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Do Firms Really Need to Collaborate with Universities? A Second Thought on Innovation of Firms' Management

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Abstract: Previous studies have demonstrated that the university–industry collaboration (UIC) can be beneficial not only for firms engaged in such a relationship, but also for the efficient transfer of innovative theories into practice and products. In the present study, general linear models (GLMs) and Tukey's honestly significant difference (HSD) tests are used to evaluate the impacts of firms' research and development (R&D) policies regarding the UIC on firms' performance. Further tests are conducted for subgroups of firms segmented by their industries (A), collaboration types (B), and their interactions (A and B). The results indicate that while the UIC can enhance firms' performance in general, its impacts across industries, collaboration types, and interactions are not consistent. The magnitudes of the UIC effects vary significantly across different combinations of industries, co-innovation types, and interactions. Furthermore, contrary to the traditional view of "the more the merrier" when it comes to the UIC, this study provides the evidence that some firms would be better off if their management voted against it. Thus, the results presented in this paper are useful for researchers, government officials, industrialists, and firm managers.

Keywords: R&D policies; University–industry collaboration; Performance evaluation; industries; collaboration types

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1 Introduction

The *university–industry collaboration (UIC)* in research and development (R&D) practices is often associated with positive impacts on the performance of enterprises. First, universities, as educational institutions, play an important role in transferring human resources and cumulated knowledge to enterprises (Amorós et al. 2019; Chen 2014). Second, the UIC contributes to the collective intelligence that stimulates encouraging innovation in business operations, which, in turn, fuels further cooperative behaviors (Schuler et al. 2018; Zhang et al. 2020). This phenomenon is particularly true for small- and medium-sized enterprises, especially in manufacturing sectors (Peña-Vinces et al. 2017; Švarc & Dabić 2019).

As indicated by Bellini et al. (2019), Sjoo & Hellstrom (2019), and Silva et al. (2018), the current studies on the UIC have generated profound results, including principal motivations for the UIC, collaboration outcomes for different types of organizations, and drivers for establishing research centers. According to Bellini et al. (2019), the performance of firms engaged in collaborative operations with universities is affected by a number of factors. Among them, the collaboration type is one of the most important factors. The interactive relationship between the collaboration type and the industrial type requires further investigation to challenge the traditional views on the UIC in R&D practices.

In this study, general linear models (GLMs) and Tukey's honestly significant difference (HSD) tests are used to study the cross-sectional effects of collaboration types and industrial sectors on the performance of firms in the UIC operations. Using the return on equity (ROE) matric as a proxy for firms' performance, hypotheses tests on whether the mean of ROEs for the tested group of firms is significantly higher (lower) than that of the controlled group of firms is performed on four levels: aggregated, collaboration type, industrial sector, and interaction between the collaboration type and the industrial sector. The results of the tests suggest that while the UIC generally enhances the performances of firms on the aggregated level, its impacts across industrial sectors, collaboration types, and interactions are not consistent. In some cases of the interaction between collaboration types and industrial sectors, firms engaging in UICs significantly under-perform compared to firms not involved in UICs.

The innovation of the research presented in this paper lies in the following three aspects. First, UIC types are explicitly classified enabling a detail analysis of the technology transfer process. This procedure extends the method of Švarc & Dabić (2019). Second, in contrast to the traditional positive view on the UIC (Skute et al. 2019), this study offers an empirical evidence that some UIC types should be avoided in certain industries to ensure a good performance of firms. Finally, firms can use the outcomes of this study as guidelines when making strategical decisions for R&D policies and technology transfer strategies. Overall, this study extends the work of Zhang et al. (2020) by providing a more practical guidance map for firms thinking of engaging in UICs.

The rest of this paper is organized as follows. Section 2 presents an overview of related studies. Section 3 introduces the proposed theoretical models, while Section 4 presents an empirical analysis and its results. Section 5 concludes the paper.

2 Related Work

According to Kobarg et al. (2018), the financial and operational performance of multinational companies is determined by their R&D and marketing capabilities. The direct correlation between R&D expenditures and corporate performance was confirmed by Wang and Zhao (2016) for China's heavy pollution industry. Gerbin & Drnovsek (2016) established that public funding is an important source of finance for R&D; firms typically perform better if they are funded. From the product point of view, the higher the proportion of a company's product technical content, the greater the impact of the UIC on the company performance.

