent individual components of each firm's annual patent technology type vector. For example, assume digital platform i filed a total of 10 patents in 2018, all of which are categorized into three technology types (three AI-related patents, three blockchain-related patents, and four autonomous driving-related patents). In this case, the patent technology type vector for digital platform i in 2018 would be (0.3, 0.3, 0.4). The total number of technology types for patents filed in 2018, denoted as C_{2018}, would be 3, and the proportion of AI-related patents in the vector would be 0.3. Additionally, $\overline{f_{i,t}}$ and $\overline{f_{j,t}}$ indicate the average values of the technology type vector components for digital platform i and the target firm j in year t. The average value of the technology similarity index calculated using this formula for the sample data is positive. The technology similarity index between the two firms with the most similar technology portfolios is 0.979, which is close to the theoretical maximum value of 1.

Using the concept of killer acquisitions mentioned earlier, we categorized past digital platform mergers into "killer acquisitions" and "non-killer acquisitions" and compared the innovation performance after these two types of mergers. To classify mergers into these two types, we utilized the technology similarity index between firms, which significantly affected the probability of M&A occurrence for digital platforms and the innovation performance post-M&A.

Table 1. Descriptive Statistics

(Unit: $ Thousands)

Variable		Observation	Mean	Standard Deviation	Minimum Value	Maximum Value
Total Assets		6,808	110,107,648	97,336,280	201,866.7	348,089,408
R&D Expenditure		6,982	7,880,365	7,618,620	15,476.59	46,394,372
Sales		6,982	71,264,808	72,042,768	24,462.46	388,872,800
Cash Flow		6,895	19,104,660	19,202,976	-1,288,538	87,706,656
EBITDA		6,982	18,434,126	18,629,224	-1,441,482	90,177,344
GAFAM	Patent Application	6,982	1,248.29	973.41	8	3,549
	Forward Citation	6,982	10,585.77	10,807.13	2	36,260
Target firm	Patent Application	6,982	43.59	361.99	1	7,036
	Forward Citation	6,982	316.49	2,864.69	1	68,718
Tech. Similarity		6,982	0.0003	0.032	-0.07	0.979

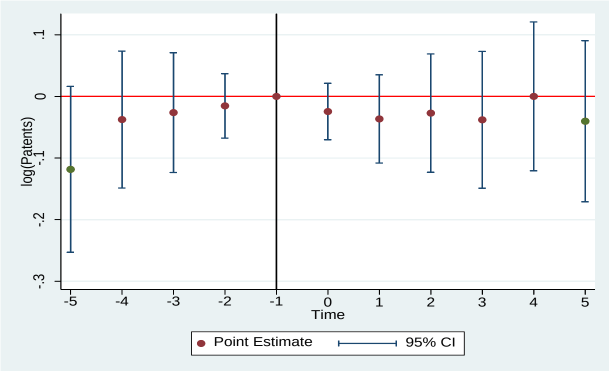
Note: Eikon Company deal DB, USPTO DB, Orbis DB

III. Estimation Results

The analysis proceeded as follows. First, we calculated the average value of the technology similarity index between firms before and after M&As conducted by GAFAM. Next, we identified killer acquisitions by subtracting the pre-transaction technology similarity average from the post-transaction technology similarity average, classifying M&As with little difference before and after the transaction as “killer acquisitions.” Specifically, we defined killer acquisitions as M&As where the difference in the average technology similarity value before and after the transaction fell within the interquartile range (25% to 75%) of the entire sample. Consequently, the remaining M&As were classified as non-killer acquisitions. The reliability of this classification method can be supported by examining the trends in the average number of patent applications of the acquired firms involved in killer and non-killer acquisitions, as presented in the following estimation results.

