informs
https://pubsonline.informs.org/journal/mnsc

MANAGEMENT SCIENCE
Articles in Advance, pp. 1–25
ISSN 0025-1909 (print), ISSN 1526-5501 (online)

Industry-University Collaboration and Commercializing Chinese Corporate Innovation

David H. Hsu,[a,*] Po-Hsuan Hsu,[b] Kaiguo Zhou,[c] Tong Zhou[d,e]

[a] Wharton School, University of Pennsylvania, Philadelphia, Pennsylvania 19104; [b] College of Technology Management, National Tsing Hua University, Hsinchu City 300044, Taiwan; [c] School of Finance, Institute of Beijing Digital Economy and Development, Capital University of Economics and Business, Beijing 100070, China; [d] School of Entrepreneurship and Management, ShanghaiTech University, Shanghai 201210, China; [e] College of Business, Southern University of Science and Technology, Shenzhen 518055, China

*Corresponding author

Contact: dhsu@wharton.upenn.edu, https://orcid.org/0000-0001-8228-5449 (DHH); pohsuan.hsu@gmail.com, https://orcid.org/0000-0001-6234-8289 (P-HH); zhoukg@cueb.edu.cn, https://orcid.org/0000-0003-2197-3090 (KZ); zhoutong@shanghaitech.edu.cn, https://orcid.org/0000-0001-7993-3003 (TZ)

Received: March 13, 2022
Revised: April 14, 2023; April 11, 2024
Accepted: April 26, 2024
Published Online in Articles in Advance: [redacted], 2024

https://doi.org/10.1287/mnsc.2022.00788

Abstract. We construct a comprehensive data set of medium- and large-sized industrial firms and research universities in China and examine how Chinese firms' commercialization of their technologies is related to their experience in industry-university collaboration (IUC). We propose that firms' IUC experience constitutes an inimitable complementary asset that facilitates their technology commercialization. Our empirical analyses show that firms generate more new product sales and produce more product-oriented patents when they have more patents that are coassigned to universities or when they have more academic publications coauthored with university staff in the past. Such a relation is strengthened when firms have higher absorptive capacity, when firms are in industries that depend more on basic science, and when firms are located closer to their collaborating universities. Additional tests point out four channels through which firms' IUC experience benefits their technology commercialization: knowledge acquisition, talent recruiting, direct technology transfers, and technological complementarity.

History: Accepted by Sridhar Tayur, entrepreneurship and innovation.

Funding: D. H. Hsu acknowledges research support from the Mack Institute for Innovation Management at the University of Pennsylvania. P.-H. Hsu acknowledges the Yushan Fellow Program by the Ministry of Education and National Science and Technology Council, Taiwan [MOE-108-YSFMS-0004-012-P1, NSTC 113-2410-H-007-008-MY3, MOST 109-2628-H-007-001-MY4] and the E.SUN Academic Award. K. Zhou acknowledges research support from the Major Project of the National Social Science Fund of China [Grant 20&ZD103], the National Natural Science Foundation of China [Grant 71991474] and the 111 Project of China [Grant D23001]. T. Zhou acknowledges research support from the National Natural Science Foundation of China [Grant 72003206].

Supplemental Material: The online appendix and data files are available at https://doi.org/10.1287/mnsc.2022.00788.

Keywords: industry-university collaboration • corporate innovation • technology commercialization • technology transfer • complementarity

1. Introduction

Although firms conduct basic research and create new technologies (Simeth and Cincera 2016; Arora et al. 2018, 2021a), their main task and contributions to society are to *commercialize* internally developed or externally acquired technologies. A key question on firms' commercialization performance, as posited by Teece (1986, 2006), is why most firms that succeed in bringing innovative products and processes to market later fail to capture value from their innovation. The literature has discussed how firm-level commercialization abilities can be related to various complementary resources and institutional environments.[1] Among these factors, industry-university collaboration (IUC) has been an important research domain given the pivotal role of universities in facilitating firms' development of new products/processes (Mansfield 1991, 1998; Klevorick et al. 1995; Cohen et al. 2002). In fact, Acs et al. (1992) showed that university spillovers influence commercialized innovations more than patented inventions.

However, whether IUC also contributes to the commercialization performance of corporations in emerging economies (which tend to lack innovation capability, infrastructure, and talent) is underexplored in the literature. In this study, we attempt to fill this gap from both theoretical and empirical perspectives.

From the theoretical perspective, universities are treated as an external supporting institution in Teece's profiting-from-innovation (PFI) framework, and they are assumed to be accessible to *all* firms (Teece 1986, 2006). However, there are substantial barriers and dissimilarities between universities and the private sector (Siegel et al. 2003, Bruneel et al. 2010, Perkmann et al. 2013). We propose that firms with past success in IUC activities have advantages in benefiting from universities' spillovers that facilitate their own technology commercialization.[2] Such IUC success reflects firms' experience in overcoming difficulties and reducing communication costs (Cockburn and Henderson 1998), acquiring needed tacit information (Zucker et al. 1998b), and building social connection and trust (Bruneel et al. 2010) in collaboration with universities. Hall et al. (2003) also observe that prior experience working with a university significantly reduces the difficulty of acquiring and assimilating basic knowledge in new projects. Thus, IUC experience (i.e., *successful* IUC records) constitutes an inimitable complementary asset as it cannot be easily purchased via the market (Agrawal 2001, p. 299). We thus hypothesize that Chinese firms succeeding in IUC later perform better in technology commercialization (subject to contingencies, including absorptive capacity, science dependence, and geographic proximity).

From the empirical perspective, we note that most prior studies rely on surveys to assess IUC activities and performance and that they focus on developed countries (see our summary of the literature in Online Appendix Table OA.1). Our approach leverages the Chinese context because of data availability via a comprehensive *census* of new product sales in that country's industrial firms (the National Bureau of Statistics (NBS) firm-level data set (hereafter, "NBS data"), which includes over 0.5 million unique industrial firms from 1998 to 2013). We also collect these firms' and Chinese universities' patent and publication records, which enable us to implement a large-scale investigation. A firm's IUC experience is measured using its joint patents and joint publications measured by patents coassigned to universities and publications with coauthors affiliated with universities, respectively.[3]

Our empirical evidence suggests that firms with more IUC experience report more new product sales and improve product-oriented patents in the next year. Such a relation is strengthened when firms have higher absorptive capacity, when firms are in industries that depend more on basic science, and when firms are located closer to their collaborating universities; all of these three contingencies are motivated by prior literature. We also implement additional tests for possible channels through which firms' IUC experience benefits their technology commercialization. We show that firms with IUC experience are more likely to access the knowledge and human capital of universities, which substantiates how IUC experience benefits firms in commercializing technologies (Audretsch and Stephan 1996). In addition, firms with IUC experience are also more likely to become new assignees of university patents, confirming direct technology transfers. Moreover, consistent with Teece's proposition about IUC as a recombination process of complementary assets, we find that the IUC-technology commercialization relation is more pronounced when the technology bases of firms and their collaborating universities are more complementary.

This study differs from prior studies and adds to the innovation literature in the following ways. First, we expand Teece's PFI framework by proposing a new inimitable complementary asset—firms' IUC experience—which was mentioned but not developed in Feldman (1994). Our extension connects the PFI framework to (i) the literature on IUC that emphasizes why firms and universities fail in commercializing technologies and (ii) the literature on spillovers that analyzes why some firms benefit more than others from universities and research institutes. We further propose three contingencies that moderate the role of IUC experience: absorptive capacity, science dependence, and geographic proximity.

Second, our research echoes the call of Agrawal (2001) to collect more IUC data across countries of different institutions and systems as the Chinese economy started with weak intellectual property protection and firms with low research and development (R&D) capacity but then escalated both investment in higher education and government guidance over the past three decades (Liu and White 2001, Appelbaum et al. 2016). Of course, the Chinese context is interesting and important in its own right because of the recent surge in science and technology alongside the country's industrial development. Our unique data set, covering about 93,000 medium- and large-sized industrial firms (and their over 2.7 million patents and 0.7 million publications) and 153 universities in China (and their 0.6 million patents and 11 million affiliated publications), enables us to implement a comprehensive analysis of corporate-level IUC in China.

Third, we provide large-scale evidence for the externalities of public research/universities in the Chinese context. Abundant studies have examined how universities shape local innovation and entrepreneurship through the lens of spillovers in the United States (Jaffe 1989b, Audretsch and Stephan 1996), but much less effort has been devoted to Chinese universities' externalities. Moreover, most prior studies in this direction are based on specific industries, surveys, or small-scale event studies (see Online Appendix Table OA.1). Our collection of the patent (assignment and reassignment), publication, and inventor records of Chinese firms and universities enables us to explore the influence of universities through various channels other than patents that have been well documented in prior Chinese IUC research. Our investigation thus offers new evidence to the ongoing debate on whether IUC has succeeded in China given various promotion policies in the past (Chen and Kenney 2007, Wu and Zhou 2012, Chen et al. 2016). Given the prominent role that universities play in science and technology infrastructure (e.g., Furman et al. 2002), this study offers insights to policymakers, university administrations, and corporate managers.

The rest of our paper is organized as follows. In Section 2, we review the literature to develop our hypotheses. In Section 3, we describe our data, and we introduce the empirical measures of industry-university collaboration, technology commercialization, and innovation outputs. In Section 4, we present the baseline results and their robustness. In Section 5, we discuss the three theory-motivated contingency tests. In Section 6, we discuss four channels that could potentially explain the IUC-technology commercialization relation. In Section 7, we perform difference-in-differences (DiD) analyses based on two events that enhance local firms' IUC experience. We conclude the paper in Section 8. The Online Appendix contains an expanded literature review, detailed descriptions of the data, and empirical robustness checks.

2. Literature Review and Theoretical Development

We focus on the literature for our main hypotheses in this section, whereas a more complete review of the literature on university research and technology transfers is provided in Section A and Table OA.1 in the Online Appendix.

2.1. IUC Experience and Technology Commercialization

The PFI framework of Teece (1986, 2006) is perhaps the most well-known model in analyzing how to commercialize innovation, which offers researchers a comprehensive structure to analyze the determinants of technology commercialization (Teece 2018). Its key concept is that successful innovation does not necessarily lead to successful commercialization as the latter requires combining complementary assets needed to convert innovation into sales and profits. Among the factors laid out in the framework, complementary assets that are less imitable or inimitable play an important role in shaping how long and how much an innovator can appropriate his or her innovation and maintain competitive advantage relative to imitators.

In the original version of the PFI framework, universities are treated as an external supporting institution in the framework and are not the focus of analyses. The implicit assumption is that university knowledge is accessible to *all* firms, although we know from the literature that there are barriers and dissimilarities between universities and the private sector (Bruneel et al. 2010, Perkmann et al. 2013). Although university knowledge is a public good easily transferred via publications, utilizing such knowledge for private benefit requires access to additional information about how it may be applied, which cannot be easily accessed by all firms (Feldman 1994, Zucker and Darby 1996). This "natural excludability" arises from the complexity or tacitness of the information required to practice the innovation (Zucker et al. 1998b). In addition, academic researchers' goals, incentives, and cultures are substantially different from those of entrepreneurs and corporate employees (Siegel et al. 2003, Perkmann and Salter 2012, Perkmann et al. 2013), which results in principal-agent issues for both sides (Poyago-Theotoky et al. 2002). Moreover, as mutual understanding and trust are critical for transferring technologies from universities (Bruneel et al. 2010), personal contact and collaboration experience are needed for firms to learn from scientists (e.g., Zucker et al. 1998a, Zucker and Darby 2001).

Despite these challenges, the positive effects of university innovation and IUC on commercialization have been discussed in the literature. Several empirical studies based on the knowledge production function of Griliches (1979) suggest that firms can improve their technology commercialization through collaborating with universities (as an external input).[4] Some firms managed to overcome the challenges and succeed in IUC activities. Such success requires identifying the right collaborating university and researchers; developing the necessary knowledge, human capital, and social connections; and overcoming barriers to negotiation and collaboration. These capabilities and resources reflect prior IUC activities and investments, and thus, they collectively constitute an important complementary asset to firms that can enhance technology commercialization (Feldman 1994).[5] This is consistent with the Hall et al. (2003) observation that prior IUC experience is a significant factor in decreasing the difficulty of acquiring and assimilating basic knowledge in new projects. Such assets are inimitable as they cannot be easily purchased via markets (Agrawal 2001, p. 299) and tend to stay within organizations because of the tacit nature of knowledge (Polanyi 1966) and the stickiness of information to solve technical issues (e.g., Von Hippel 1994). We thus propose that firms' IUC experience becomes an inimitable complementary asset, which in turn, extends the PFI framework to the university knowledge context.

There is an increasing trend for Chinese firms to engage in IUC (Motohashi and Yun 2007), and local surveys suggest that over 10% of firms engage in research collaboration with universities. There is, however, little evidence on the effect of IUC experience—with the exception of Kafouros et al. (2015), which uses the survey data of 400 innovative Chinese companies for the 2008–2011 period. Given Chinese firms' relatively weaker internal innovation capability in the face of gradually strengthened intellectual property protection (Wu 2010, Wang and Shapira 2012, Appelbaum et al. 2016, Chen et al. 2016), these firms may benefit more from IUC experience (Hong and Su 2013, Sun et al. 2020).[6] We thus posit our primary hypothesis as follows.