Many university staff members acknowledge their active participation in the local and regional economic development and facilitation of academic research commercialization (Bellini et al. 2019; Sjoo & Hellstrom 2019; Silva et al. 2018). Evidence suggests that the UIC is widely practiced and focuses on the effects of university–industry links on innovation-specific variables such as patents and firm innovativeness (Guerrero et al. 2019). The promotion of the UIC among enterprises is mainly focused on case studies summarized by countries and collaboration types (Skute 2019). The collaboration type of UIC is usually measured by the closeness of collaboration relationship (Bellini et al. 2019; Skute 2019).

To get a cross-sectional view of the UIC in China, it can be divided into the following three types based on different standards: student academic background (under- or post-graduate), collaboration duration (whole process, anaphases collaboration, or internship), and collaboration tightness (loose, tight, or semi-tight). The collaboration type within an industry often defines whether the industry can be found at the top or bottom of the market ladder.

Many studies link the ownership with the R&D performance of firms (Silva et al. 2018). Wu & Ni (2016)define the following five types of the UIC: 1) universities and industries jointly co-initiated; 2) colleges and universities collaborate to provide scientific research and promote technological innovation; 3) enterprises training their technicians; 4) enterprises engaged in technical innovation; and 5) joint business ventures by universities and industries. In this study, the UIC types are classified according to the amount of funds a firm dedicates to its UIC in relation to the entire R&D budget of the firm. A detailed explanation of this classification method is provided in Section 3.

Furthermore, this study examines the impact of the industry type, collaboration type, and the relationship between the industry and collaboration types on the performance of firms engaged in UICs. This detailed analysis provides a good theoretical basis for researchers and firm management when making decisions regarding investments and R&D budgets. In particular, contrary to the traditional view on the UIC, this study demonstrates that some industries should not promote collaborations with universities due to limited gains such collaborations can provide.

3 Hypotheses and Statistics

In this study, we first test whether the collaborative behavior of universities and firms positively contributes to the performance of firms on the aggregated level. Second, we test the impact of the UIC by controlling the industrial sector and collaboration type variables to present refined results. Finally, we test the effects of the interaction between these variables to provide a practical guidance for firms in different industrial sectors on R&D strategies (collaboration types) to adopt when collaborating with universities. Section 3.1 provides the definition of the collaboration type, while Section 3.2 presents the hypotheses tested in this study on the aggregated, controlling variables, and interaction levels. Section 3.3 introduces the GLM procedure for testing the equality of the means for different groups and Tukey's HSD test for comparing the means between two groups.

3.1 Collaboration type definition

While several indirect approaches to collaboration type classification have been proposed in the literature, including geographic proximity (Ferreira et al. 2019), channels of collaboration (consultancy and contract research, joint research, or training; (D'Este and Patel 2007), and technological relatedness (Petruzzelli 2011), we propose a more direct method as follows. For each of the 3,207 companies publically listed on China's stock market, Hajmohammadi, Ibrahim, and Othman's (2012) algorithm is applied to search for public announcements made by the companies on their official websites regarding their involvement in UICs from 2010-2015. The algorithm is set to parse the following fields: project title, company name, university name, and investment amount involved. If one company has multiple projects with the same university, the amounts invested are cumulated into one figure. The annual financial reports followed the latest announcements for UICs are used, while all previous records are ignored. If a company has UICs with more than one university, all projects are treated as separate cases. We differentiate between different types of collaboration according to the following criteria. A company is classified as a Type 1 collaborator if its accumulated UIC investment higher than 50% of its total R&D expense of the following fiscal year. A company is classified as a Type 2 collaborator if its accumulated UIC investment is between 10%–50% of its total R&D expense. A company that invests above 0.01% but below 10% of its total R&D budget is considered to be a Type 3 collaborator.

3.2 Hypotheses

There following four hypotheses are tested in this study.

H1: the UIC has no impact on firms' performances at the aggregated level.

H2: the UIC has no impact on firms' performances at the collaboration type level.

H3: the UIC has no impact on firms' performances at the industrial sector level.

