The Effects of Technological Similarity and Diversity on Merger and Innovation

Gu Sang Kang

We examine determinants of merger partner choice and impacts of those factors on post-merger innovation outcomes analyzing 1,432 merger deals in U.S. ICT industries. This paper suggests that technological similarity between merging firms increases merger values, meaning the importance of similar technologies between firms in their merger partner selection. Moreover, we find that technological diversity of an individual firm has positive effects on merger value creation. Thus, firms are more likely to choose their merger partners with diverse technologies for the purpose of maximizing their expected merger values. When it comes to post-merger innovation performances, estimated merger values increase the number of merged firms’ patents after merger, implying that expected merger values are realized through the channel of post-merger innovation outputs.
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Executive Summary

This paper examines drivers of merger partner selection and impacts of those factors on post-merger innovation outcomes analyzing 1,432 merger transactions in U.S. ICT industries. Throughout the paper, technological similarity between merging firms and technological diversity of an individual firm are important factors affecting firms' merger partner choice. In order to show their impacts on merger partner selection, we use a two-sided matching model as a theoretical framework and employ a maximum score estimation as an empirical methodology. With these empirical strategies, our findings are summarized as follows. First, technological similarity between merging firms has positive effects on merger value creation. This implies that similar technologies between merging firms plays an important role in choosing their merger partners. Second, technological diversity of an individual firm increases expected merger values. This means that firms tend to choose their deal partners with diverse technologies for the purpose of maximizing their expected merger values. Lastly, we estimate post-merger innovation impacts for actual merger transactions. As a result, estimated merger values created by technological similarity and diversity increase the number of merged firms’ patents after merger. This implies that expected merger values are realized through the channel of post-merger innovation outputs.

Keywords: Merger, Innovation, Two-Sided Matching Model, Technological Similarity, Technological Diversity

JEL Classification: C78, G34
Contributors

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The Effects of Technological Similarity and Diversity on Merger and Innovation

Gu Sang Kang†

I. Introduction

Merger has been one of the crucial vehicles among firms’ various growth strategies. In the perspective of resource-based growth tactics, acquiring firms can purchase non-marketable knowledge and technological resources of target firms through merger transactions (Wernerfelt, 1984). Thus, the merged entity can resolve relatively new problems by combining the acquirer’s existing knowledge with technological resources of the target firm newly acquired in a merger market. Moreover, firms purchase another innovative companies possessing cutting-edge technologies in response to rapid and complicated technological change in the era of fourth industrial revolution. In this case, acquirers can obtain gains from the mergers by saving the costs and time required to train workers lack of knowledge for new technologies as well as catching up with state-of-the-art businesses such as digital platforms. Some representative examples of this type of mergers are Google’s purchase of DeepMind and Facebook’s acquisition of WhatsApp.

Our paper investigates impacts of technological similarity and diversity on both merger partner choice and post-merger innovation outcomes. These two technological factors are regarded as sources of merger value creation. In case of technology similarities between potential merging firms, the merged firm can benefit

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from technological spillovers between acquirers’ and target firms’ similar R&D area. These spillovers play an important role in utilizing the existing information to resolve new problems due to technological change. Cohen and Levinthal (1990) point out this mechanism based on their seminal hypothesis of absorptive capacity. The hypothesis also suggests that old problems can be addressed by new knowledge set constructed from the combination of two firms’ technologies, meaning a cross-fertilization impacts.

Many researchers have focused on technological diversities of individual firms as a driver of firms’ innovation (Garcia-Vega, 2006; Bolli and Woerter, 2013; Jung, Oh, and Hwang, 2014). Garcia-Vega (2006) explores the impacts of technological diversity on firms’ innovation activities using a sample of R&D intensive European firms. She finds that technological diversity has positive effects on innovation measures such as R&D intensity and the number of patents. Employing panel data composed of Switzerland firms, Bolli and Woerter (2013) suggest that if a firm has diverse technologies, its number of patents will increase. Jung, Oh, and Hwang (2014) use the data of Korean manufacturing firms and conclude that there is a positive correlation between technological diversity and R&D intensity. They also find that firms with various technologies within related fields can have more patents due to spillover effects.

When it comes to a merger analysis, we need to consider some issues related to characteristics of the merger event. First, we cannot observe merger values driven by key factors such as technological similarity and diversity. Although there are transaction prices for each merger deal, those prices do not reflect true values of individual mergers. Second, actual merging firms consider many companies as their potential merger partners because of their different characteristics. Thus, observed merger transactions are consequences of interaction among all the firms within an identical merger market. After an acquirer merges with another firm, the latter is eliminated from the list of merger partners for other acquirers within the same merger market. This implies that every merger deal affects other merger transactions in the identical merger market. For this reason, we should use an empirical approach that can address these strategic interactions among potential merging firms in competitive situations.