Hypothesis 1. *Chinese firms' performance in technology commercialization increases with their IUC activities.*

2.2. Moderating Factors: Absorptive Capacity, Science Dependence, and Geographic Proximity

The concept of absorptive capacity was proposed in the seminal work of Cohen and Levinthal (1989, 1990), which highlights that corporate R&D investment helps develop firms' absorptive capacity; this benefits organizations in ways other than directly creating in-house innovation. This concept has received empirical support from Jaffe (1986, 1989a) and follow-up studies. As firms' internal R&D enhances their absorptive capacity to learn from universities, the benefits associated with IUC experience in technology commercialization may be strengthened by corporate R&D (Cassiman and Veugelers 2002).

We expect R&D-based absorptive capacity to moderate Chinese firms' IUC experience and technology commercialization as well. Several studies support a positive relation between Chinese firms' R&D investment and their IUC experience (Motohashi and Yun 2007, Brehm and Lundin 2012, Zhou 2012). The advantages associated with IUC experience are expected to be greater if Chinese firms have higher R&D investment to prepare themselves to absorb knowledge from or collaborate with university researchers. We thus propose that Chinese firms' internal R&D complements their IUC experience in enhancing technology commercialization. This proposition echoes the call of Chen et al. (2016) to develop a better understanding of the quality and economic applicability of the university research and measure the absorptive capacity of domestic firms. Our discussions lead to the second hypothesis.

Hypothesis 2. *The IUC-commercialization relation is stronger among Chinese firms with stronger absorptive capacity.*

It is also well documented that some industries are more dependent on basic science (and university research) than others (Nelson 1986; Mansfield 1991, 1998; Pavitt 1991; Klevorick et al. 1995; Cohen et al. 2002). Such industry heterogeneity also exists in technology commercialization because the appropriability of innovation varies across industries (Teece 1986). For instance, Acs et al. (1992) show that commercialized innovations of firms in the electronics industry (which is in the entrepreneurial regime) are more sensitive to local university spillovers that those in other industries.

We propose that the relations between IUC experience and technology commercialization also hinge on industry-specific degrees of science dependence in China (Motohashi and Yun 2007, Brehm and Lundin 2012). Given the escalating investments from the Chinese government in universities and basic science in China over the past two decades, we expect Chinese universities to offer stronger support to their industry collaborators. Thus, firms in industries that are more connected to basic science may benefit more through their IUC experience. We thus propose our third hypothesis based on the moderating role of industry-specific science dependence as follows.

Hypothesis 3. *The IUC-commercialization relation is stronger among Chinese firms in industries that are more dependent on basic science.*

Finally, capturing technology spillovers depends on locality (e.g., Krugman 1991). As discussed earlier, given tacit know-how in technology applications, the difficulties in codifying knowledge, and necessary interpersonal communications and mutual trust, the effectiveness of collaborations with universities hinges on geographic proximity. An extensive set of prior studies has documented the effect of universities' R&D on local firms' R&D and patents (Jaffe 1989b; Acs et al. 1992, 1994), commercialized innovation (Audretsch and Feldman 1996), and licensing and transfer from universities (Mowery and Ziedonis 2015). Empirical evidence, therefore, supports the argument of Mansfield and Lee (1996) that nearby firms are more likely than other firms to seize the opportunity in IUC.

The role of geographic proximity in firms' IUC could be even more pronounced in China because of traffic and congestion costs, crossprovince barriers, and heterogeneous development. Such a locality issue in firms' access to university research and IUC has been documented in Hong (2008) and Hong and Su (2013). The Chen et al.'s (2016) review of Chinese IUC concludes that the lack of communication, a natural consequence of geographic separation, is the major barrier of technology transfer in China. These results motivate a moderating role in the benefits of IUC experience because like university spillovers, the expected benefits from IUC experience likely decay with geographic distance. We thus form our fourth hypothesis as follows.

Hypothesis 4. *The IUC-commercialization relation is stronger among Chinese firms that are geographically proximate to their collaborating universities.*

3. Data Sources and Variable Construction

3.1. Data Sources

We start from the National Bureau of Statistics firm-level data set, which provides the complete accounting information of a full set of over 0.5 million unique industrial firms with annual revenue equal to or higher than 5 million Renminbi (RMB) (approximately $725,000 U.S. dollars (USD)) that operated from 1998 to 2013. This set of firms is not subject to any selection or survivorship issues, is not limited to specific industries and provinces, and therefore, is representative of the heterogeneous characteristics of Chinese industrial firms.[7]

We then collect patent information from the China National Intellectual Property Administration (CNIPA) and restrict our analysis to a sample of innovative firms that have patent records. After matching the firm names with the patent assignee names, we identify 2,789,133 patent applications (which were subsequently successfully granted) from 1994 to 2016 and 93,303 unique firms with at least one granted patent. Given the existence of university-run firms, university spin-offs, and professor-run firms that may bias our analysis of the IUC effect, we exclude any firm from our sample if it files any patents coassigned to universities in its first three sample years. We thus have 92,521 unique patenting firms in our final sample.

We also collect the information on university patents. We focus on 39 "985"-entitled universities, 112 "211"-entitled universities, and notable research institutes, such as the Chinese Academy of Sciences and the Chinese Academy of Social Sciences.[8] This results in a set of 153 universities (listed in Online Appendix Table OA.12) that all have at least one IUC patent. As research resources are concentrated in well-established universities and research institutes in China, our sample of university patents is reasonably representative. We identify 553,316 university patents that were applied for by (and were later granted to) these universities from 1994 to 2016.

We then collect the publication information of these innovative firms and research-intensive universities from China National Knowledge Infrastructure (CNKI), the platform with the most coverage of Chinese journals.[9] We explain our search procedure in Section C in the Online Appendix. After matching the firm and university names with the paper author affiliations, we identify 742,164 published papers for NBS firms and 11,091,518 for universities from 1994 to 2016.

3.2. IUC Experience Measures

Our first measure of IUC experience is the occurrence or the number of IUC patents that are defined as patents being coassigned to both a firm and a university (Hong 2008, Walsh et al. 2016). In our sample period from 1994 to 2016, we identify 20,388 IUC patents. Then, based on our data sets of corporate and university publications, our second measure of IUC experience is the occurrence and the number of IUC papers that are defined as Chinese publications coauthored by a firm employee and a university staff member (Godin and Gingras 2000, Brehm and Lundin 2012, Wang and Shapira 2012). We identify 66,200 IUC papers.

Similar to most prior studies on IUC, our use of granted patents and published papers to measure IUC activities unavoidably focuses on a "successful" IUC outcome (Lim 2009).[10] We argue that this data limitation does not bias our statistical inference because we use successful IUC records to measure IUC experience (successes are more likely to result in or reflect useful capabilities and connections, which are an inimitable complementary asset to firms).[11] In addition, other data sources for IUC experience, such as licensing or patent reassignment (Wu 2010, Sun et al. 2020), are only available through surveys or undisclosed to the public—which is a common problem for IUC research (Wu and Zhou 2012, Perkmann et al. 2013).

We measure a firm's IUC experience in year t by both incidence and frequency. Specifically, *Patent-Based (Paper-Based) IUC Dummy* equals one if the focal firm has an IUC patent filed (paper published) in years $t-4$ to t and zero otherwise.[12] *Patent-Based (Paper-Based) IUC Count* denotes the number of IUC patents (IUC papers) that are filed by (published with affiliation to) the focal firm in years $t-4$ to t.

Table 1 shows the pooled distribution of the four measures of IUC intensity. Overall, 0.9% of firm-year observations have nonzero IUC patents (*Patent-Based IUC Dummy*), and 3.9% of firm-year observations have nonzero IUC papers (*Paper-Based IUC Dummy*). In addition, among the firm-year observations with at least one IUC patent (paper), the mean and median of *Patent-Based IUC Count* (*Paper-Based IUC Count*) are 2.68 and 1 (2.91 and 1), respectively.

3.3. Technology Commercialization and Innovation Output

In the NBS data, firms are required to report their new product sales (i.e., revenue from new products) in each year. According to the guidance provided by the NBS, new products are defined by two nonmutually exclusive standards: first, products that are introduced to the market for the first time in a fiscal year and second, products that are recognized as new products by relevant government departments (e.g., the Science and Technology Committee, the Development and Reform Commission, the Economic Information Bureau, the Bureau of Economy and Information Technology, and the Market Supervision Bureau).

We measure a firm's future technology commercialization performance using its new product sales in year $t+1$ (Kelm et al. 1995, Laursen and Salter 2006, Berchicci 2013). As our sample only includes innovative industrial firms, higher new product sales are likely to be attributed to their stronger performance in realizing revenue from commercializing their technologies. Table 1 shows that the average annual new product sales (*New Product*

Table 1. Summary Statistics

Panel A: Statistical distribution

	Mean	Std	Min	Q1	Median	Q3	Max	No. of observations
Industry-university collaboration								
Patent-Based IUC Dummy	0.009	0.094	0.00	0.00	0.00	0.00	1.00	784,025
Patent-Based IUC Count	0.024	0.714	0.00	0.00	0.00	0.00	431.00	784,025
Conditional on nonzero observations	2.676	7.089	1.00	1.00	1.00	3.00	431.00	6,978
Paper-Based IUC Dummy	0.039	0.193	0.00	0.00	0.00	0.00	1.00	784,025
Paper-Based IUC Count	0.113	1.216	0.00	0.00	0.00	0.00	186.00	784,025
Conditional on nonzero observations	2.912	5.464	1.00	1.00	1.00	3.00	186.00	30,483
Technology commercialization								
New Product Sales	13.88	60.12	0.00	0.00	0.00	0.00	473.85	784,025
Conditional on nonzero observations	56.52	110.96	0.00	2.50	11.35	46.27	473.85	192,479
Product-Oriented PatCount	1.05	2.99	0.00	0.00	0.00	0.00	19.00	784,025
Conditional on nonzero observations	4.85	4.77	1.00	1.00	3.00	6.00	19.00	169,802
Product-Oriented PatCite	0.06	0.20	0.00	0.00	0.00	0.00	1.19	784,025
Conditional on nonzero observations	0.55	0.36	0.01	0.25	0.50	1.00	1.19	79,228
Product-Oriented PatBasic	0.00	0.04	0.00	0.00	0.00	0.00	0.33	784,025
Conditional on nonzero observations	0.26	0.10	0.00	0.20	0.33	0.33	0.33	13,002
Product-Oriented PatExplore	0.15	0.34	0.00	0.00	0.00	0.00	1.00	784,025
Conditional on nonzero observations	0.86	0.23	0.02	0.75	1.00	1.00	1.00	135,200
Product-Oriented TechBreadth	0.24	0.50	0.00	0.00	0.00	0.00	2.00	784,025
Conditional on nonzero observations	1.19	0.32	1.00	1.00	1.00	1.30	2.00	160,963
Channel variables								
CiteUniv Ratio	0.004	0.036	0.000	0.000	0.000	0.000	0.333	784,025
Conditional on nonzero observations	0.263	0.099	0.002	0.171	0.333	0.333	0.333	13,287
CiteUniv Product-Oriented Number	0.013	0.113	0.000	0.000	0.000	0.000	1.000	784,025
Conditional on nonzero observations	1.000	0.000	1.000	1.000	1.000	1.000	1.000	10,143
HireUniv Ratio	0.020	0.065	0.000	0.000	0.000	0.000	0.376	784,025
Conditional on nonzero observations	0.159	0.103	0.000	0.080	0.136	0.217	0.376	100,732
HireUniv Product-Oriented Number	0.083	0.341	0.000	0.000	0.000	0.000	2.000	784,025
Conditional on nonzero observations	1.315	0.464	1.000	1.000	1.000	2.000	2.000	97,140
ReassignUniv Ratio	0.001	0.030	0.000	0.000	0.000	0.000	1.000	784,025
Conditional on nonzero observations	0.968	0.149	0.016	1.000	1.000	1.000	1.000	755
ReassignUniv Product-Oriented Number	0.001	0.096	0.000	0.000	0.000	0.000	39.000	784,025
Conditional on nonzero observations	1.889	3.144	1.000	1.000	1.000	2.000	39.000	542
Ratio of Commonly Cited Technology Classes	0.01	0.09	0.00	0.00	0.00	0.00	0.99	784,025
Conditional on nonzero observations	0.92	0.05	0.55	0.90	0.93	0.96	0.99	7,908
Moderator variables								
R&D Intensity	0.01	0.02	0.00	0.00	0.00	0.00	0.15	784,025
Conditional on nonzero observations	0.02	0.03	0.00	0.00	0.01	0.02	0.15	277,227
Ratio of Backward Citations to Academic Papers	0.03	0.08	0.00	0.00	0.00	0.00	0.51	784,025
Conditional on nonzero observations	0.16	0.14	0.00	0.07	0.10	0.22	0.51	126,321
Within 100KM Commuting Distance	0.00	0.05	0.00	0.00	0.00	0.00	1.00	784,025
Conditional on nonzero observations	0.91	0.22	0.04	1.00	1.00	1.00	1.00	1,825
Scale of sales								
Total Sales	236.76	605.69	3.54	23.32	58.82	170.00	4,517.19	784,025
Innovation-related control variables								
Patent Portfolio Size	3.37	8.29	0.00	0.00	0.00	3.00	56.00	784,025
Conditional on nonzero observations	7.84	11.16	1.00	1.00	4.00	9.00	56.00	337,478
R&D Intensity	0.36	1.17	0.00	0.00	0.00	0.04	7.81	784,025
Conditional on nonzero observations	1.16	1.87	0.00	0.07	0.33	1.30	7.81	243,425
Other control variables								
Total Assets	226.30	636.89	2.17	17.26	46.25	140.55	4,761.17	784,025
Age	11.02	11.00	1.00	4.00	8.00	13.00	56.00	784,025
Cash Ratio	54.30	26.85	0.04	36.87	57.74	75.02	100.00	784,025
Capital Expenditure Intensity	18.70	25.89	0.00	2.42	10.60	22.65	153.72	784,025
Profitability Ratio	4.29	8.72	−30.67	0.43	2.84	7.45	36.42	784,025
Sales Growth	25.97	93.67	−81.21	−1.07	0.00	28.28	651.20	784,025
Export Ratio	13.25	27.66	0.00	0.00	0.00	7.46	100.00	784,025
Leverage Ratio	57.87	25.07	3.52	39.87	59.03	76.80	100.00	784,025