H4: the UIC has no impact on firms' performances at the interaction level.

If the null hypothesis is rejected for H1, firms with the UIC behavior generally out-perform those without it. For H2, we can identify the collaboration types that may enable companies to have comparative advantages in their R&D practices. H3 can reveal the industrial sector(s), for which the UIC can provide significantly positive impacts. Finally, H4 can inform R&D polices by suggesting the UIC types that should be implemented by each industrial sector (or abandoned altogether).

3.3 Statistics for comparing means

The GLM procedure is employed to test whether the means between two groups are the same, while Tukey's HSD test is used to determine which one of the means is larger. These two procedures are applied in pairs: the GML test is used to verify whether the performances of firms with UICs are significantly different from those of firms without UICs, while Tukey's test is used to demonstrate which firms perform better. The GLM and HSD tests are preferred because they enable the inclusion of vertically non-uniform mass flux distributions, clearly indicate the significance of certain preferences, and help finding important determinants.

Let $\tau_i, i=1,2$ be the means of two groups, $c_i\tau_i$ be the contract to test the equality $\sum c_i\tau_i \in \left(\sum c_i\bar{y}_i \pm t_{n-v,\alpha/2}\sqrt{msE\sum c_i^2/r_i}\right)$, and thus the null hypothesis be $H_0:\sum c_i\tau_i=0$. The null hypothesis that the means are equal would be rejected with confidence level α if

$$\left|\frac{\sum c_i\bar{y}_i}{\sqrt{msE\sum c_i^2/r_i}}\right| > t_{n-v,\alpha}=F_{1,n-v,\alpha}, \tag{1}$$

where r_i denotes the lengths for each group; msE is the mean square error estimated as $msE(\bar{x})=E(\bar{x}-x)^2$; $\bar{y}_i$ denote observations; and $t_{n-v,\alpha}$ is the two-tailed *t* distribution with parameters *n* (the total numbers of observations), *v* (the degree of freedom), and α (the confidence level). $F_{1,n-v,\alpha}$ is the *F* distribution. The Tukey's test for directional testing can be written as the one-tail test $H_0:\sum c_i\tau_i<0$. The null hypothesis would be rejected if

$$\frac{\sum c_i\bar{y}_i}{\sqrt{msE\sum c_i^2/r_i}} < -t_{n-v,\alpha/2}, \tag{2}$$

Note that the confidence level for the equality testing is α, while that for the directional testing is $\alpha/2$.

4 Empirical Analysis

For the empirical analysis, public announcements published on official websites of companies between 2010 and 2015 were mined using the algorithm suggested by Hajmohammadi et al. (2012). The immediate impact on the firms' ROEs can be observed by taking the average of the next three years' ROEs following the announcements as the performance measurement. Since the annual reports for 2018 and 2019 were not available at the time of writing this paper, the announcements posted in 2016 and 2017 were ignored. A total of 120,783 announcements were issued by 3,207 publically listed companies between 2010 and 2015, of which 17,052 legitimate announcements were deleted as duplicates or follow-ups. Firms' annual reports between2011 and 2017 were extracted from the database provided by Wind®, a commercial data vender granting universities full access to data for research purposes only. The GLM and HSD tests were implemented in SAS® on a 9.2-Windows 64-bit server. The results for *H1 – H4* are summarized and discussed in Sections 4.1 – 4.4, respectively.

4.1 H1 test results

H1 tests whether firms with UICs would perform differently from firms without UICs and establishes which firms would perform better. Tables 1 and 2 present the GLM and Tukey's test results for *H1*, respectively.

Table 1. Analysis of variance for hypothesis 1

Source	Sum of Squares	Mean Square	F-value	Pr > F
Model	86.23	2.77	8.53	0.0000
Error	80.11	5.66		
Total	32.98			
Contrast	Contrast SS	Mean Square	F-value	Pr > F
Coop	5.87	2.87	7.63	0.0000
Parameter	T for H0：Parameter = 0	Pr >∣T∣	Std. Error of Estimate	
Coop	17.05	0.0000	9. 93	

Table 2. Tukey's test for the Coop variable

	Coop Comparison	Simultaneous Lower Confidence Limit	Difference Between Means	Simultaneous Upper Confidence Limit	
2	-1	0.02	0.10	0.15	***

The results listed in Table 1 indicate that the mean of firms' performances with UICs is significantly different from that of firms' performances without UICs (F-value = 8.53 and P-value < 0.000 at the 95% confidence level; the *t*-value of the control variable (Coop) = 7.63 and P-value < 0.000). The Tukey's test results in Table 2 indicate that the difference between the means of the two groups (with and without UICs) is significantly larger than 0, which means that firms with UICs perform significantly better than firms without UICs. This proves that the UIC has positive impacts on firms' performances at the aggregated level.