To this end, we put merger transactions between two firms into a two-sided matching framework. In this model setting, we assume that there are heterogeneities in firms’ technological capacity, and that merger values are determined by expected
synergies from a merger between two deal partners. Since key variables explaining merger value creation in our paper are technological similarity between firms and diversity of individual firms’ technologies, we postulate that merger values are a function of those two technological factors. Specifically, we use a correlation between two firms’ vector of patent shares in diverse patent classes as a measure of technology similarities between them. The rationale for using this measure is that there are spillover effects across broadly similar technologies. Another technological factor is a measure of firms’ technological diversity constructed by using a type of Herfindahl-Hirshman index in terms of patent shares over patent technological classes. Following previous literature showing positive impacts of technology diversity on innovation outcomes, we argue that if firms with diverse technologies merge with each other, their expected merger gains will rise. Our merger value function also contains control variables such as a quadratic term of technological similarity measure, a dummy variable for same industry, and an interaction term between the number of patents for acquirers and targets before their merger transaction.

We estimate a structural two-sided matching model to identify drivers of merger partner choice. Although an actual acquirer combines with a specific target firm, every merger with potential targets within the same merger market considered by the former creates different values. Moreover, all the merger markets achieve a pairwise stable matching equilibrium at the end. In other words, a counterfactual merger match cannot be better than an observed merger pair at the stable equilibrium. Based on this equilibrium condition, we use a maximum score estimation to derive key determinants of merger value creation similar to Akkus, Cooksons, and Hortacsu (2015). By comparing values from actual and counterfactual merger matches, we can identify how much technology similarity and diversity contribute to merger value creation. The relative importance of those technological factors is indicated by the estimated coefficients in our merger value function. Furthermore, those estimates make the actual merger matches survive at the stable matching equilibrium. A necessary condition for the stable equilibrium is that the values of actual merging firms should be greater than the values of counterfactual mergers constructed by exchanging merger partners.

We find that technological similarity between merger partners and technology diversity of individual firms have positive impacts on merger value creation. Since we estimate merger value function through a structural approach, it allows us to use counterfactual experiments for technological similarity and diversity in merger
partner selection framework. According to results of the first counterfactual model, assuming no effects of technological similarity on merger partner choice lowers the model prediction rate, a measure of model fitness, from 6.4% of the benchmark model to 5.7%. When it comes to turning off the impacts of technological diversity on merger value creation, the rate of model prediction decreases by 0.3% points (6.4% → 6.1%). These results of counterfactual models imply that those technological factors, similarity and diversity, play an important role in firms’ merger partner selection.

Our study contributes to the previous empirical literature on the two-sided matching model with the topic of merger partner selection such as Akkus, Cookson, and Hortacsu (2015), Ozcan (2015), and Linde and Siebert (2016). Those papers are similar to ours in that the two-sided matching model with transferable utility is used as a theoretical framework. Analyzing factors of partner selection in bank mergers, Akkus, Cookson, and Hortacsu (2015) suggest positive impacts of the economies of scale. In other words, similar banks in terms of asset size and branch numbers tend to choose each other as their merging partner. Ozcan (2015) and Linde and Siebert (2016) are two studies emphasizing the importance of similarities in technologies and product markets, respectively, when firms consider their merger partners for the purpose of maximizing expected merger synergies. Our contribution to the literature using two-sided merger matching model is to consider both technological similarity and diversity as critical factors in merger partner choice. There has been no studies to examine these two technological factors together in the two-sided merger matching framework.

There have been also studies jointly estimating both merger value function and post-merger outcomes through the two-sided matching model with non-transferable utility. This model assumes that merger values are split between acquirers and targets with a rule of the fixed ratio. Thus, each merging firm does not have any incentive to change its merger partner when there are differences in merger values for potential diverse merger counterparts. One example of using this non-transferable utility model with the two-sided matching model is Park (2013). Investigating merger deals in U.S. mutual fund industry, she concludes that firms in this sector tend to choose their merger partners with similar distribution channel of funds. Moreover, she finds that combined firms formed by the merger between acquirers and targets with similar fund distribution channels experience higher growth rate of assets during post-merger period. Rao, Yu, and Umashankar (2016)
also examine the issue of both merger partner selection and post-merger innovation performance using 1,979 merger transactions in diverse sectors. Their conclusion is that similarity in merging firms’ knowledge is a key determinant of choosing their merger partners as well as the number of patents after the merger. Finally, Ishihara and Rietveld (2017) use 85 acquisition deals and 5,916 game products in U.K. video game industry. They suggest that the count of collaborations and geographical proximity between video game developers and publishers have positive impacts on expected merger values. This is because game developers can make high-quality products and improve sales performances in the post-merger period by collaborating with game publishers.