Table 1. (Continued)

Panel A: Statistical distribution

	Mean	Std	Min	Q1	Median	Q3	Max	No. of observations
Labor Ratio	6.92	8.66	0.13	2.02	4.20	8.28	56.38	784,025
Wage per Employee	28.84	40.54	2.50	11.09	17.78	29.89	309.36	784,025
Subsidy Ratio	0.24	0.86	0.00	0.00	0.00	0.02	6.04	784,025

Panel B: Correlation matrix

	Var01	Var02	Var03	Var04	Var05	Var06	Var07	Var08	Var09	Var10	Var11	Var12	Var13	Var14
Patent-Based IUC Count (Var01)		0.13	0.06	0.06	0.05	0.07	0.04	0.05	0.08	0.08	0.07	0.09	0.02	0.01
Patent-Based IUC Count (Var02)	0.09		0.11	0.07	0.07	0.09	0.05	0.07	0.09	0.08	0.10	0.12	0.01	0.01
New Product Sales (Var03)	0.05	0.15		0.12	0.10	0.06	0.09	0.11	0.06	0.06	0.12	0.12	0.01	0.01
Product-Oriented PatCount (Var04)	0.05	0.10	0.16		0.67	0.26	0.86	0.96	0.24	0.22	0.69	0.49	0.02	0.02
Product-Oriented PatCite (Var05)	0.02	0.05	0.08	0.39		0.28	0.59	0.67	0.27	0.25	0.55	0.44	0.02	0.02
Product-Oriented PatBasic (Var06)	0.04	0.07	0.06	0.20	0.24		0.22	0.27	0.34	0.31	0.26	0.26	0.02	0.02
Product-Oriented PatExplore (Var07)	0.01	0.02	0.06	0.52	0.45	0.19		0.90	0.20	0.18	0.62	0.43	0.02	0.02
Product-Oriented TechBreadth (Var08)	0.02	0.05	0.10	0.63	0.55	0.25	0.83		0.24	0.22	0.71	0.49	0.02	0.02
CiteUniv Ratio (Var09)	0.04	0.08	0.07	0.22	0.20	0.26	0.15	0.22		0.87	0.27	0.29	0.02	0.01
CiteUniv Product-Oriented Number (Var10)	0.06	0.10	0.08	0.30	0.21	0.23	0.14	0.22	0.80		0.24	0.26	0.02	0.01
HireUniv Ratio (Var11)	0.03	0.05	0.08	0.40	0.35	0.19	0.50	0.56	0.20	0.19		0.70	0.03	0.01
HireUniv Product-Oriented Number (Var12)	0.06	0.12	0.17	0.53	0.33	0.24	0.35	0.45	0.28	0.30	0.65		0.02	0.01
ReassignUniv Ratio (Var13)	0.01	0.01	0.01	0.02	0.01	0.02	0.02	0.02	0.02	0.02	0.03	0.02		0.85
ReassignUniv Product-Oriented Number (Var14)	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.02	0.42	

Notes. In panel A, we report the statistical distribution of all variables. In panel B, we report the correlation matrix of key outcome variables. Pearson (Spearman) correlation coefficients are reported in the lower (upper) space off the diagonal. In the category of "industry-university collaboration," all variables are measured in a window from year $t-4$ to t. *Patent-Based (Paper-Based) IUC Dummy* equals one if the focal firm files for an IUC patent (publishes an IUC paper); otherwise, it equals to zero. *Patent-Based (Paper-Based) IUC Count* denotes the number of patents applied (papers published) by both a university and the focal firm. In the category of "technology commercialization," all variables are measured in a window from year t to $t+1$. *New Product Sales* denotes the output value of new products (in million RMB). *Product-Oriented PatCount* denotes the number of product-oriented patents solely applied by the focal firm. *Product-Oriented PatCite* denotes the average number of forward five-year citations of product-oriented patents solely applied by the focal firm. *Product-Oriented PatBasic* denotes the ratio of academic papers over total backward citations of product-oriented patents that are solely applied by the focal firm. *Product-Oriented PatExplore* denotes the ratio of exploratory patents over the number of product-oriented patents that are solely applied by the focal firm. A patent applied in year $t+1$ is defined as exploratory if its primary International Patent Classification (IPC) codes are different from those of patents applied in the past. *Product-Oriented TechBreadth* denotes the average number of unique primary IPC codes per product-oriented patent that is solely applied by the focal firm. In the category of "channel tests," all except the last variables are measured in a window from year t to $t+1$. *CiteUniv Ratio* denotes the ratio of university patents cited divided by total patents cited by patents that are solely applied by the focal firm. *CiteUniv Product-Oriented Number* denotes the number of university product-oriented patents cited by patents that are solely applied by the focal firm. *HireUniv Ratio* denotes the ratio of former inventors from universities over total inventors filing patents that are solely applied by the focal firm. A former university inventor is defined if he or she files a sole corporate patent in the focal firm in year $t+1$ but files a sole university patent before year t. *HireUniv Product-Oriented Number* denotes the number of former product-oriented inventors from universities filing patents that are solely applied by the focal firm. *ReassignUniv Ratio* denotes the ratio of university patents reassigned divided by total patents reassigned to the focal firm. *ReassignUniv Product-Oriented Number* denotes the number of university product-oriented patents reassigned to the focal firm. *Ratio of Commonly Cited Technology Classes* of a firm is computed as a window from the first sample year to year t and is measured by its ratio of commonly cited technology class pairs divided by total technology class pairs. In the category of "contingency tests," all variables are measured in a window from the first sample year to year t. *R&D Intensity* of a firm is measured by its ratio of R&D expenditure divided by total assets. *Ratio of Backward Citations to Academic Papers* of a firm is measured by its ratio of patents' backward citations to academic papers divided by total backward citations. *Within 100KM Commuting Distance* of a firm is measured by the weighted average of dummy variables indicating whether the focal firm and its collaborating universities are within a 100-km distance. In the category of "scale of sales," *Total Sales* denotes the total value of outputs (in billion RMB) in year t. In the category of "innovation-related variables," *Patent Portfolio Size* denotes the number of patents applied by (and later granted to) the focal firm in year $t-4$ to t. *R&D Intensity* denotes the ratio of R&D expenditure over total assets in year t. In the category of "other control variables," all variables are measured in year t. *Total Sales* denotes the total value of sales (in million yuan). *Total Assets* denotes the value of total assets (in million yuan). *Age* denotes the number of years gap between the registration year and the data year. *Cash Ratio* denotes the ratio of cash over total assets (in percentage). *Capital Expenditure Intensity* denotes the ratio of capital expenditure over total physical assets (in percentage). *Profitability Ratio* denotes the ratio of net profits over total sales (in percentage). *Sales Growth* denotes the ratio of this year's total sales over last year's total sales minus one (in percentage). *Export Ratio* denotes the ratio of total exports over total sales (in percentage). *Leverage Ratio* denotes the ratio of total debts over total assets (in percentage). *Labor Ratio* denotes the ratio of employees over total assets (in person per million RMB). *Wage per Employee* denote the ratio of labor costs over employees (in thousand RMB per person). *Subsidy Ratio* denotes the ratio of subsidies over total revenue (in percentage). All variables in the categories of "technology commercialization," "channel variables," "contingency tests," "scale of sales," "innovation-related control variables," and "other control variables" are winsorized at their 1st and 99th percentiles. Std, standard deviation. Q1, first quartile. Q3, third quartile.

Sales) are 13.88 million RMB (about 2 million USD) as compared with the average annual total sales of 237 million RMB (about 34.5 million USD), which are included as a control variable.

As product innovation represents direct improvement to products, firms undertake stronger product-oriented innovation to promote their performance in technology commercialization (Roberts 1999, Danneels 2002). As such, we also measure a firm's technology commercialization performance using its number of product-oriented patents in year $t+1$ and the forward five-year citations.[13] We exclude patents that are also granted to coassignees. Table 1 shows that among 784,025 regression observations, 22% of firm-year observations have at least one product-oriented patent. The average annual number of product-oriented patents (*Product-Oriented PatCount*) is 1.05; the forward five-year citations per product-oriented patent (*Product-Oriented PatCite*) are 0.06.

4. IUC Experience and Technology Commercialization

4.1. Baseline Results

We employ an ordinary least squares regression model to examine the association between firms' IUC experience and their technology commercialization performance. In particular, we estimate the following:

$$TechCom_{t+1} = \beta \cdot IUC_{t-4 \to t} + Controls + FEs + \varepsilon_t, \quad (1)$$

in which the dependent variable, $TechCom_{t+1}$, denotes *New Product Sales*, *Product-Oriented PatCount*, or *Product-Oriented PatCite* plus one in logarithm in year $t+1$. Our regression model is based on the Cobb–Douglas function for how innovation production is determined by complementary assets and factors (Griliches 1979, Jaffe 1989b, Acs et al. 1992). The key independent variable, $IUC_{t-4 \to t}$, represents various operationalized measures of IUC experience: *Patent-Based IUC Dummy* and *Patent-Based IUC Count* (*Paper-Based IUC Dummy* and *Paper-Based IUC Count*), which are the dummy and number of IUC patents filed (IUC papers published) by a firm from year $t-4$ to t. Besides total sales, innovation-related variables, and other firm characteristic control variables as discussed in the prior section, we include as regressors firm fixed effects, province-by-year fixed effects, and industry-by-year fixed effects.[14] We have included an extensive list of control variables.[15] We cluster standard errors by firm to accommodate firm-specific variation in estimation errors, such as autocorrelation. The estimation results for Equation (1) are presented in Tables 2 and 3.

Panel A of Table 2 (panel B of Table 2) presents a positive relation between IUC patents (papers) and future new product sales. All coefficient estimates are both statistically significant and economically significant. For instance, panels A.1 and B.1 of Table 2 show that when a sample firm is engaged in joint patenting and joint publishing, its new product sales increase by 5% and 2%, respectively. When we do not take the logarithmic value of the dependent variable in Online Appendix Table OA.2, we find that being engaged in joint patenting and joint publishing is related to increases of 3.67 and 1.75 million RMB in new product sales, respectively; such magnitudes correspond to 13%–26% of the sample mean or 3%–6% of the sample standard deviation of *New Product Sales* (as shown in Table 1). Panels A.2 and B.2 of Table 2 imply that when a firm's IUC intensity measured by *Patent-Based IUC Count* and *Paper-Based IUC Count* doubles, its *New Product Sales* increase by 5%.

Panel A of Table 3 (panel B of Table 3) presents a significantly positive relation between IUC and the future quantity (quality) of product-oriented patents. All coefficient estimates are both statistically and economically significant. For instance, panels A.1.1 and A.2.1 of Table 3 indicate that when a sample firm is engaged in joint patenting and joint publishing, its number of product-oriented patents increases by 11% and 5%, respectively. Panels B.1.1 and B.2.1 of Table 3 imply that becoming engaged in joint patenting and joint publishing is associated with an increase in the forward citations of its product-oriented patents by 0.5%–1.3%. Panels A.1.2, A.2.2, B.1.2, and B.2.2 of Table 3 confirm the relation in the intensive margin using the number of IUC patents and papers as the explanatory variable. Online Appendix Table OA.3 further confirms that our results are robust to the regression specification.

All results presented in Tables 2 and 3 point to a significant and robust positive association between IUC experience and technology commercialization, supporting Hypothesis 1. In additional (untabulated) results, we find that the significant, positive relation between IUC experience and technology commercialization holds in both the subsamples of state-owned enterprises (SOEs) and non-SOEs. Nevertheless, we find a more robust relation among non-SOEs.