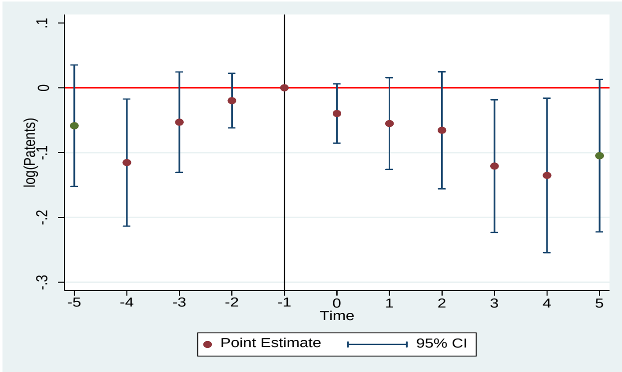
Figures 1 and 2 show the results of an event study analysis, distinguishing between killer acquisitions and non-killer acquisitions, and their respective impacts on the dependent variable, the number of patent applications. According to the results, killer acquisitions have a statistically significant negative impact on the total innovation output, as measured by the number of patent applications, following the acquisition transaction. Specifically, as shown in Figure 1, at the time of the killer acquisition (Time: 0), the difference in the estimated number of patent applications between the M&A success group (experimental group) and the failure group (control group) showed a negative coefficient at the 10% significance level. Notably, the difference in estimates between the two groups expanded in a negative direction at the 5% statistical significance level three and four years after the event (Time: 3, 4).

Figure 1. Impact of Digital Platform Mergers on Patent Applications (Killer Acquisitions)



Note: Author's estimation

Figure 2. Impact of Digital Platform Mergers on Patent Applications (Non-Killer Acquisitions)

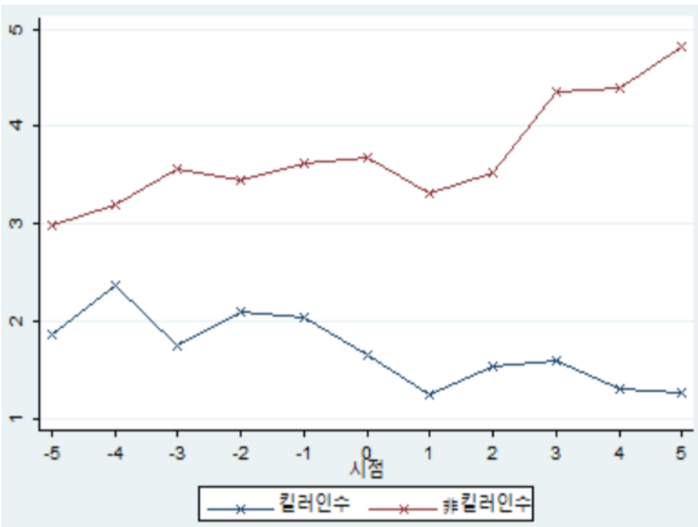


Note: Author's estimation

As shown above, the results indicating a decline in the total innovation output, as measured by the number of patent applications, in the "killer acquisitions" group are also supported by Figure 3. This figure shows the trend of changes in the average number of patent applications held by acquired companies before and after the acquisition transaction, comparing killer acquisitions and non-killer acquisitions.

The patterns of patent application numbers differ between the two groups. Specifically, the number of patent applications for companies involved in killer acquisitions tends to gradually decrease, with some fluctuations, after the acquisition transaction (Time: 0). In contrast, in the case of non-killer acquisitions, the number of patent applications shows an increasing

Figure 3. Average Change in the Number of Patent Applications of Acquired Companies: Killer Acquisitions vs. Non-Killer Acquisitions



Note: Author's calculation

trend after a certain period following the acquisition transaction. These results suggest that the post-acquisition behavior of the acquiring digital platform company could act as a killer acquisition, potentially restricting the innovation output of the acquired company that might otherwise grow into a potential competitor.

IV. Policy Implications

The identification of "killer acquisitions," highlighted in this report, makes it necessary to review and apply various methodologies. As emphasized multiple times in the previous sections, killer acquisitions are anticompetitive corporate actions where large digital platforms acquire small-scale startups that have the potential to grow into future competitors, thus aiming to reduce future market competition. Therefore, it is crucial to review various methodologies to identify such competition-restricting killer acquisitions.

In our report, we construct a technological similarity index using patent technology type data from both digital platforms and target companies. Using this index, we compared the innovation performance of M&A transactions that do not qualify as killer acquisitions and observed some negative innovation effects following the acquisition event. There are no unified criteria in academia or among competition authorities for identifying killer acquisitions in the digital platform sector, and the criteria proposed in this report may not be able to perfectly identify such "killer acquisitions." However, considering the complexity of the digital platform market structure and the difficulty of predicting at the time of acquisition whether the target company will grow into a future competitor, the technological similarity index used in this report could serve as a supplementary tool in merger reviews or post-merger impact assessments. KIEP