Investigating 1,432 merger transactions implemented by U.S. ICT firms between 1990 and 2018, we find that technological similarities between merging firms play an important role in merger partner selection. Moreover, technological diversities of individual firms contribute to an increase in expected values from merger deals with their partner firms. Further, estimated merger values created by technological similarity between merging firms and technological diversity of individual firms have positive impacts on post-merger innovation outcomes. This result implies that expected merger values can be realized through the channel of innovation outputs after merger.

The structure of this paper is as follows. We explain our model and empirical approach (including data) in Section 2 and 3, respectively. Section 4 presents our empirical results, and then our concluding remarks follow in Section 5.
II. Two-Sided Matching Model

The two-sided matching model is often used in the analysis of situations in which values from matches between two agents are unobserved. In this paper, those two players represent firms involved in mergers. We assume that there are heterogeneities between firms’ technological capacities and that merger values depend on match-specific characteristics. And we also assume that a merger market is defined by a year when a merger between two firms is completed. Since we analyze merger deals done during 1990-2018, there are 29 merger markets where potential firms can find their merger partners. In this two-sided merger matching game, we need two sets of firms: one is the set of acquiring firms, and the other one is the set of target firms. A matching $\mu$ is a collection of all the observed merger matches in a merger market $m$.

We assume that a merger between two firms $a$ and $t$ creates merger values, $V(a,t)$. These merger values can be distributed between two merger partners. Among them, an acquirer $a$’s share of values is $V_a(a,t)=V(a,t)-p(a,t)$, where $p(a,t)$ is a transfer payment from $a$ to $t$. Also, a target $t$’s share of merger values is $V_t(a,t)=p(a,t)$. Thus, the sum of two merger partners’ values is $V(a,t)=V_a(a,t)+V_t(a,t)$). A matching $\mu$ is pairwise stable if there is no blocking firm pair whose components want to break their current match and form a new match by themselves. This stable matching equilibrium implies that

$$V(a,t)-p(a,t) \geq V(\hat{a},t)-p(\hat{a},t), \quad (1)$$
$$V(\hat{a},\hat{t})-p(\hat{a},\hat{t}) \geq V(\bar{a},\bar{t})-p(\bar{a},\bar{t}), \quad (2)$$

for two observed merger matches $(a,t), (\hat{a},\hat{t}) \in \mu$.

For an acquirer $a$ to merge with its partner $t$ against its rival $\hat{a}$, $p(a,t)$ should be larger than $p(\hat{a},t)$. However, if $a$’s price offer to $t$, $p(a,t)$, is strictly higher than its competitor’s to $t$, $p(\hat{a},t)$, the acquirer $a$’s share of merger values will be diminished. Therefore, at the stable matching equilibrium, the following condition holds:

$$p(a,t)=p(\hat{a},t). \quad (3)$$
Similarly, for two merger matches \((\hat{a}, \hat{t}), (a, \hat{t}), p(\hat{a}, \hat{t})=p(a, \hat{t})\). Then, the equations (1) and (2) can be rewritten as

\[ V(a, t) - p(\hat{a}, t) \geq V(\hat{a}, \hat{t}) - p(\hat{a}, \hat{t}), \quad (4) \]

\[ V(\hat{a}, \hat{t}) - p(a, \hat{t}) \geq V(a, t) - p(a, \hat{t}). \quad (5) \]

Adding the inequality (4) to (5), we derive the following inequality condition for the stable matching equilibrium:

\[ V(a, t) + V(\hat{a}, \hat{t}) \geq V(\hat{a}, \hat{t}) + V(a, t). \quad (6) \]

This condition means that merging firms cannot be better off by exchanging their merger partners at the equilibrium.
III. Empirical Strategy

1. Data Description

In this paper, we employ 1,432 merger deals implemented by firms in U.S. ICT industries during 1990-2018. The data of these merger transactions is obtained from Bloomberg. There are two motivations for choosing ICT sectors in this analysis. First, technologies have changed at a dramatic pace in those sectors (Cohen et al., 2002). Thus, potential merging partners are more likely to consider similarities and differences between their technologies for the purpose of finding synergies from their merger. Second, a success of the fourth industrial revolution sectors such as IoT or AI depends on improvement of ICT technologies. Accordingly, investigating determinants of choosing merger partners in ICT industries in terms of firms' technologies will allow us to provide a guideline to merger policies in the era of the fourth industrial revolution.