4.2 H2 test results

Three collaboration types were considered according to Lyu (2019). In the GLM test, the order of testing was not taken into account and the expression of Type1 – Type 2 – Type 3 was used to perform the initial test. Tables 3 and 4 present the GLM and Tukey's test results for *H2*, respectively.

Table 3. Analysis of variance for hypothesis 2

Source	Sum of Squares	Mean Square	F-value	Pr > F
Model	56.30	6.77	5.32	0.0001
Error	60.12	5.62		
Total	28.56			
Contrast	Contrast SS	Mean Square	F-value	Pr > F
Type	7.45	3.70	5.32	0.0003

Parameter	T for H0: Parameter = 0	Pr >∣T∣	Std. Error of Estimate
Type	7.05	0.0000	5.66

Table 4. Tukey's test for the Type variable

	Coop Comparison	Simultaneous Lower Confidence Limit	Difference Between Means	Simultaneous Upper Confidence Limit	
2	-1	0.05	0.12	0.17	***
2	-3	0.03	0.09	0.13	***
1	-3	-0.07	0.05	0.09	

According to the results listed in Table 3, the performances of firms of the three collaboration types are significantly different from each other, with the model's F-value of 5.32, P-value less than 0.0003 at the 95% confidence level, and the *t*-value of the control variable Type of 7.05 and P-value less than 0.000. The results of the Tukey's test indicate that the performances of firms of collaboration Type 1 and Type 3 are significantly better than those of firms of collaboration Type 2, while there is no significant differences between the performances of firms of collaboration Type 1 and Type 3.

4.3 H3 testing results

There are 16 codes for industrial sectors in the Wind® database. Providing that several sectors have fewer than five firms with UICs and aiming to obtain meaningful results from the GLM and Tukey's tests, we combined industrial sectors so that each sector (except for the financial sector) had at least 20 firms with UICs. The resulting sector classification is presented in Table 5.

Table 5. Sector classification and the number of firms with UICs

Code	Sectors	Industrial Sectors Included	UIC Firms
1	Financial	Financial (Banking Included)	13
2	Mining	Mining	56
3	Infrastructures	Construction/Real Estate	31
4	Information	Computer/Electronics/Telecom	96
5	Sales	Wholesale/Retail	45
6	Logistic	Transportation/Logistic/Distribution	69
7	Machinery	Machinery/Equipment/Heavy	47
8	Healthcare	Healthcare/Medicine/Public Health/Education	63
9	Utilities	Utilities/Energy/Service	39

It can be noticed from Table 5 that there are only 13 firms with UICs in the financial sector, while there are almost 100 firms with UIC practices in the information sector. These two sectors were selected for the *H3* hypothesis testing. Tables 6 and 7 present the GLM and Tukey's test results for the financial sector, respectively.

Table 6. Analysis of variance for hypothesis 3

Source	Sum of Squares	Mean Square	F-value	Pr > F
Model	127.12	27.70	3.53	0.0785
Error	32.12	10.66		
Total	10.98			

Contrast	Contrast SS	Mean Square	F-value	Pr > F
Coop	12.23	12.23	2.56	0.0832

Parameter	T for H0: Parameter = 0	Pr > ∣T∣	Std. Error of Estimate
Coop	7.13	0.0537	3. 13

Table 7. Tukey's test for Financial vs. Coop

	Coop Comparison	Simultaneous Lower Confidence Limit	Difference Between Means	Simultaneous Upper Confidence Limit
2	-1	-0.10	0.02	0.05

According to the results listed in Table 6, the performances of firms with UICs in the financial sector are not significantly different from those of firms without UICs (the F-value and P-value for the model are 3.53 and 0.0785, respectively, which is confirmed by the t-value of 2.56 and P-value of 0.0832 for the variable Coop). The results of the Tukey's test indicate that the performances of firms with UICs are not significantly larger than those of firms without UICs. At the same time, the GLM and Tukey's tests show a different scenario for the information sector. Both tests indicate that the sector should advocate UIC behaviors (see Tables 8 and 9).