4.2. Other Innovation Measures

In addition to counts and forward citations, we further construct three measures for the quality of product-oriented patents: basicness of product-oriented patents (Trajtenberg et al. 1997, Fleming and Sorenson 2004), exploration of product-oriented patents, and breadth of product-oriented patents (Lerner 1995). We leave all of the details to Section D in the Online Appendix. We find in Online Appendix Table OA.4 that IUC experience is associated with significantly higher reliance on basic research, significantly higher exploration, and significantly higher breadth. These results are intuitive and consistent with the common belief that university-generated technologies can be applied to broader

Table 2. Industry-University Collaboration and Future Technology Commercialization

Dependent variable = *New Product Sales*								
	Panel A: Patent-based IUC				Panel B: Paper-based IUC			
	Panel A.1		Panel A.2		Panel B.1		Panel B.2	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
IUC Dummy	0.0554**	0.0529**			0.0250*	0.0236*		
	(0.0222)	(0.0222)			(0.0128)	(0.0127)		
IUC Count			0.0560***	0.0536***			0.0485***	0.0475***
			(0.0203)	(0.0202)			(0.0142)	(0.0142)
Total Sales	0.5188***	0.4622***	0.5186***	0.4620***	0.5187***	0.4621***	0.5166***	0.4597***
	(0.0189)	(0.0198)	(0.0189)	(0.0198)	(0.0189)	(0.0199)	(0.0189)	(0.0198)
Patent Portfolio Size	0.0482***	0.0456***	0.0480***	0.0455***	0.0485***	0.0460***	0.0480***	0.0454***
	(0.0022)	(0.0022)	(0.0023)	(0.0023)	(0.0022)	(0.0022)	(0.0022)	(0.0022)
R&D Intensity	0.7231***	0.7321***	0.7226***	0.7319***	0.7220***	0.7306***	0.7178***	0.7285***
	(0.2102)	(0.2102)	(0.2102)	(0.2102)	(0.2103)	(0.2103)	(0.2102)	(0.2102)
Total Assets		0.0274***		0.0274***		0.0273***		0.0275***
		(0.0029)		(0.0029)		(0.0029)		(0.0029)
Age		−0.0131***		−0.0130***		−0.0132***		−0.0131***
		(0.0030)		(0.0030)		(0.0030)		(0.0030)
Cash Ratio		0.0101		0.0101		0.0100		0.0099
		(0.0062)		(0.0062)		(0.0062)		(0.0062)
Capital Expenditure Intensity		0.0393***		0.0393***		0.0393***		0.0394***
		(0.0040)		(0.0040)		(0.0040)		(0.0040)
Profitability Ratio		0.1403***		0.1404***		0.1407***		0.1415***
		(0.0169)		(0.0169)		(0.0169)		(0.0169)
Sales Growth		0.0009		0.0009		0.0009		0.0009
		(0.0009)		(0.0009)		(0.0009)		(0.0009)
Export Ratio		0.0674***		0.0674***		0.0674***		0.0674***
		(0.0078)		(0.0078)		(0.0078)		(0.0078)
Leverage Ratio		0.0131**		0.0131**		0.0130**		0.0131**
		(0.0063)		(0.0063)		(0.0063)		(0.0063)
Labor Ratio		1.4443***		1.4443***		1.4376***		1.4368***
		(0.1873)		(0.1872)		(0.1873)		(0.1872)
Wage per Employee		0.0006***		0.0005***		0.0006***		0.0005***
		(0.0000)		(0.0000)		(0.0000)		(0.0000)
Subsidy Ratio		0.5540***		0.5537***		0.5544***		0.5530***
		(0.1704)		(0.1703)		(0.1704)		(0.1704)
Number of observations	784,025	784,025	784,025	784,025	784,025	784,025	784,025	784,025
Number of firms	92,521	92,521	92,521	92,521	92,521	92,521	92,521	92,521
R^2	0.8280	0.8283	0.8280	0.8283	0.8280	0.8283	0.8280	0.8283
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes. We execute pooled regressions to estimate the effect of industry-university collaboration on a firm's future performance of technology commercialization. We regress the dependent variable, *New Product Sales*, in year $t + 1$ in a natural logarithm form on patent-based and paper-based measures of IUC as independent variables in year $t - 4$ to t. As the dependent variable, *New Product Sales* denotes the output value of new products (in million RMB). As the independent variables in panels A.1 and B.1, *Patent-Based (Paper-Based) IUC Dummy* equals one if the focal firm has an IUC patent (paper); otherwise, it equals to zero. As the independent variables in panels A.2 and B.2, *Patent-Based (Paper-Based) IUC Count* denotes the number of patents applied by (papers published by) both a university and the focal firm. We control for *Total Sales* (in billion RMB). We also control for innovation-related variables, such as *Patent Portfolio Size* and *R&D Intensity*. We further control for firm characteristics, such as *Total Assets* (in billion RMB), *Age*, *Cash Ratio*, *Capital Expenditure Intensity*, *Profitability Ratio*, *Sales Growth*, *Export Ratio*, *Leverage Ratio*, *Labor Ratio*, *Wage per Employee*, and *Subsidy Ratio*, as well as firm fixed effects, province-year fixed effects, and industry-year fixed effects. All control variables are defined in Table 1. The sample period of t is from 1998 to 2013. A firm is included if it has at least one patent in 1994–2016. We exclude the firms that file any IUC patents or publish any IUC papers in their first three sample years. The outcome variable and all control variables are winsorized at their 1st and 99th percentiles. Numbers in parentheses denote standard errors clustered by firms. FE, fixed effect.

*Significance level of 10%; **significance level of 5%; ***significance level of 1%.

Table 3. Industry-University Collaboration and Future Output of Product-Oriented Patents

Panel A: Dependent variable = *Product-Oriented PatCount*								
	Panel A.1: Patent-based IUC				Panel A.2: Paper-based IUC			
	Panel A.1.1		Panel A.1.2		Panel A.2.1		Panel A.2.2	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
IUC Dummy	0.1207***	0.1142***			0.0580***	0.0511***		
	(0.0169)	(0.0167)			(0.0083)	(0.0083)		
IUC Count			0.1226***	0.1176***			0.0728***	0.0678***
			(0.0168)	(0.0168)			(0.0090)	(0.0089)
Patent Portfolio Size	0.0279***	0.0175***	0.0276***	0.0171***	0.0286***	0.0182***	0.0280***	0.0176***
	(0.0021)	(0.0021)	(0.0021)	(0.0021)	(0.0021)	(0.0021)	(0.0021)	(0.0021)
R&D Intensity	−1.0309***	−0.4459***	−1.0294***	−0.4439***	−1.0346***	−0.4507***	−1.0350***	−0.4500***
	(0.1271)	(0.1264)	(0.1271)	(0.1264)	(0.1271)	(0.1264)	(0.1271)	(0.1264)
Total Assets		0.0790***		0.0790***		0.0788***		0.0789***
		(0.0019)		(0.0019)		(0.0019)		(0.0019)
Age		−0.0066***		−0.0065***		−0.0069***		−0.0067***
		(0.0018)		(0.0018)		(0.0018)		(0.0018)
Cash Ratio		0.0148***		0.0148***		0.0144***		0.0144***
		(0.0051)		(0.0051)		(0.0051)		(0.0051)
Capital Expenditure Intensity		−0.0090***		−0.0089***		−0.0090***		−0.0089***
		(0.0028)		(0.0028)		(0.0028)		(0.0028)
Profitability Ratio		0.2621***		0.2622***		0.2628***		0.2631***
		(0.0118)		(0.0118)		(0.0118)		(0.0118)
Sales Growth		−0.0048***		−0.0048***		−0.0048***		−0.0048***
		(0.0008)		(0.0008)		(0.0008)		(0.0008)
Export Ratio		0.0385***		0.0385***		0.0385***		0.0384***
		(0.0051)		(0.0051)		(0.0051)		(0.0051)
Leverage Ratio		0.0115**		0.0115**		0.0114**		0.0113**
		(0.0049)		(0.0049)		(0.0049)		(0.0049)
Labor Ratio		3.1776***		3.1751***		3.1645***		3.1576***
		(0.1478)		(0.1478)		(0.1478)		(0.1478)
Wage per Employee		0.0007***		0.0007***		0.0007***		0.0007***
		(0.0000)		(0.0000)		(0.0000)		(0.0000)
Subsidy Ratio		0.8635***		0.8630***		0.8647***		0.8650***
		(0.1220)		(0.1219)		(0.1220)		(0.1220)
Number of observations	784,025	784,025	784,025	784,025	784,025	784,025	784,025	784,025
Number of firms	92,521	92,521	92,521	92,521	92,521	92,521	92,521	92,521
R^2	0.4401	0.4441	0.4402	0.4442	0.4401	0.4441	0.4402	0.4442
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 3. (Continued)

Panel B: Dependent variable = *Product-Oriented PatCite*								
	Panel B.1: Patent-based IUC				Panel B.2: Paper-based IUC			
	Panel B.1.1		Panel B.1.2		Panel B.2.1		Panel B.2.2	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
IUC Dummy	0.0130***	0.0125***			0.0053***	0.0046***		
	(0.0034)	(0.0034)			(0.0018)	(0.0017)		
IUC Count			0.0108***	0.0104***			0.0071***	0.0067***
			(0.0032)	(0.0032)			(0.0018)	(0.0018)
Patent Portfolio Size	0.0027***	0.0015***	0.0027***	0.0015***	0.0028***	0.0016***	0.0027***	0.0015***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
R&D Intensity	−0.0409	0.0332	−0.0408	0.0333	−0.0413	0.0327	−0.0413	0.0328
	(0.0341)	(0.0342)	(0.0341)	(0.0342)	(0.0341)	(0.0342)	(0.0341)	(0.0342)
Total Assets		0.0093***		0.0093***		0.0093***		0.0093***
		(0.0004)		(0.0004)		(0.0004)		(0.0004)
Age		−0.0006		−0.0006		−0.0007*		−0.0006*
		(0.0004)		(0.0004)		(0.0004)		(0.0004)
Cash Ratio		0.0025**		0.0025**		0.0024**		0.0024**
		(0.0011)		(0.0011)		(0.0011)		(0.0011)
Capital Expenditure Intensity		−0.0011*		−0.0011*		−0.0011*		−0.0011*
		(0.0007)		(0.0007)		(0.0007)		(0.0007)
Profitability Ratio		0.0345***		0.0345***		0.0346***		0.0346***
		(0.0027)		(0.0027)		(0.0027)		(0.0027)
Sales Growth		−0.0004**		−0.0004**		−0.0004**		−0.0004**
		(0.0002)		(0.0002)		(0.0002)		(0.0002)
Export Ratio		0.0050***		0.0050***		0.0050***		0.0050***
		(0.0010)		(0.0010)		(0.0010)		(0.0010)
Leverage Ratio		0.0010		0.0010		0.0010		0.0010
		(0.0011)		(0.0011)		(0.0011)		(0.0011)
Labor Ratio		0.4667***		0.4667***		0.4657***		0.4648***
		(0.0306)		(0.0306)		(0.0306)		(0.0306)
Wage per Employee		0.0001***		0.0001***		0.0001***		0.0001***
		(0.0000)		(0.0000)		(0.0000)		(0.0000)
Subsidy Ratio		0.1544***		0.1545***		0.1546***		0.1546***
		(0.0308)		(0.0307)		(0.0308)		(0.0308)
Number of observations	784,025	784,025	784,025	784,025	784,025	784,025	784,025	784,025
Number of firms	92,521	92,521	92,521	92,521	92,521	92,521	92,521	92,521
R^2	0.3013	0.3026	0.3013	0.3026	0.3013	0.3026	0.3013	0.3026
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes. We execute pooled regressions to estimate the association between industry-university collaboration and a firm's future quantity and forward citations of product-oriented patents. Specifically, we regress the dependent variables, *Product-Oriented PatCount*, in year $t + 1$ in a natural logarithm form in panel A and *Product-Oriented PatCite* in year $t + 1$ in a natural logarithm form in panel B on patent-based and paper-based measures of IUC as independent variables in year $t - 4$ to t. As the dependent variables, *Product-Oriented PatCount* denotes the number of product-oriented patents solely applied by the focal firm. *Product-Oriented PatCite* denotes the average forward five-year citations of product-oriented patents solely applied by the focal firm. As the independent variables, *Patent-Based (Paper-Based) IUC Dummy* equals one if the focal firm has an IUC patent (paper); otherwise, it equals to zero. *Patent-Based (Paper-Based) IUC Count* denotes the number of patents applied by (papers published by) both a university and the focal firm. We also control for innovation-related variables, such as *Patent Portfolio Size* and *R&D Intensity*. We further control for firm characteristics, such as *Total Assets* (in billion RMB), *Age*, *Cash Ratio*, *Capital Expenditure Intensity*, *Profitability Ratio*, *Sales Growth*, *Export Ratio*, *Leverage Ratio*, *Labor Ratio*, *Wage per Employee*, and *Subsidy Ratio*, as well as firm fixed effects, province-year fixed effects, and industry-year fixed effects. All control variables are defined in Table 1. The sample period of t is from 1998 to 2013. The outcome variable and all control variables are winsorized at their 1st and 99th percentiles. Numbers in parentheses denote standard errors clustered by firms. FE, fixed effect.

*Significance level of 10%; **significance level of 5%; ***significance level of 1%.

applications, which may lead to more commercialization opportunities for firms with IUC experience. As patents that are based on basic research tend to have broader applications (Trajtenberg et al. 1997), we expect firms with IUC experience to produce more exploratory corporate innovation (i.e., different from the firm's existing technology expertise). Similarly, the strengthened base on basic science could also be reflected in firms' technology breadth (i.e., corporate patents could be more general across and within technology classes).

5. Contingencies

In Section 2, we proposed that the positive relation between IUC experience and technology commercialization is subject to three contingencies: absorptive capacity, science dependence, and geographic proximity. We proceed to test these contingencies for Hypotheses 2–4.