There are 7 types of U.S. ICT industries analyzed in this paper. Table 1 shows the number of acquiring and target firms belonging to each industrial sector. Based on the statistics, merger transactions are more actively implemented in U.S. Semiconductor industry relative to other sectors. The number of horizontal mergers which acquirers and target firms belong to a same industry is 559 among 1,432 deals (39%). Furthermore, the trend of merger waves in Figure 1 is similar to the time series of merger transactions suggested in Ahern and Harford (2014).
III. Empirical Strategy

### Table 1. Type of Industries in the Sample

<table>
<thead>
<tr>
<th>Type of Industries</th>
<th>The number of Acquirers</th>
<th>The number of Targets</th>
</tr>
</thead>
<tbody>
<tr>
<td>Electronics</td>
<td>154</td>
<td>76</td>
</tr>
<tr>
<td>IT Consulting &amp; Services</td>
<td>296</td>
<td>166</td>
</tr>
<tr>
<td>Internet Software</td>
<td>269</td>
<td>124</td>
</tr>
<tr>
<td>Semiconductors</td>
<td>306</td>
<td>210</td>
</tr>
<tr>
<td>Telecommunication Equipment</td>
<td>160</td>
<td>131</td>
</tr>
<tr>
<td>Telecommunication Services</td>
<td>164</td>
<td>113</td>
</tr>
<tr>
<td>Wireless</td>
<td>83</td>
<td>70</td>
</tr>
<tr>
<td>Other Sectors</td>
<td>542</td>
<td></td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>1,432</strong></td>
<td><strong>1,432</strong></td>
</tr>
</tbody>
</table>

Note: Other sectors include Software, Computers & Peripherals, and Healthcare Equipment, etc.

### Figure 1. The Number of Mergers by Year

Note: Author's Calculation based on merger samples in this paper.
We acquire the data of U.S. ICT firms’ patents from the United States Patent and Trademark Office (USPTO). Many authors use firms’ number of patents in their analysis of innovation outcomes (Hausman, Hall, and Griliches, 1984; Fleming, 2001; Benner and Waldfogel, 2008). The number of patents applied by acquirers and target firms before their merger is used as a possible determinant of merger value creation through the channel of innovation outputs. Moreover, we take merged firms’ patent counts during post-merger period as a measure of innovation outcomes after the merger.

Figure 2. Share of Patents in ICT Technologies during 1987-2018

Note: Author's Calculation based on patent samples in this paper.

1 http://www.patentsview.org/download/.
Figure 2 shows the share of patents in ICT industries from 1987 to 2018. As we expected, the portion of high technologies related to the fourth industrial revolution has been growing in recent decades such as static information storage and retrieval and pulse & digital communications. Since those technologies are relatively new compared to the existing IT technologies like semiconductor device manufacturing, firms dealing with the former are more likely to find merger partners with broadly similar technologies as well as diverse technological capacity. This technological trend suggests the importance of technological characteristics of potential merging firms as sources of realizing expected merger synergies.

Accordingly, there are two key explanatory variables used in this analysis of merger partner selection. The one is a measure of technology similarities between merging firms. Previous literature has employed technological similarities between merging partners as the one of critical factors affecting post-merger innovation (Ahuja & Katila, 2001; Cassiman et al., 2005; Makri, Hitt, Lane, 2010). Those studies conclude that technology similarity between firms has negative impacts on innovation after merger, especially for horizontal merger deals. However, we provide evidences of positive effects of technological similarity between merger partners on both merger value creation and post-merger innovation outputs.

In this paper, we define the measure of technological similarity of firms as a correlation between two firms’ vectors of patent class distribution. Thus, we calculate the similarity between technologies of firms $a$ and $t$ as follows:

$$CR_{a,t} = corr(F_a, F_t),$$

where $F_a$ ($F_t$) indicates the firm $a$’s ($t$’s) vector of patent shares in 557 patent technology classes categorized by the USPTO.

The other independent variable is a measure of technological diversity of an individual firm. Many researchers exploring drivers of firms’ innovation performance have paid attention to technological diversity (Garcia-Vega, 2006; Wang et al., 2016). Those authors find that technology diversity can improve firms’ innovative activity such as R&D investment or the number of patents. In this paper, we measure the technological diversity of a firm using both a Herfindahl type index and the firm’s patent shares in the 557 patent classes. The formula for the measure
of the firm $i$'s technology diversity is

$$TD_i = \left(1 - \sum_{c=1}^{557} F_{i,c}^2 \right) \left( \frac{N_i}{N_i - 1} \right),$$

where $N_i$ represents the number of the firm $i$'s patents granted during 3 years before the merger and $F_{i,c}$ indicates the firm $i$'s share of patents belonging to technological class $c$ over total number of its patents. The following table shows summary statistics of sample firms analyzed.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Number of Observations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Acquirer's number of patents</td>
<td>2.66</td>
<td>2.78</td>
<td>1,432</td>
</tr>
<tr>
<td>Target's number of patents</td>
<td>1.07</td>
<td>1.6</td>
<td>1,432</td>
</tr>
<tr>
<td>Deal size</td>
<td>4.98</td>
<td>1.77</td>
<td>1,432</td>
</tr>
<tr>
<td>Correlation between two firms' technologies</td>
<td>0.11</td>
<td>0.24</td>
<td>1,432</td>
</tr>
<tr>
<td>Interaction between two firms’ diversities of technologies</td>
<td>0.15</td>
<td>0.3</td>
<td>1,432</td>
</tr>
</tbody>
</table>

Note: Acquirer's and Target's number of patents, and Deal size are logged variables.