Table 8. Analysis of variance for hypothesis 3

Source	Sum of Squares	Mean Square	F-value	Pr > F
Model	26.21	6.02	6.11	0.0001
Error	12.12	3.66		
Total	10.38			

Contrast	Contrast SS	Mean Square	F-value	Pr > F
Coop	7.21	7.21	5.63	0.0002

Parameter	T for H0: Parameter = 0	Pr > ∣T∣	Std. Error of Estimate
Coop	5.22	0.0003	2. 13

Table 9. Tueky's test for the variable

	Coop Comparison	Simultaneous Lower Confidence Limit	Difference Between Means	Simultaneous Upper Confidence Limit	
2	-1	0.02	0.09	0.11	***

Table 10 presents the Tukey's test results for all industrial sectors. The sectors, where the performances of firms with UICs are significantly better than those without UICs at the 95% confidence level are indicated by '***'.

Table 10. Tukey's test results for all industrial sectors with UIC behaviors

Code	Sectors	Industrial Sectors	Tukey's Tests (Significant at the 95% level are indicated by '***')
1	Financial	Financial (Banking Included)	
2	Mining	Mining	***

3	Infrastructures	Construction/Real Estate	***
4	Information	Computer/Electronics/Telecom	***
5	Sales	Wholesale/Retail	
6	Logistic	Transportation/Logistic/Distribution	***
7	Machinery	Machinery/ Equipment/Heavy Industries	***
8	Healthcare	Healthcare/Medicine/Public Health/Education	***
9	Utilities	Utilities/Energy/Service	

The results in Table 10 indicate that six sectors would significantly benefit from UIC behaviors, including the mining, infrastructures, information, logistic, machinery, and healthcare sectors. At the same time, the financial, sales, and utilities sectors do not seem to be rewarded by engaging in UICs.

In more detail, the UIC is preferred in the mining industry, where corporate social responsibility is counted more than ever (Gerbin & Drnovsek 2016). Transforming and innovate, construction, and real estate industries frequently turn to UICs because such collaborations improve the performance of innovating firms, especially in the form of R&D investments (Guerrero et al. 2019; Hanel and St-Pierre 2006). In addition, collaborations favor both intended and unintended flows of knowledge and facilitate the learning processes between partners from different organizations (D'Este and Patel 2007). For the power electronic industry, UICs can strengthen research teams by fostering new contacts and research areas. Amorós et al. (2019) considered this industry as a model of successful UICs. The logistic industry also benefits from the cooperation with colleges. For the machinery industry, UICs by Canadian manufacturing firms are typical.. The innovation and invention are boosted by UICs in the medicine and healthcare industries (D'Este et al. 2013). The establishment of school–university partnerships and transformation of school and university cultures are an important part of the education renewal itself; thus, the education industry naturally benefits from UICs (Horne & Dutot 2017).

4.4 H4 test results

This section presents a further interaction analysis to study the cooperation effects of industrial sectors and UIC types. Only GLM testing was employed in this analysis to identify the most (least) favorable UIC type for each industrial sector. First, GLM testing was performed for each combination of the sector and UIC type (represented as Contrast in Table 11). Second, the results were sorted according to the P-values for each sector. The results of the most (least) preferred type for each sector are presented in Tables 12 and 13. In the Contrast column, the numbers are all 2-digit; the first digit refers to the industrial sector code and the second stands for the collaboration type. For instance, '12' stands for the financial sector with collaboration Type 2. The P-value of 0.0527 for Contrast '11-12' indicates that the mean of firms' ROEs (performances) in the financial sector with UIC collaboration Type 1 is significantly higher than (or perform better than) the mean of firms' ROEs in the financial sector with UIC collaboration Type 2. Given the P-value of 0.0319 for Contrast '12-13', it can be concluded that the most preferred UIC collaboration type is Type 2 and the least preferred type is Type 3.