5.1. Absorptive Capacity

To test the first contingency of absorptive capacity, we estimate the following regression model that includes interacted explanatory variables:

$$TechCom_{t+1} = \alpha \cdot IUC_{t-4\to t} \times HighGroup_t + \beta \cdot IUC_{t-4\to t} + Controls + FEs + \varepsilon_t. \quad (2)$$

$HighGroup_t$ denotes an indicator variable that equals one if a firm's absorptive capacity measure is above the sample median and zero otherwise. We use *R&D Ratio*, the ratio of its R&D expenditure divided by total assets across all historical years up to year t, as our primary measure of absorptive capacity (Eun et al. 2006). We also consider *Ratio of Backward Citations to IUC Patents* and *Ratio of Backward Citations to IUC Papers* as alternative measures of absorptive capacity. Specifically, *Ratio of Backward Citations to IUC Patents* of a firm is measured by its ratio of backward citations to IUC patents divided by total backward citations of patents across all historical years up to year t, and *Ratio of Backward Citations to IUC Papers* of a firm is measured by its ratio of backward citations to IUC papers divided by total backward citations of papers across all historical years up to year t. We also control for innovation-related variables, other firm characteristics, and fixed effects that have been defined in Section 4.1. Hypothesis 2 predicts the coefficient of α for the interaction term to be positive.

Table 4, based on *R&D Ratio* as a measure of absorptive capacity, provides supportive evidence for Hypothesis 2. In panels A.1 and A.2 of Table 4, we measure IUC experience by *Patent-Based IUC Dummy* and *Paper-Based IUC Dummy*, respectively. In panels B.1 and B.2 of Table 4, we measure IUC experience by *Patent-Based IUC Count* and *Paper-Based IUC Count*, respectively. Columns (1)–(3) in panels A and B of Table 4 are results when the dependent variables are *New Product Sales*, *Product-Oriented PatCount*, and *Product-Oriented PatCite*, respectively. We find that the coefficients of the interaction terms of *IUC* × *High Group* are significantly positive in all columns, confirming that the relation between IUC experience and technology commercialization is more pronounced when firms possess stronger absorptive capacity.

We further report the estimation results using *Ratio of Backward Citations to IUC Patents* and *Ratio of Backward Citations to IUC Papers* as alternative measures in Online Appendix Table OA.5. In panel A of Online Appendix Table OA.5, we find that the coefficients of *IUC* × *High Group* are significantly positive in most columns. Panel B of Online Appendix Table OA.5 reports significantly positive coefficients of *IUC* × *High Group* in 8 of 12 columns. Overall, we find strong support for Hypothesis 2: that firms with stronger absorptive capacity can benefit more from IUC experience.

5.2. Science Dependence

To test the second contingency of science dependence, we estimate regression Model (2) using *Ratio of Backward Citations to Academic Papers*, the industry-level ratio of patents' backward citations to academic papers divided by total backward citations across all historical years up to year t, as our primary measure of science dependence. We also consider *Ratio of Paper Publication over Patent Issuance*, the industry-level ratio of paper publications divided by patent issuance across all historical years up to year t, as an alternative measure of science dependence. We also control for innovation-related variables, other firm characteristics, and fixed effects, which have been defined in Section 4.1.

As shown in Table 5, based on *Ratio of Backward Citations to Academic Papers*, the coefficients of the interaction terms of *IUC* × *High Group* are significantly positive in all columns. This finding indicates that the relation between IUC experience and technology commercialization is more pronounced when firms' technologies are more closely developed from basic science. We further report the estimation results using *Ratio of Paper Publication over Patent Issuance* as an alternative measure in Online Appendix Table OA.6. We find that the coefficients of *IUC* × *High Group* are significantly positive in most columns. As a result, our test results offer supportive evidence for Hypothesis 3: that firms in industries more dependent on basic science can benefit more from IUC experience.

5.3. Geographic Proximity

To test the third contingency of geographic proximity, we estimate regression Model (2) using *Within 100KM Commuting Distance*, the weighted average of dummy variables indicating whether universities that have a

Table 4. Absorptive Capacity as a Moderator of the IUC-Technology Commercialization Relation

Panel A: IUC measured in *Dummy*

	Panel A.1: Patent-based IUC			Panel A.2: Paper-based IUC		
Dependent variable =	*New Product Sales* (1)	*Product-Oriented PatCount* (2)	*Product-Oriented PatCite* (3)	*New Product Sales* (1)	*Product-Oriented PatCount* (2)	*Product-Oriented PatCite* (3)
IUC × High Group	0.2064***	0.1042***	0.0213***	0.0885***	0.0343***	0.0098***
	(0.0251)	(0.0191)	(0.0044)	(0.0139)	(0.0108)	(0.0025)
IUC	−0.0729***	0.0416***	−0.0024	−0.0228*	0.0274***	−0.0021
	(0.0214)	(0.0160)	(0.0037)	(0.0118)	(0.0091)	(0.0021)
Number of observations	784,025	784,025	784,025	784,025	784,025	784,025
Number of firms	92,521	92,521	92,521	92,521	92,521	92,521
R^2	0.8274	0.4441	0.3026	0.8274	0.4441	0.3026
Innovation-related controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm characteristics controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Province-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: IUC measured in *Count*

	Panel B.1: Patent-based IUC			Panel B.2: Paper-based IUC		
Dependent variable =	*New Product Sales* (1)	*Product-Oriented PatCount* (2)	*Product-Oriented PatCite* (3)	*New Product Sales* (1)	*Product-Oriented PatCount* (2)	*Product-Oriented PatCite* (3)
IUC × High Group	0.1976***	0.1062***	0.0234***	0.1046***	0.0461***	0.0151***
	(0.0231)	(0.0171)	(0.0039)	(0.0133)	(0.0103)	(0.0024)
IUC	−0.0802***	0.0377**	−0.0072**	−0.0142	0.0333***	−0.0047**
	(0.0204)	(0.0148)	(0.0034)	(0.0117)	(0.0089)	(0.0021)
Number of observations	784,025	784,025	784,025	784,025	784,025	784,025
Number of firms	92,521	92,521	92,521	92,521	92,521	92,521
R^2	0.8274	0.4442	0.3027	0.8274	0.4442	0.3027
Innovation-related controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm characteristics controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Province-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes. We execute pooled regressions to estimate the effects of industry-university collaboration on a firm's future performance of technology commercialization conditional on absorptive capacity. Specifically, the dependent variables are *New Product Sales* in year $t + 1$ in a natural logarithm form in column (1), *Product-Oriented PatCount* in year $t + 1$ in a natural logarithm form in column (2), and *Product-Oriented PatCite* in year $t + 1$ in a natural logarithm form in column (3). As the independent variables, *Patent-Based IUC* and *Paper-Based IUC* are measured in *Dummy* and *Count* in panels A and B, respectively. All firm-year observations are split into two groups according to their measures of *Absorptive Capacity*. If a *measure* is higher than the median, then it is included in the high group; otherwise, it is included in the low group. We measure *Absorptive Capacity* with *R&D Intensity*. Specifically, *R&D Ratio* of a firm is measured by its ratio of R&D expenditure divided by total assets. We also control for innovation-related variables, such as *Patent Portfolio Size* and *R&D Intensity*. We further control for firm characteristics, such as *Total Assets* (in billion RMB), *Age*, *Cash Ratio*, *Capital Expenditure Intensity*, *Profitability Ratio*, *Sales Growth*, *Export Ratio*, *Leverage Ratio*, *Labor Ratio*, *Wage per Employee*, and *Subsidy Ratio*, as well as firm fixed effects, province-year fixed effects, and industry-year fixed effects. All control variables are defined in Table 1. The sample period of t is from 1998 to 2013. The outcome variable and all control variables are winsorized at their 1st and 99th percentiles. Numbers in parentheses denote standard errors. FE, fixed effect.

*Significance level of 10%; **significance level of 5%; ***significance level of 1%.

collaborative relationship with the focal firm up to year t are within a 100-km distance, as our primary measure of geographic proximity.[16] We also consider *Inverse of Location Distance*, the inverse of the weighted average of the distance between the focal firm and its collaborating universities up to year t, as an alternative measure of geographic proximity.

As indicated in Table 6, which uses *Within 100KM Commuting Distance* as a measure of geographic proximity, the coefficients of the interaction terms of *IUC* × *High Group* are significantly positive in most columns. This finding implies that the relation between IUC experience and technology commercialization is more pronounced when firms are geographically closer to

Table 5. Science Dependence as a Moderator of the IUC-Technology Commercialization Relation

Panel A: IUC measured in *Dummy*

	Panel A.1: Patent-based IUC			Panel A.2: Paper-based IUC		
Department variable =	*New Product Sales* (1)	*Product-Oriented PatCount* (2)	*Product-Oriented PatCite* (3)	*New Product Sales* (1)	*Product-Oriented PatCount* (2)	*Product-Oriented PatCite* (3)
IUC × *High Group*	0.1615***	0.2062***	0.0124**	0.1268***	0.1775***	0.0126***
	(0.0314)	(0.0245)	(0.0056)	(0.0144)	(0.0113)	(0.0026)
IUC	0.0525***	0.0852***	0.0107***	0.0152**	0.0156***	0.0021
	(0.0123)	(0.0095)	(0.0022)	(0.0070)	(0.0056)	(0.0013)
Number of observations	784,025	784,025	784,025	784,025	784,025	784,025
Number of firms	92,521	92,521	92,521	92,521	92,521	92,521
R^2	0.8274	0.4442	0.3026	0.8274	0.4443	0.3026
Innovation-related controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm characteristics controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Province-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: IUC measured in *Count*

	Panel B.1: Patent-based IUC			Panel B.2: Paper-based IUC		
Dependent variable =	*New Product Sales* (1)	*Product-Oriented PatCount* (2)	*Product-Oriented PatCite* (3)	*New Product Sales* (1)	*Product-Oriented PatCount* (2)	*Product-Oriented PatCite* (3)
IUC × *High Group*	0.1135***	0.1526***	0.0067	0.1219***	0.1337***	0.0100***
	(0.0245)	(0.0186)	(0.0043)	(0.0109)	(0.0086)	(0.0020)
IUC	0.0522***	0.0899***	0.0092***	0.0321***	0.0302***	0.0038***
	(0.0108)	(0.0082)	(0.0019)	(0.0065)	(0.0052)	(0.0012)
Number of observations	784,025	784,025	784,025	784,025	784,025	784,025
Number of firms	92,521	92,521	92,521	92,521	92,521	92,521
R^2	0.8274	0.4442	0.3026	0.8274	0.4443	0.3026
Innovation-related controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm characteristics controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Province-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes. We execute pooled regressions to estimate the effects of industry-university collaboration on a firm's future performance of technology commercialization conditional on science dependence. Specifically, the dependent variables are *New Product Sales* in year $t + 1$ in a natural logarithm form in column (1), *Product-Oriented PatCount* in year $t + 1$ in a natural logarithm form in column (2), and *Product-Oriented PatCite* in year $t + 1$ in a natural logarithm form in column (3). As the independent variables, *Patent-Based IUC* and *Paper-Based IUC* are measured in *Dummy* and *Count* in panels A and B, respectively. All firm-year observations are split into two groups according to their measures of *Science Dependence*. If a *measure* is higher than the median, then it is included in the high group; otherwise, it is included in the low group. We measure *Science Dependence* with *Ratio of Backward Citations to Academic Papers*. Specifically, *Ratio of Backward Citations to Academic Papers* of an industry is measured by its ratio of patents' backward citations to academic papers divided by total backward citations. We also control for innovation-related variables, such as *Patent Portfolio Size* and *R&D Intensity*. We further control for firm characteristics, such as *Total Assets* (in billion RMB), *Age*, *Cash Ratio*, *Capital Expenditure Intensity*, *Profitability Ratio*, *Sales Growth*, *Export Ratio*, *Leverage Ratio*, *Labor Ratio*, *Wage per Employee*, and *Subsidy Ratio*, as well as firm fixed effects, province-year fixed effects, and industry-year fixed effects. All control variables are defined in Table 1. The sample period of t is from 1998 to 2013. The outcome variable and all control variables are winsorized at their 1st and 99th percentiles. Numbers in parentheses denote standard errors. FE, fixed effect.

**Significance level of 5%; ***significance level of 1%.

their collaborating universities. We further report the estimation results using *Inverse of Location Distance* as an alternative measure in Online Appendix Table OA.7. The coefficient estimates of *IUC* × *High Group* are significantly positive in 8 of 12 columns. These empirical findings collectively support Hypothesis 4: that firms located geographically closer to their collaborating universities can gain more advantage from their IUC experience.