Acquirers’ number of patents is more than targets’ in our sample. This may be due to size effects in ICT industries in that large ICT firms focus on patenting activity based on their technological capacities.

2. Estimation Methodology

We use the method of maximum score estimation (MSE) to identify match-specific characteristics that allow merging firms to maximize their expected merger values. The principle of this estimation method is to maximize the number of satisfying inequalities, (6), at the stable matching equilibrium. To this end, we need to define a merger value function as follows:
$V(a, t) = \beta_1 CR_{a,t} + \beta_2 CR_{a,t}^2 + \beta_3 (TD_a \times TD_t) + \beta_4 SameIndustry_{a,t} + \beta_5 (Patents_a \times Patents_t), \quad (9)$

where $SameIndustry_{a,t}$ indicates a dummy variable when two merging firms belong to the identical industry, and $Patents_a (Patents_t)$ represents the number of acquirers’ (targets’) patents before their merger.

We first indicate a gross merger value function as $G(a,t) = V(a,t) + \varepsilon(a,t)$. Since we define the merger value function in (9), $V(a,t)$ represents observable parts in the gross merger values and $\varepsilon(a,t)$ corresponds to unobservable match-specific errors. For two actual merger matches, $(a,t)$, $(\hat{a}, \hat{t}) \in \mu$, we also define the following function of merger values from observed matches and counterfactual pairs constructed by exchanging their merger partners:

$$d(\beta) = V(a, t|\beta) + V(\hat{a}, \hat{t}|\beta) - V(a, \hat{t}|\beta) - V(\hat{a}, t|\beta), \quad (10)$$

where $\beta$ indicates a vector of estimated parameters showing marginal effects of explanatory variables on expected merger values in (9). The function $d(\beta)$ is derived from the inequality condition of stable matching equilibrium, (6). In other words, $d(\beta)$ is greater than 0 at the stable equilibrium. As we mentioned above, the maximum score estimation provides parameter estimates to maximize the number of satisfying inequalities for the equilibrium. Thus, an objective function for MSE is

$$D(\beta) = \sum_{m=1}^{2^9} \left\{ \sum_{(a,t) \in \mu \epsilon m} 1[d(\beta) \geq 0] \right\}, \quad (11)$$

over the parameter space at the stable matching equilibrium. A necessary condition to estimate the vector of parameters in the merger value function is the following rank order condition suggested in Fox (2010):

$$d(\beta) \geq 0 \text{ iff } P(\langle a,t \rangle, \langle \hat{a}, \hat{t} \rangle \in \rho) \geq P(\langle a, \hat{t} \rangle, \langle \hat{a}, t \rangle \in \rho).$$

That is, observing actual merger matches with a higher probability than counterfactual merger pairs implies that the sum of values from two observed mergers is greater than total merger values anticipated from two counterfactual merger deals, and vice versa.
IV. Empirical Results

1. Determinants of Merger Partner Selection

We first discuss about determinants of merger partner selection. Here, we normalize a parameter estimate of interaction terms between acquirers’ and targets’ number of patents before their merger to 1. The rationale for this normalization is that previous literature supports positive impacts of patents granted to individual merging firms on expected merger values. Since we use the normalized coefficient for the interaction between merging firms’ patent counts, we interpret other estimated coefficients as an increase of merger values relative to a rise in merger values in response to the interaction of patent counts.

<table>
<thead>
<tr>
<th>Table 3. Merger Value Estimation</th>
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<tbody>
<tr>
<td>(1)</td>
</tr>
<tr>
<td>$CR_{a,t}$</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>$CR_{a,t}^2$</td>
</tr>
<tr>
<td>$TD_a \times TD_t$</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>SameIndustry$_{a,t}$</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Patents$_a \times$ Patents$_t$</td>
</tr>
<tr>
<td>The Number of Inequalities</td>
</tr>
<tr>
<td>% of Inequalities Satisfied</td>
</tr>
<tr>
<td>The Number of Merger Markets</td>
</tr>
</tbody>
</table>

Note: 95% confidence intervals are shown in brackets. The estimates are significant at the 5% level when the confidence interval does not contain 0. Merger market is defined by merger transaction year.
Table 3 shows maximum score estimation results of our benchmark model. According to Column (4) in the table, merger values increase with the measure of technology similarity between merging firms, $CR_{\alpha,t}$. This implies that a potential merging firm try to find its deal partner with similar technologies. However, the estimate for a quadratic term of technological similarity has a negative sign, meaning that a marginal effect of technology similarity between merger partners on merger values decreases. Thus, we suggest that two merging firms with quite similar technologies do not create merger synergies, whereas technology similarity between merger partners generally increases merger values. Moreover, an interaction term between two firms' measures of technology diversities has positive effects on expected merger values. Accordingly, we conclude that a potential merging firm tends to search its merger partner with diverse technologies for the purpose of maximizing their merger synergies. We explain this result by employing the absorptive capacity hypothesis suggested in Cohen and Levinthal (1990). According to the hypothesis, when two firms with diverse technologies combine with each other, they solve old problems that can be addressed via new technological approaches. In addition, if two firms operate in the same industry, their merger values will increase.