Table 11. Interaction analysis of variance for hypothesis 4

Source	Sum of Squares	Mean Square	F-value	Pr > F
Model	21.16	4.30	9.32	0.0010
Error	15.33	0.36		
Total	24.03			
Source	Type I SS	Mean Square	F-value	Pr > F
Indus	21.72	19.01	6.12	0.0621
Type	20.51	15.10	18.52	0.0048
Indus*Type	9.14	9.13	3.56	0.0632

Contrast	Contrast SS	Mean Square	F-value	Pr > F
11-12	8.76	8.76	1.32	0.0527
12-13	7.21	7.21	1.54	0.0319
21-22	6.78	6.78	8.21	0.0013
22-23	5.32	5.32	9.21	0.0001
31-32	9.23	9.23	3.32	0.0620
32-33	8.34	8.34	8.19	0.0032
41-42	4.22	4.22	18.12	0.0000
42-43	5.21	5.21	2.22	0.0832
51-52	5.33	5.33	2.34	0.0421
52-53	6.21	6.21	5.23	0.0089
61-62	6.75	6.75	12.23	0.0001
62-63	6.89	6.89	7.23	0.0084
71-72	5.87	5.87	12.69	0.0001
72-73	5.69	5.69	5.67	0.0103
81-82	7.57	7.57	9.69	0.0530
82-83	5.69	5.69	5.69	0.0102
91-92	6.23	6.23	7.26	0.0085
92-93	5.21	5.21	3.24	0.0387

Table 12. The most preferred UIC types for each sector

Code	Sectors	Tukey's Tests (Significant at the 95% level are indicated by '***')	The Most Preferred UIC Type
1	Financial		Type 2
2	Mining	***	Type 1
3	Infrastructures	***	Type 2
4	Information	***	Type 1
5	Sales		Type 1
6	Logistic	***	Type 1
7	Machinery	***	Type 1
8	Healthcare	***	Type 2
9	Utilities		Type 1

Table 13 The least preferred UIC types for each sector

Code	Sectors	Tukey's Tests (Significant at the 95% level are indicated by '***')	The Least Preferred UIC Type
1	Financial		Type 3
2	Mining	***	Type 3
3	Infrastructures	***	Type 1
4	Information	***	Type 3
5	Sales		Type 3
6	Logistic	***	Type 3
7	Machinery	***	Type 3
8	Healthcare	***	Type 3
9	Utilities		Type 3

The results listed in Tables 12 and 13 reveal some noteworthy phenomena. According to Table 12, Type 3 is not preferred by any industrial sector, not even by sectors, where the UIC effects are not significant. The results in Table 13 also confirm that collaboration Type 3 is the least preferred by all sectors, except the infrastructures sector. This outcome suggests that UICs should be conducted with caution. On the one hand, investing a fair percentage of the entire R&D budget into the UIC practice may enable the UIC to make a real difference (Link & Scott 2019). On the other hand, insufficient funds for UICs are ineffective in improving firms' performances and can damage the entire firms' ROEs. Firms should be very careful in making budgeting decisions related to their R&D policies.

5 Conclusion

This paper investigated the impact of the UIC on the performance of firms, as indicated by their ROEs, for different collaboration types and industrial sectors. Using the GLM and Tukey's test approaches, the study found that while firms can benefit from the UIC in general, some industrial sectors (e.g., the financial, sales, and utilities sectors) might be better off without engaging in UICs. In any case, it should be left to the managerial discretion whether and which collaboration types to participate. The empirical results of this study complement the study of Kobarg et al. (2018), which provides evidences for UIC benefits, and serve as a guide for making R&D decisions (Kirby & Hadidi 2019).

In the future, we plan to address the following limitations of this study. First, the definition of collaboration types can be refined to reflect the real-world business operations. Second, the essence of the UIC should be considered to distinguish between long- and short-term R&D projects. In this study, we considered only the average of three years' ROEs following the firms' announcements to measure the performance of firms. Finally, more sophisticated statistical methods can be employed to consider high moments in data such as the variance, skewness, and kurtosis. Nevertheless, the results presented in this paper can be useful for researchers, government officials, industrialists, and firm managers.

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