6. Channels

In this section, we examine several possible channels through which firms' IUC experience may enhance

Table 6. Geographic Proximity as a Moderator of the IUC-Technology Commercialization Relation

Panel A: IUC measured in *Dummy*						
	Panel A.1: Patent-based IUC			Panel A.2: Paper-based IUC		
Dependent variable =	*New Product Sales* (1)	*Product-Oriented PatCount* (2)	*Product-Oriented PatCite* (3)	*New Product Sales* (1)	*Product-Oriented PatCount* (2)	*Product-Oriented PatCite* (3)
IUC × High Group	0.0642**	0.0360*	0.0084*	0.1257***	0.1428***	0.0366***
	(0.0262)	(0.0206)	(0.0047)	(0.0364)	(0.0283)	(0.0065)
IUC	0.0595***	0.1056***	0.0105***	0.0377***	0.0482***	0.0039***
	(0.0131)	(0.0102)	(0.0023)	(0.0065)	(0.0051)	(0.0012)
Number of observations	784,025	784,025	784,025	784,025	784,025	784,025
Number of firms	92,521	92,521	92,521	92,521	92,521	92,521
R^2	0.8274	0.4441	0.3026	0.8274	0.4441	0.3026
Innovation-related controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm characteristics controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Province-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: IUC measured in *Count*						
	Panel B.1: Patent-based IUC			Panel B.2: Paper-based IUC		
Dependent variable =	*New Product Sales* (1)	*Product-Oriented PatCount* (2)	*Product-Oriented PatCite* (3)	*New Product Sales* (1)	*Product-Oriented PatCount* (2)	*Product-Oriented PatCite* (3)
IUC × High Group	0.0418**	0.0310*	0.0018	0.0441**	0.1192***	0.0222***
	(0.0192)	(0.0161)	(0.0037)	(0.0193)	(0.0153)	(0.0035)
IUC	0.0546***	0.1082***	0.0098***	0.0634***	0.0607***	0.0053***
	(0.0128)	(0.0089)	(0.0021)	(0.0059)	(0.0046)	(0.0011)
Number of observations	784,025	784,025	784,025	784,025	784,025	784,025
Number of firms	92,521	92,521	92,521	92,521	92,521	92,521
R^2	0.8274	0.4442	0.3026	0.8274	0.4442	0.3027
Innovation-related controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm characteristics controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Province-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes. We execute pooled regressions to estimate the effects of industry-university collaboration on a firm's future performance of technology commercialization conditional on geographic proximity. Specifically, the dependent variables are *New Product Sales* in year $t + 1$ in a natural logarithm form in column (1), *Product-Oriented PatCount* in year $t + 1$ in a natural logarithm form in column (2), and *Product-Oriented PatCite* in year $t + 1$ in a natural logarithm form in column (3). As the independent variables, *Patent-Based IUC* and *Paper-Based IUC* are measured in *Dummy* and *Count* in panels A and B, respectively. All firm-year observations are split into two groups according to their measures of *Geographic Proximity*. If a *measure* is higher than the median, then it is included in the high group; otherwise, it is included in the low group. We measure *Geographic Proximity* with *Within 100KM Commuting Distance*. Specifically, *Within 100KM Commuting Distance* of a firm is measured by the weighted average of dummy variables indicating whether the focal firm and its collaborating universities are within a 100-km distance. We also control for innovation-related variables, such as *Patent Portfolio Size* and *R&D Intensity*. We further control for firm characteristics, such as *Total Assets* (in billion RMB), *Age*, *Cash Ratio*, *Capital Expenditure Intensity*, *Profitability Ratio*, *Sales Growth*, *Export Ratio*, *Leverage Ratio*, *Labor Ratio*, *Wage per Employee*, and *Subsidy Ratio*, as well as firm fixed effects, province-year fixed effects, and industry-year fixed effects. All control variables are defined in Table 1. The sample period of t is from 1998 to 2013. The outcome variable and all control variables are winsorized at their 1st and 99th percentiles. Numbers in parentheses denote standard errors. FE, fixed effect.

*Significance level of 10%; **significance level of 5%; ***significance level of 1%.

their technology commercialization. The first two are knowledge acquisition and talent recruiting (Prager and Omenn 1980, Mowery and Ziedonis 2015, Babina et al. 2020). As argued by Prager and Omenn (1980), firms could benefit from IUC because of "additional sources of ideas, knowledge, and technology on which to base potential new products and processes" and for "source[s] of potential research employees sympathetic to industry needs." In addition, we also consider direct technology transfer and the complementarity between firms' and universities' innovation capabilities as another two possible channels. These channels are nonexclusive; thus, a firm with IUC experience may be subject to one or more channels.

Table 7. Industry-University Collaboration and Future Acquisition of Product-Oriented Knowledge

Panel A: Dependent variable = *CiteUniv Ratio*				
	Panel A.1: Patent-based IUC		Panel A.2: Paper-based IUC	
	(1)	(2)	(1)	(2)
IUC Dummy	0.0125***		0.0043***	
	(0.0014)		(0.0006)	
IUC Count		0.0113***		0.0060***
		(0.0013)		(0.0007)
Number of observations	784,025	784,025	784,025	784,025
Number of firms	92,521	92,521	92,521	92,521
R^2	0.2339	0.2340	0.2335	0.2338
Innovation-related controls	Yes	Yes	Yes	Yes
Firm characteristics controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Province-year FE	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes
Panel B: Dependent variable = *CiteUniv Product-Oriented Number*				
	Panel B.1: Patent-based IUC		Panel B.2: Paper-based IUC	
	(1)	(2)	(1)	(2)
IUC Dummy	0.0458***		0.0148***	
	(0.0046)		(0.0018)	
IUC Count		0.0471***		0.0227***
		(0.0051)		(0.0024)
Number of observations	784,025	784,025	784,025	784,025
Number of firms	92,521	92,521	92,521	92,521
R^2	0.2572	0.2576	0.2566	0.2571
Innovation-related controls	Yes	Yes	Yes	Yes
Firm characteristics controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Province-year FE	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes

Notes. We execute pooled regressions to estimate the effect of industry-university collaboration on a firm's future knowledge acquisition. Specifically, we regress the dependent variables, *CiteUniv Ratio* in year $t + 1$ in panel A or *CiteUniv Product-Oriented Number* in year $t + 1$ in panel B, on patent-based and paper-based IUC measures as independent variables in year $t - 4$ to t. As dependent variables, *CiteUniv Ratio* denotes the ratio of university patents cited divided by total patents cited by patents that are solely applied by the focal firm. *CiteUniv Product-Oriented Number* denotes the number of university product-oriented patents cited by patents that are solely applied by the focal firm. As the independent variables, *Patent-Based (Paper-Based) IUC Dummy* equals one if the focal firm has an IUC patent (paper); otherwise, it equals to zero. *Patent-Based (Paper-Based) IUC Count* denotes the number of patents applied by (papers published by) both a university and the focal firm. We control for innovation-related variables, such as *Patent Portfolio Size* and *R&D Intensity*. We also control for firm characteristics, such as *Total Assets* (in billion RMB), *Age*, *Cash Ratio*, *Capital Expenditure Intensity*, *Profitability Ratio*, *Sales Growth*, *Export Ratio*, *Leverage Ratio*, *Labor Ratio*, *Wage per Employee*, and *Subsidy Ratio*, as well as firm fixed effects, province-year fixed effects, and industry-year fixed effects. All control variables are defined in Table 1. The sample period of t is from 1998 to 2013. The outcome variable and all control variables are winsorized at their 1st and 99th percentiles. Numbers in parentheses denote standard errors clustered by firms. FE, fixed effect.

***Significance level of 1%.

6.1. Knowledge Acquisition

To measure knowledge acquired from universities, we use *CiteUniv Ratio*, which denotes the ratio of backward citations to university patents over all backward citations made by corporate patents filed by the focal firm in year $t + 1$. Because patent citations reflect knowledge flows (Tijssen 2001, Peri 2005, Alcácer and Gittelman 2006, Gomes-Casseres et al. 2006), firms with higher *CiteUniv Ratio* are likely to be those acquiring more knowledge from universities. To dig into firm behavior in acquiring product-oriented technologies from universities, we consider *CiteUniv Product-Oriented Number*, which denotes the number of universities' product-oriented patents cited by patents of the focal firm.

Table 7 presents estimation results of Equation (1) by using *CiteUniv Ratio* and *CiteUniv Product-Oriented Number* as the dependent variables in panels A and B, respectively. Panels A.1 and A.2 of Table 7 show that engaging in joint patenting and joint publishing is significantly and positively associated with firms' *CiteUniv Ratio* (0.013 and 0.004, respectively). The estimated

Table 8. Industry-University Collaboration and the Future Recruitment of Product-Oriented Talents

Panel A: Dependent variable = *HireUniv Ratio*				
	Panel A.1: Patent-based IUC		Panel A.2: Paper-based IUC	
	(1)	(2)	(1)	(2)
IUC Dummy	0.0137***		0.0041***	
	(0.0015)		(0.0008)	
IUC Count		0.0114***		0.0050***
		(0.0013)		(0.0007)
Number of observations	784,025	784,025	784,025	784,025
Number of firms	92,521	92,521	92,521	92,521
R^2	0.3097	0.3097	0.3095	0.3096
Innovation-related controls	Yes	Yes	Yes	Yes
Firm characteristics controls	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes
Province-year FE	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes
Panel B: Dependent variable = *HireUniv Product-Oriented Number*				
	Panel B.1: Patent-based IUC		Panel B.2: Paper-based IUC	
	(1)	(2)	(1)	(2)
IUC Dummy	0.1603***		0.0659***	
	(0.0139)		(0.0062)	
IUC Count		0.1516***		0.0839***
		(0.0139)		(0.0074)
Number of observations	784,025	784,025	784,025	784,025
Number of firms	92,521	92,521	92,521	92,521
R^2	0.4589	0.4591	0.4584	0.4589
Innovation-related controls	Yes	Yes	Yes	Yes
Firm characteristics controls	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes
Province-year FE	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes

Notes. We execute pooled regressions to estimate the effect of industry-university collaboration on a firm's future recruitment of product-oriented talents. Specifically, we regress the dependent variables, *HireUniv Ratio* in year $t+1$ in panel A or *HireUniv Product-Oriented Number* in year $t+1$ in panel B, on patent-based and paper-based IUC measures as independent variables in year $t-4$ to t. As dependent variables, *HireUniv Ratio* denotes the ratio of former inventors from universities over total inventors filing patents that are solely applied by the focal firm. A former university inventor is defined if he or she files a sole corporate patent in the focal firm in year $t+1$ but files a sole university patent before year t. *HireUniv Product-Oriented Number* denotes the number of former product-oriented inventors from universities filing patents that are solely applied by the focal firm. As the independent variables, *Patent-Based (Paper-Based) IUC Dummy* equals one if the focal firm has an IUC patent (paper); otherwise, it equals to zero. *Patent-Based (Paper-Based) IUC Count* denotes the number of patents applied by (papers published by) both a university and the focal firm. We control for innovation-related variables, such as *Patent Portfolio Size* and *R&D Intensity*. We also control for firm characteristics, such as *Total Assets* (in billion RMB), *Age*, *Cash Ratio*, *Capital Expenditure Intensity*, *Profitability Ratio*, *Sales Growth*, *Export Ratio*, *Leverage Ratio*, *Labor Ratio*, *Wage per Employee*, and *Subsidy Ratio*, as well as firm fixed effects, province-year fixed effects, and industry-year fixed effects. All control variables are defined in Table 1. The sample period of t is from 1998 to 2013. The outcome variable and all control variables are winsorized at their 1st and 99th percentiles. Numbers in parentheses denote standard errors clustered by firms. FE, fixed effect.

***Significance level of 1%.

magnitude is also economically significant as the sample mean and standard deviation of *CiteUniv Ratio* are 0.004 and 0.036, respectively (as shown in Table 1). Panel B of Table 7 further implies that product-oriented technologies acquired from universities increase with IUC activities. Table 7 thus supports that (a part of) the effect of IUC experience may result from firms' acquisition of universities' general knowledge and that product-related technologies increases with their IUC experience.

6.2. Talent Recruiting

To measure firms' recruitment of general talent from universities, we use *HireUniv Ratio*, which is the ratio of former university inventors over total inventors of all patents filed by the focal firm in year $t+1$. An inventor is defined as a former university inventor if he or she files a corporate patent in year $t+1$ but files a university patent before year t.[17] Firms with higher *HireUniv Ratio* are likely to be those recruiting more talent

Table 9. Industry-University Collaboration and Future Technology Transfers

Panel A: Dependent variable = *ReassignUniv Ratio*				
	Panel A.1: Patent-based IUC		Panel A.2: Paper-based IUC	
	(1)	(2)	(1)	(2)
IUC Dummy	0.0087***		0.0007	
	(0.0025)		(0.0010)	
IUC Count		0.0117***		0.0029***
		(0.0028)		(0.0011)
Number of observations	784,025	784,025	784,025	784,025
Number of firms	92,521	92,521	92,521	92,521
R^2	0.1813	0.1814	0.1812	0.1812
Innovation-related controls	Yes	Yes	Yes	Yes
Firm characteristics controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Province-year FE	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes
Panel B: Dependent variable = *ReassignUniv Product-Oriented Number*				
	Panel B.1: Patent-based IUC		Panel B.2: Paper-based IUC	
	(1)	(2)	(1)	(2)
IUC Dummy	0.0114***		0.0023	
	(0.0040)		(0.0016)	
IUC Count		0.0180***		0.0049***
		(0.0057)		(0.0018)
Number of observations	784,025	784,025	784,025	784,025
Number of firms	92,521	92,521	92,521	92,521
R^2	0.1756	0.1757	0.1755	0.1756
Innovation-related controls	Yes	Yes	Yes	Yes
Firm characteristics controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Province-year FE	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes

Notes. We execute pooled regressions to estimate the effect of industry-university collaboration on a firm's future technology transfers. Specifically, we regress the dependent variables, *ReassignUniv Ratio* in year $t + 1$ in panel A or *ReassignUniv Product-Oriented Number* in year $t + 1$ in panel B, on patent-based and paper-based IUC measures as independent variables in year $t - 4$ to t. As dependent variables, *ReassignUniv Ratio* denotes the ratio of university patents reassigned divided by total patents reassigned to the focal firm. *ReassignUniv Product-Oriented Number* denotes the number of university product-oriented patents reassigned to the focal firm. As the independent variables, *Patent-Based (Paper-Based) IUC Dummy* equals one if the focal firm has an IUC patent (paper); otherwise, it equals to zero. *Patent-Based (Paper-Based) IUC Count* denotes the number of patents applied by (papers published by) both a university and the focal firm. We control for innovation-related variables, such as *Patent Portfolio Size* and *R&D Intensity*. We also control for firm characteristics, such as *Total Assets* (in billion RMB), *Age*, *Cash Ratio*, *Capital Expenditure Intensity*, *Profitability Ratio*, *Sales Growth*, *Export Ratio*, *Leverage Ratio*, *Labor Ratio*, *Wage per Employee*, and *Subsidy Ratio*, as well as firm fixed effects, province-year fixed effects, and industry-year fixed effects. All control variables are defined in Table 1. The sample period of t is from 1998 to 2013. All control variables are winsorized at their 1st and 99th percentiles. Numbers in parentheses denote standard errors clustered by firms. FE, fixed effect.