2. Model Goodness-of-Fit

<table>
<thead>
<tr>
<th>Sample Period</th>
<th>Number of Mergers</th>
<th>Predicted Match for Benchmark Model</th>
<th>Prediction Rate (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1990-1999</td>
<td>439</td>
<td>27</td>
<td>6.2</td>
</tr>
<tr>
<td>2000-2009</td>
<td>717</td>
<td>35</td>
<td>4.9</td>
</tr>
<tr>
<td>2010-2018</td>
<td>276</td>
<td>30</td>
<td>10.9</td>
</tr>
<tr>
<td>Total</td>
<td>1,432</td>
<td>92</td>
<td>6.4</td>
</tr>
</tbody>
</table>

Note: Predicted Match for Benchmark Model represents the number of observed matches consistent with equilibrium matches driven by the match values computed using estimates in Table 3.
Table 4 indicates a predictive power of our two-sided matching model. Previous studies using the two-sided matching model employ a model prediction rate as a measure of model fitness (Akkus, Cookson, and Hortacsu, 2015). The procedure of computing our model prediction rate is as follows. First, we calculate merger values derived from the maximum score estimation. Then, we compare actual and counterfactual merger matches within a same merger market based on their estimated merger values. Employing a deferred acceptance algorithm, we can find merger matches survived in the stable matching equilibrium. After we compare observed merger matches and stable equilibrium matches, we can compute the prediction rate of our two-sided matching model for observed merger matches. According to Table 4, our model prediction rate is 6.4%, indicating 92 actual merger matches predicted by the model among total 1,432 observed merger matches.

Another approach to test the goodness of model fit is using the prediction rate of counterfactual model. In Table 5, we turn off the parameter estimates for measures of technological similarity as well as the interaction term between merging firms’ technology diversities. The implications of using counterfactual models are two-folds. First, we can evaluate the importance of key explanatory variables in merger partner selection by assuming no effect of those factors on merger value creation. Second, if the prediction rate of counterfactual model is lower than the

<table>
<thead>
<tr>
<th>Sample Period</th>
<th>Number of Mergers</th>
<th>Predicted Match for Counterfactual Model ($β_{CR,α} = 0$)</th>
<th>Prediction Rate (%)</th>
<th>Predicted Match for Counterfactual Model ($β_{TD×TD,τ} = 0$)</th>
<th>Prediction Rate (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1990-1999</td>
<td>439</td>
<td>24</td>
<td>5.5</td>
<td>29</td>
<td>6.6</td>
</tr>
<tr>
<td>2000-2009</td>
<td>717</td>
<td>32</td>
<td>4.5</td>
<td>30</td>
<td>4.2</td>
</tr>
<tr>
<td>2010-2018</td>
<td>276</td>
<td>25</td>
<td>9.1</td>
<td>28</td>
<td>10.1</td>
</tr>
<tr>
<td>Total</td>
<td>1,432</td>
<td>81</td>
<td>5.7</td>
<td>87</td>
<td>6.1</td>
</tr>
</tbody>
</table>

Note: Predicted Match for Counterfactual Model ($β_{CR,α} = 0$) represents the number of observed matches consistent with equilibrium matches driven by the match values computed using estimates in Table 3 when assuming the estimate for $CR,α$ equal to 0. Predicted Match for Counterfactual Model ($β_{TD×TD,τ} = 0$) indicates the number of observed matches consistent with equilibrium matches driven by the match values computed using estimates in Table 3 when setting the estimate for $TD,α × TD,τ$ equal to 0.
rate of benchmark model, then it will imply that the latter better explains the mechanism of merging partner choice than the former.

Table 5 suggests that our benchmark model fits better than other counterfactual models. For example, if we assume no effects of technological similarity on merger value creation, the model prediction rate will decrease from 6.4% of the benchmark model to 5.7%. This also implies that technological similarity between merging firms is an important factor in terms of merger partner selection. Moreover, if we turn off the estimated coefficient for the interaction between firms’ technology diversities, the prediction rate of the counterfactual model will drop by 0.3% points (6.4% → 6.1%). Although the magnitude of decrease in the model prediction rate is smaller than the first counterfactual model, we still interpret this result as the evidence of importance of firms’ technology diversities in merger partner choice.

3. The Impacts of Technology Similarity and Diversity on Post-Merger Innovation

In previous sections, we identify the key drivers of merger partner selection, both technological similarity and diversity, leading to the increase in merger values. The next step is to investigate post-merger innovation outcomes either when firms with similar technologies merge with each other or when firms with diverse technologies combine with each other. If those innovation outputs after merger of two firms with similar technologies and technological diversities improve, then we can interpret that expected merger values are realized through the channel of post-merger innovation outputs.

Here, we need to consider an endogeneity of estimated merger values to post-merger innovation outcomes, the number of patents after merger. In other words, merged firms with more patents are more likely to be regarded as combined entities with higher expected merger values. Thus, if we simply regress those firms’ patent counts on merger values estimated from the two-sided matching model, then we will overestimate innovation effects due to merger value creation.
In order to avoid this endogeneity problem in the estimation of post-merger innovation outcomes, we employ 2SLS estimation in this paper. We use preference rankings of individual matches as an instrumental variable (IV). Preference rankings among actual and counterfactual merger matches are determined based on merger values derived from the maximum score estimation. The rationale for using this IV is that those preference rankings are correlated with estimated merger values, while they are not directly correlated with combined firms’ patent counts after merger. This is because preference rankings are not a function of merger values from only observed matches but the function of all the values of matches including counterfactual merger transactions. That is, preference rankings containing all the observed and counterfactual merger matches can be free of selection bias. Specifically, the correlation between preference rankings and the number of post-merger patents is about 0.23.

### Table 6. Post-Merger Innovation Estimation (1st Stage)

<table>
<thead>
<tr>
<th>Dependent Variable: Estimated Merger Values</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Preference Rankings</td>
<td>0.014***</td>
</tr>
<tr>
<td></td>
<td>(0.0009)</td>
</tr>
<tr>
<td>The Number of Observations</td>
<td>1,432</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.127</td>
</tr>
</tbody>
</table>

Note: Robust standard errors are in parentheses.

According to Table 6, preference rankings among merger matches have a positive correlation with expected merger values. That is, if there is one unit increase in preference rankings, merger values will rise by 1.4%. This is because estimated merger values are derived from technological similarity between firms and technology diversity of individual firms which determine preference rankings of merger pairs based on merger synergies in ICT industries. Thus, obtaining residuals of merger values excluding the impacts of preference rankings will allow us to use them in identifying the effects of merger values on innovation outcomes during the post-merger period.
### Table 7. Post-Merger Innovation Estimation (2nd Stage)

<table>
<thead>
<tr>
<th>Dependent Variable: The Number of Patents during Post-Merger Period</th>
<th>OLS</th>
<th>2SLS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Merger Value</td>
<td>0.425***</td>
<td>0.63**</td>
</tr>
<tr>
<td></td>
<td>(0.035)</td>
<td>(0.182)</td>
</tr>
<tr>
<td>Year Dummy Included</td>
<td>Included</td>
<td>Included</td>
</tr>
<tr>
<td>The Number of Observations</td>
<td>1,432</td>
<td>1,432</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.216</td>
<td>0.139</td>
</tr>
</tbody>
</table>

Note: Robust standard errors are in parentheses. Merger Value represents predicted value from the 1st stage regression. When it comes to OLS estimation results, Merger Value is not the predicted value but the actual value from each observation.

As shown in Table 7, predicted merger values have positive impacts on post-merger innovation outcomes, patent counts, in both columns. According to OLS estimation result, the logarithm of post-merger patent counts are positively correlated with merger values. This result, however, is biased because there are unobserved factors affecting both merger values and the number of patents after merger. Thus, we use 2SLS estimation employing the predicted merger values estimated from the 1st stage regression with IV of preference rankings to control the endogeneity. As a result, 1% rise in merger values lead to increase in the logged number of post-merger patents by 0.63%. This means that if firms with similar technologies and technological diversities merge with each other, then their innovation performance after merger will be better. According to previous literature, higher technological similarity between merging firms may prevent combined entities from obtaining innovative outputs (Ahuja & Katila, 2001; Makri, Hitt, Lane, 2010). Interaction between merger partners' technology diversities, however, can complement each firm’s technological limitation resulted from similar technologies in terms of solving old problems.
V. Conclusion and Discussion

Throughout this paper, we examine the determinants of merger partner selection in U.S. ICT industries in terms of technological factors such as similarity between firms and diversity of individual firms. These factors are critical for potential merging firms belonging to ICT industries in that the pace of technological change has been rapid due to convergence of existing and new technologies in ICT sectors. We find that firms tend to choose their merger partners with similar technologies for the purpose of increasing expected merger values. Furthermore, if two firms with higher technological diversities merge with each other, their expected merger values will rise. Then, we use a regression analysis to identify a mechanism for those expected merger values connected to innovation outputs after merger. As a result, we conclude that anticipated merger values driven by two technological factors, similarity and diversity, are realized through the channel of post-merger innovation outcomes, the number of merged firms’ patents.