***Significance level of 1%.

from universities. To localize firms' behavior in recruiting product-oriented talent, we also examine *HireUniv Product-Oriented Number*, which measures the number of former product-oriented inventors[18] from universities filing patents that are solely applied by the focal firm.

Table 8 presents the estimation results of Equation (1) by using *HireUniv Ratio* and *HireUniv Product-Oriented Number* as the dependent variables in panels A and B, respectively. For example, panel A of Table 8 shows that engaging in joint patenting and joint publishing increases firms' *HireUniv Ratio* by 0.014 and 0.004, respectively ($p < 0.01$ in both cases). The estimates are also economically significant given the sample mean (0.020) and standard deviation (0.065) of *HireUniv Ratio* (as shown in Table 1). Panel B of Table 8 further points out that the product-oriented talent from universities that is recruited by firms also increase with firms' IUC activities. Table 8 thus supports that the effect of IUC experience is at least partially attributable to firms' recruiting university talent.

6.3. Direct Technology Transfers

To measure technologies that are transferred from universities to firms, we use *ReassignUniv Ratio*, which is the ratio of university-reassigned patents over total patents reassigned to the focal firm in year $t + 1$.[19] As an alternate measure of firms' behavior in acquiring product-oriented technologies, we construct *ReassignUniv Product-Oriented Number,* which is the number of university product-oriented patents reassigned to the focal firm.

Table 9 reports the estimation results of Equation (1) by using *ReassignUniv Ratio* and *ReassignUniv Product-Oriented Number* as the dependent variables in panels A and B, respectively. For example, panel A of Table 9 indicates that engaging in joint patenting and joint publishing increases firms' *ReassignUniv Ratio* by 0.009 and 0.0004, respectively ($p < 0.01$ in both cases). The estimated magnitude is also economically considerable, when compared with the sample mean and standard deviation of *ReassignUniv Ratio*, respectively (0.001 and 0.030 as shown in Table 1). Panel B of Table 9 presents a consistent pattern. Thus, our evidence supports that at least a part of the effect of IUC experience may result from firms' access to technology transferred from universities.

6.4. Technological Complementarity Between Universities' and Firms' Innovation

The literature has suggested that universities' and firms' innovations can complement each other in creating commercializable inventions (Arora and Gambardella 1994, Kaiser et al. 2018). We test whether the positive effect of IUC on technology commercialization could be attributed to the recombination of complementary assets. To do so, we estimate regression Model (2) using *Ratio of Commonly Cited Technology Classes*, a firm's ratio of commonly cited technology class pairs divided by total technology class pairs in the previous five years (from $t - 4$ to t), as our primary measure of technological complementarity.[20] A technology class X of firm F and class Y of the firm's collaborating university U are commonly cited if they are included in two different patents that are cited by at least one other patent. We also consider *Ratio of Synergistic Technology Classes*, a firm's ratio of the number of synergistic technology class pairs divided by the number of total technology class pairs across all historical years up to year t, as an alternative measure of technological complementarity.[21]

As shown in Table 10, which is based on *Ratio of Commonly Cited Technology Classes* as a measure of technological complementarity, the coefficients of the interaction terms of *IUC* × *High Group* are significantly positive in most columns. This finding indicates that the relation between IUC experience and technology commercialization is more pronounced when firms' technologies are more complementary to their collaborating universities. A similar pattern is found in Online Appendix Table OA.8 when we use *Ratio of Synergistic Technology Classes* as an alternative measure. Overall, our empirical results imply that firms with higher technological complementarity can benefit more from IUC experience.

7. Additional Event Analyses

In this section, we design staggered difference-in-differences analyses based on two events that are directly related to local firms' IUC experience but are arguably unrelated to firms' selection and local governments' policies. These tests help us to assess the extent to which our empirical results are driven primarily by omitted variables. We summarize our results in this section and present further details in Section E in the Online Appendix.

Our first DiD test exploits the promotion of university science parks (USPs) from the local level to the national level. USPs in China were first initiated by local governments associated with universities and industrial practitioners to enhance regional technology transfer and economic development (Tan 2006). When a local-level USP performs well in specific criteria (mainly IUC performance), it can be promoted by the central government to be a "national USP," and then, it receives stronger support.

We then design a DiD analysis to difference away the local factors that are present before and after the events, allowing us to estimate the effects of the central government's support on national USPs that directly enhance the value of local firms' IUC experience (but not other aspects of corporate activities). For example, their collaborations with and connections to local universities may benefit from new incentives and/or subsidies. As discussed in Online Appendix Section E.1, we find that both local firms' IUC activities and technology commercialization increase significantly after local USPs are promoted to national USPs. We do not find more active IUC or higher technology commercialization among treated firms *before* the promotion. This finding helps mitigate the concern of local governments' policies or specific industry trends being an omitted variable because if local governments' policies or the growth opportunities of specific industries are driving the positive IUC experience-technology commercialization relation, we should have observed increases in IUC activities or technology commercialization before the events (as firms can change their activities/improve performance before the occurrence year of upgrading and establishment).

Our second DiD test exploits the establishment of university subcampuses in *neighboring* provinces (within a 100-km distance). We expect that the establishment of university (sub-)campuses creates arguably exogenous benefits for firms with IUC experience in neighboring provinces because these firms possess know-how about IUC and connections to universities; however, such an

Table 10. Technological Complementarity as a Moderator of the IUC-Technology Commercialization Relation

Panel A: IUC measured in *Dummy*

	Panel A.1: Patent-based IUC			Panel A.2: Paper-based IUC		
Dependent variable =	*New Product Sales* (1)	*Product-Oriented PatCount* (2)	*Product-Oriented PatCite* (3)	*New Product Sales* (1)	*Product-Oriented PatCount* (2)	*Product-Oriented PatCite* (3)
IUC × High Group	0.0434**	0.1040***	0.0119***	0.0737***	0.0198	0.0131**
	(0.0208)	(0.0161)	(0.0037)	(0.0282)	(0.0221)	(0.0051)
IUC	0.0528***	0.0579***	0.0060**	0.0378***	0.0505***	0.0042***
	(0.0157)	(0.0125)	(0.0029)	(0.0065)	(0.0051)	(0.0012)
Number of observations	784,025	784,025	784,025	784,025	784,025	784,025
Number of firms	92,521	92,521	92,521	92,521	92,521	92,521
R^2	0.8274	0.4441	0.3026	0.8274	0.4441	0.3026
Innovation-related controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm characteristics controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Province-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: IUC measured in *Count*

	Panel B.1: Patent-based IUC			Panel B.2: Paper-based IUC		
Dependent variable =	*New Product Sales* (1)	*Product-Oriented PatCount* (2)	*Product-Oriented PatCite* (3)	*New Product Sales* (1)	*Product-Oriented PatCount* (2)	*Product-Oriented PatCite* (3)
IUC × High Group	0.0282	0.0979***	0.0106***	0.0440**	0.0044	0.0095***
	(0.0178)	(0.0136)	(0.0031)	(0.0171)	(0.0135)	(0.0031)
IUC	0.0566***	0.0597***	0.0041	0.0632***	0.0675***	0.0061***
	(0.0140)	(0.0110)	(0.0025)	(0.0059)	(0.0046)	(0.0011)
Number of observations	784,025	784,025	784,025	784,025	784,025	784,025
Number of firms	92,521	92,521	92,521	92,521	92,521	92,521
R^2	0.8274	0.4442	0.3026	0.8274	0.4442	0.3026
Innovation-related controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm characteristics controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Province-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes. We execute pooled regressions to estimate the effects of industry-university collaboration on a firm's future performance of technology commercialization conditional on technological complementarity. Specifically, the dependent variables are *New Product Sales* in year $t + 1$ in a natural logarithm form in column (1), *Product-Oriented PatCount* in year $t + 1$ in a natural logarithm form in column (2), and *Product-Oriented PatCite* in year $t + 1$ in a natural logarithm form in column (3). As the independent variables, *Patent-Based IUC* and *Paper-Based IUC* are measured in *Dummy* and *Count* in panels A and B, respectively. All firm-year observations are split into two groups according to their measures of *Technological Complementarity*. If a *measure* is higher than the median, then it is included in the high group; otherwise, it is included in the low group. We measure *Technological Complementarity* with *Ratio of Commonly Cited Technology Classes*. Specifically, *Ratio of Commonly Cited Technology Classes* of a firm is measured by its ratio of commonly cited technology class pairs divided by total technology class pairs. A technology class X of firm F and class Y of the firm's collaborating university U are commonly cited if they are included in two different patents that are cited by at least one other patent. We also control for innovation-related variables, such as *Patent Portfolio Size* and *R&D Intensity*. We further control for firm characteristics, such as *Total Assets* (in billion RMB), *Age*, *Cash Ratio*, *Capital Expenditure Intensity*, *Profitability Ratio*, *Sales Growth*, *Export Ratio*, *Leverage Ratio*, *Labor Ratio*, *Wage per Employee*, and *Subsidy Ratio*, as well as firm fixed effects, province-year fixed effects, and industry-year fixed effects. All control variables are defined in Table 1. The sample period of t is from 1998 to 2013. The outcome variable and all control variables are winsorized at their 1st and 99th percentiles. Numbers in parentheses denote standard errors. FE, fixed effect.

**Significance level of 5%; ***significance level of 1%.

event does not affect other policies and institutional environments that these firms encounter. As discussed in Section E.2 in the Online Appendix, we find that local firms' IUC activities and technology commercialization increase significantly after the establishment of university subcampuses in neighboring provinces. Furthermore, we do not find more active IUC or higher technology commercialization among treated firms *before* the establishment. Similar to the prior DiD test, these results mitigate the concern of omitted variables related to local governments' policies or industry trends because if the positive IUC experience-technology commercialization relation is driven by those omitted variables, IUC activities or technology commercialization should have increased significantly before the event.

8. Discussion

Following Teece's profiting-from-innovation framework, we propose that a firm's successful experience in industry-university collaboration constitutes a hard-to-imitate complementary asset that enhances its technology commercialization. Unlike the prior literature that tends to treat universities as public information sources, we highlight that firms with IUC experience gain more know-how, tacit knowledge, social connections, and trust with collaborating universities. This know-how is not tradable in external markets and helps firms possessing such experience profit from their innovations.

To empirically test this hypothesis, we use modern Chinese high-tech firms as our sample as such firms may benefit from engaging with university knowledge, particularly in the emerging market context. To do so, we collect patent and publication data covering over 90,000 patenting medium- and large-sized firms and 153 notable research universities and institutes in China. We measure firms' IUC experience using the occurrence and frequency of patents coassigned to and academic papers affiliated with both firms and universities. To measure firms' performance of technology commercialization, we first take advantage of the accounting information about new product sales, which is a compulsory item in the NBS census. We broaden our measure of technology commercialization by exploiting a unique feature of China's patent system to capture product-oriented patents.

Our empirical analyses suggest that firms' IUC experience, in the forms of joint patents and joint publications, is positively associated with our measures of technology commercialization. The findings are robust when we conduct identification tests based on two sets of arguably exogenous shocks to local firms' IUC: the promotion of university science parks from the local level to the national level and the establishment of university subcampuses in neighboring provinces. These tests help us mitigate concerns of omitted variables.

Motivated by related theories, we develop contingent hypotheses that the IUC-technology commercialization relation is strengthened when firms have higher absorptive capacity, when firms are in industries that depend more on basic science, and when firms are located closer to their collaborating universities. These hypotheses are also supported in data. Additional tests point out four channels through which firms' IUC experience benefits their technology commercialization: knowledge acquisition, talent recruiting, direct technology transfer, and combining complementary technologies.