Our empirical results provide some implications about M&A policies of our competitive authority. First, since the pace of technological change in the era of the fourth industrial revolution is quite rapid, firms do not catch up with cutting-edge technologies and businesses only by investing in-house R&D. In this regard, allowing potential merging firms to combine with another companies operating broadly similar technologies make the merged firm achieve continuous innovation based on technology convergence. Moreover, technology redundancy resulted from similar technological resources can be removed when the authority encourage merger deals between firms which have individually diverse technology portfolios as we identify the positive impacts of technological diversity on merger value creation. Once the number of mergers between firms with technological similarity and diversity increases, post-merger innovation outcomes will be improved according to our results of innovation impacts due to expected merger values. Third, the existing M&A policies have only focused on the impacts of merger transactions on limitation to market competition or merger synergies resulted from cost savings. Our empirical results, however, suggest that technological similarity and diversity of
merging firms should be considered as one of important criteria in merger reviews, especially for high-tech firms in ICT sectors. Since innovation plays a significant role in firms’ growth in those industries, merger motivations of those firms are more likely to improve post-merger innovation outcomes based on combination of their technologies. Thus, our competition authority has to address technological features as well as financial factors in its examination of merger applications. Finally, our government have implemented various R&D policies in order to make our ICT firms competitive in Global innovation ecosystems. While a huge amount of R&D funds is invested into a variety of different firms’ R&D projects, there has been few consideration on relationship between technological diversity and R&D policies. Based on positive influences of diverse technologies on innovative outcomes, the government R&D support needs to encourage firms with technological diversities to combine with each other.

Note that there are some drawbacks in this paper. Similar to previous literature, this study concentrates on technological similarity within patent classes, which does not address merger deals driven by technology complementarity across patent classes or product complementarity. Representative examples of mergers implemented by firms with complementary technologies and products are merger deals between Wellfleet and Synoptics in 1994 and merger transaction between Amazon and Whole Foods in 2017, respectively. The first one is based on the combination of technologies about information transfer in a single network and in information control among diverse networks. The expected values of this complementary merger were an increase in processing capacity for various data such as video and voice. The next deal is summarized by product complementarity between on-line delivery platform and off-line selling system. Merger values anticipated from this transaction were based on Amazon’s additional profits driven by food retailing as well as the application of Amazon’s diverse distribution channels to operation of Whole Foods sectors. Once we consider technological similarity and complementarity between firms together in a model of merger, we can suggest which factor is more important in merger partner selection as well as post-merger innovation impacts.
References


Innovativeness, Quality, and Sales Performance: Evidence from the Console Video Game.”
본 연구는 1990년부터 2018년까지 미국의 정보통신기술(ICT) 산업에서 일어난 인수합병(M&A) 사례를 대상으로 합병기업간 기술적 유사성과 합병에 참여하는 개별기업의 기술적 다양성이 기업들의 합병상대를 결정하는 데 어떠한 영향을 미치는지를 분석하였다. 또한 기술적으로 유사한 기업들이 합병하거나 다양한 기술을 갖춘 기업들이 서로 합병했을 경우 합병 이후 통합된 기업의 혁신성과에 어떠한 영향이 발생하는지 조사하였다. 연구 결과, 해당 ICT 산업에서 기업간 기술 유사성과 개별기업의 기술 다양성은 합병상대 선택의 기준인 예상합병가치를 증가시키는 데 긍정적 영향이 있음을 밝혔다. 이는 서로 비슷한 기술을 보유한 기업이 합병하거나 다양한 기술 포트폴리오를 가진 기업들이 합병했을 때 특허 출원건수로 측정한 합병기업의 혁신성과도 개선됨을 보였다.

핵심용어: 인수합병, 기술 유사성, 기술 다양성, 혁신
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The Effects of Technological Similarity and Diversity on Merger and Innovation

Gu Sang Kang

We examine determinants of merger partner choice and impacts of those factors on post-merger innovation outcomes analyzing 1,432 merger deals in U.S. ICT industries. This paper suggests that technological similarity between merging firms increases merger values, meaning the importance of similar technologies between firms in their merger partner selection. Moreover, we find that technological diversity of an individual firm has positive effects on merger value creation. Thus, firms are more likely to choose their merger partners with diverse technologies for the purpose of maximizing their expected merger values. When it comes to post-merger innovation performances, estimated merger values increase the number of merged firms' patents after merger, implying that expected merger values are realized through the channel of post-merger innovation outputs.