Our empirical evidence supports our hypothesis that firms' IUC experience is an inimitable complementary asset in Teece's profiting-from-innovation framework—which adds to the literature by analyzing *why* some firms gain more/less from university spillovers, despite the public availability of such benefits. Our three theory-based contingencies are also supported by additional tests, which enhance the framework by highlighting the heterogeneous roles of IUC under different scenarios; these offer important science and education implications for policymakers in emerging countries that aim to promote high-tech industries through investing in university research.

The role and effect of IUC in emerging economies have not received as much attention in the prior literature. It is unclear whether IUC functions as well as there as we have observed in developed countries. Prior studies on IUC in China focus on measurement and performance issues from the university perspective, whereas we highlight the *consequences* of such collaboration from the corporate perspective. Our large-scale evidence offers new insights to these questions. In addition, there has been a debate on the *effectiveness* of Chinese universities in technology transfer.[22] Furthermore, although prior studies in IUC in China are limited to specific industries or selected universities, our study may be one of the first to provide large-scale evidence for corporate IUC and associated consequences. Our data on publications, patents, inventors, and crossreferences allow us to offer fresh results on the channels through which Chinese firms may benefit from their IUC experience in future technology commercialization.

We acknowledge several limitations. First, although we have compiled large-scale data for joint patents and joint publications (and their references), we acknowledge the difficulty of assembling a comprehensive data set for all IUC activities, like contract research, consulting, research grants, licensing, etc.[23] Second, our IUC measures based on patents and publications only capture successful outcomes of IUC activities, which reflects a common challenge for innovation research. Nevertheless, as we have discussed earlier, successful IUC experience is likely more valuable as it reflects appropriate matching and the acquisition and/or possession of necessary capabilities, resources, and connections to work with universities. To have a comprehensive understanding of all types of IUC activities (and their success or failure), one may need to rely on in-depth surveys (as has been the case in the literature), although with their own limitations of response selectivity;[24] but, even with surveys, we are unlikely to quantify the associated costs of IUC.[25] Third, although it would be nice to analyze the effect of IUC on universities, we are unaware of any comprehensive data sources of Chinese universities' income from IUC activities, which is a sensitive issue to university administrators in China (Wu and Zhou 2012).

Fourth, we acknowledge that even though our measures of technology commercialization follow the literature, they may be subject to industry-specific bias.[26] For instance, in the pharmaceutical and biotechnology industries, firms may write their new drug patents as "methods"; hence, these patents will not be counted as product oriented (and "commercialized") in our analysis. Also, our technology commercialization measures based on new product sales and product-oriented patents may not be applicable to some industries and contexts, such as information technology system consulting service firms. Finally, we acknowledge that universities' engagement in IUC or the establishment of science parks can be entrepreneurial and strategic. The entrepreneurial purpose relates to nurturing local firms, whereas the strategic purpose could be related to matching universities' capabilities and local firms' strengths. We find that it is empirically challenging to tease these two motives apart, but we would welcome future research in this direction.

Acknowledgments

The authors thank the *Management Science* editorial and review teams, Sam Arts, Benjamin Balsmeier, Philipp Boeing, Hanming Fang, Dingwei Gu, Suting Hong, Kenneth Huang, Guangwei Li, Ruiming Liu, Zhuoran Lu, Jiawei Mo, Michael Moedl, Mattia Nardotto, Bettina Peters, Xiang Shao, Guangjun Shen, Jeroen Van den bosch, Bart Van Looy, Dennis Verhoeven, Yanbo Wang, Mingtao Xu, Wentao Yao, Bernard Yeung, Arvids Ziedonis, and Xin Zheng for their insightful comments. The authors also thank conference discussants at the Asian Bureau of Finance and Economic Research and the Taiwan Symposium on Innovation Economics and Entrepreneurship and seminar participants at Fudan, KU Leuven, Shanghai Jiao Tong, ShanghaiTech, Southern University of Science and Technology (SUSTech), and ZEW for their insightful comments. The authors are grateful to Haijin Chen, Rui Dou, and Jianneng Wu for sharing their practical views. All authors contributed equally to this research.

Endnotes

[1] Commercialization is a crucial step of a firm that translates invention into innovation, competitiveness, and long-term performance (Adams 1990, Damanpour 1991, Cooper 2000, Zahra and Nielsen 2002).

[2] Although university knowledge is a public good easily transferred via publications, only some firms have the human capital to access and acquire such knowledge because of the complexity or tacitness of such knowledge, communication costs, and trust needed (Cohen and Levinthal 1989, 1990; Feldman 1994; Zucker and Darby 1996; Cockburn and Henderson 1998; Zucker et al. 1998b; Lim 2009; Nelson 2009).

[3] Our measures of IUC experience in joint patents follow Hong (2008) and Walsh et al. (2016), and our measures of IUC experience in joint publications follow Godin and Gingras (2000), Brehm and Lundin (2012), and Wang and Shapira (2012). Prior studies use these measures based on the successful outcome of IUC activities and acknowledge the unavoidable survival bias (Lim 2009). This issue does not systematically bias our statistical inferences because in comparison with failed IUC operations, successful IUC records reflect better selection and absorbing capabilities (as well as coassigned patents and coauthored papers) have a larger chance to form an inimitable complementary asset.

[4] From a broader perspective, university R&D expenditures have been found to benefit local firms' commercialized innovations through spillovers in the United States (Acs et al. 1992, 1994). Link and Rees (1990) find that in their survey, 60% of firms initiate IUC to pursue new product development. This incentive is further confirmed by the empirical evidence of Feldman (1994), Kaufmann and Tödtling (2001), and Motohashi (2005) based on U.S., Europe, and Japan data, respectively.

[5] For instance, Feldman (1994) commented that "[t]he increased complexity and uncertainty of engaging in innovative activity suggests that interactions and cooperation among autonomous organizations commanding specialized complementary assets and sources of knowledge may be critical to innovative success" (Teece 1986).

[6] Nevertheless, prior surveys also highlight firms' challenges in engaging with universities (Guan et al. 2005, Hong 2008, Wu and Zhou 2012). Chinese universities may lack the incentive to cooperate with firms (Liu and White 2001, Eun et al. 2006, Wu 2010, Wu and Zhou 2012). Also, some studies argue that it has been challenging for Chinese firms to absorb and internalize innovation generated from universities (Liu and Jiang 2001, Guan et al. 2005). As a result, it is unclear how much Chinese firms are able to benefit from their IUC experience.

[7] We follow the code of Brandt et al. (2014) that allows us to track the same firm that changed its names over time. To ensure continuous operation, we restrict to a sample of firms with at least five consecutive years of accounting data, yielding a firm-year data set of 539,709 unique firms. Online Appendix Table OA.11 provides a comprehensive list of the variables that are included in the NBS data.

[8] Project 985 was first announced in May 1998, and Project 211 was initiated in November 1995. Both projects aim to promote the quality and reputation of the higher education system by founding world-class universities. The Chinese Academy of Sciences and the Chinese Academy of Social Sciences were founded by the State Council in 1949 and 1977, respectively, with the purposes of developing fundamental sciences and supporting policymaking. Since then, Chinese central and provincial governments have consistently and disproportionately increased their investment in these research-oriented universities and institutes (Zhang et al. 2013, Jia and Li 2021).

[9] The website for CNKI is https://www.cnki.net/. We did not choose other search engines, such as Google Scholar, Web of Science, and Scopus, for two reasons. First, most of our sample firms are not public firms, so they do not have standardized English names. Second, a majority of them do not have experience or incentive to publish papers in English (Hsu et al. 2021).

[10] In Online Appendix Table OA.16, we confirm that the effect of unsuccessful IUC patent applications on technology commercialization is much weaker than the effect of granted IUC patents.

[11] We acknowledge that firms collaborating with universities but failing to deliver output still gain experience; however, such failure reflects mismatches, and thus, experience from failed projects will not be as useful as successful experience to firms' technology commercialization.

[12] We use this five-year window because of the low frequency of patents of our sample firms following Rothaermel and Deeds (2004), Matolcsy and Wyatt (2008), Hirshleifer et al. (2018), and Hsu et al. (2022).

[13] An institutional feature of Chinese patents enables us to differentiate product- and process-oriented innovations. A process-oriented patent application contains a patent title and an abstract that always

specifies that its main invention is a new process; otherwise, a product-oriented patent specifies that it invents a new product using existent or new processes. Following this rule of thumb, we analyze the text of patent titles to identify 2,598,165 product-oriented patents for corporations and 546,687 product-oriented patents for universities. For forward citations, we use the Item 56 references listed on the front page of each patent issuance document. Sections B and D in the Online Appendix offer more discussion and examples about the categorization of product-oriented patents.

[14] Firm fixed effects control for all time-invariant firm characteristics, such as an organization's culture of innovation; industry-by-year fixed effects control for time-varying industry-specific factors, such as industry life cycles and innovation opportunities; and province-by-year fixed effects absorb all time-varying local factors, such as local institutional environments or government policies. These fixed effects are included because Chinese firms' innovation activities are sensitive to local institutional environments and government policies (including subsidies) (Huang et al. 2017, Fang et al. 2020).

[15] The detailed definitions of all controls are provided in the note of Table 1. We control for the total sales for the scaling effect and the following two innovation-related variables: the number of patents filed by (and later granted to) the focal firm and the ratio of a focal firm's R&D expenditure over its total assets. In addition, we include the following firm characteristic control variables for focal firms, including firm size, firm age, cash over total assets, capital expenditure over total physical assets, profitability, sales growth, leverage, total exports over total sales, the ratio of employees over total assets, the ratio of labor costs over employees, and government subsidies.

[16] If a sample firm has no IUC experience, then this variable is set to be zero.

[17] We acknowledge the difficulty in identifying individual Chinese inventors using their names. In untabulated results, we confirm the robustness of our findings by disambiguating the identities of inventors in alternative ways.

[18] Suppose that an inventor has filed four patents, three of which are product oriented and one which is nonproduct oriented. Then, the inventor is classified as 75% of a product-oriented inventor and 25% of a process-oriented inventor. We then sum up this ratio across all inventors originally from universities.

[19] It is common in the literature to use the patent reassignment to measure technology transfers; see De Marco et al. (2017), Graham et al. (2018), and Arora et al. (2021b). Different from the U.S. patent system, the transfer of patent rights is valid only when the transfer has been registered in the CNIPA (source: https://www.cnipa.gov.cn/jact/front/mailpubdetail.do?transactId=360525&sysid=6).

[20] Following Chari et al. (2022), complementary technologies are those necessary for patentability. When patent classes X and Y are cited by other patents, these classes are likely to be complementary in producing new technologies.

[21] We define classes X and Y as synergistic technology class pairs if there exists at least one patent (other than IUC patents) that is classified into both X and Y. Following Fleming and Sorenson (2004) and Nasiriyar et al. (2014), we measure technological complementarity with the co-occurrences within patents for each pair of technologies. The advantage of this approach is that it does not rely on backward or forward citations and thus, is free of the criticism of mixing technological complementarity with technology transfer.

[22] Chen et al. (2016) highlight the debate on the effectiveness of technology transfers from Chinese universities and call for further evidence; Wu and Zhou (2012) concluded that the technology transfer mission was stalling, whereas Wang et al. (2013) disagreed.

[23] Perkmann et al. (2013) have acknowledged that although universities' records of their IUC contracts would be an ideal source, such data are not readily available because they are often considered commercially sensitive by university administrators. The lack of IUC contract data is also a major obstacle in China (Wu and Zhou 2012).

[24] Although a survey-based method has the advantage of being able to incorporate all possible ways in which corporations can work with universities for technology and knowledge transfer, including hard-to-observe phenomenon such as consulting, the large downside is selectivity of responses. For example, it may be the case that industrial managers who had a positive experience with university staff are more likely to respond to such surveys. In addition, most prior surveys on firm-level technology commercialization are limited to developed countries (Kaufmann and Tödtling 2001, Becker and Dietz 2004, Belderbos et al. 2004, Motohashi 2005, Laursen and Salter 2006, Berchicci 2013, Maietta 2015, Walsh et al. 2016).

[25] Prior literature has discussed that private firms could face substantial costs in IUC activities (such as potential mismatches in project scope, different time horizons, different degrees of openness, government-related barriers, etc.) (Siegel et al. 2003, Bruneel et al. 2010, Perkmann and Salter 2012, Perkmann et al. 2013).

[26] Nevertheless, we re-examine our baseline results in each of the 38 industrial industries covered in our NBS data set and find fairly consistent results. As shown in Online Appendix Table OA.15, all coefficient estimates on IUC experience are positive, and over half of these coefficient estimates are statistically significant.

References

Acs ZJ, Audretsch DB, Feldman MP (1992) Real effects of academic research. *Amer. Econom. Rev.* 82(1):363–367.

Acs ZJ, Audretsch DB, Feldman MP (1994) R&D spillovers and recipient firm size. *Rev. Econom. Statist.* 76(2):336–340.

Adams JD (1990) Fundamental stocks of knowledge and productivity growth. *J. Political Econom.* 98(4):673–702.

Agrawal AK (2001) University-to-industry knowledge transfer: Literature review and unanswered questions. *Internat. J. Management Rev.* 3(4):285–302.

Alcácer J, Gittelman M (2006) Patent citations as a measure of knowledge flows: The influence of examiner citations. *Rev. Econom. Statist.* 88(4):774–779.

Appelbaum RP, Gebbie MA, Han X, Stocking G, Kay L (2016) Will China's quest for indigenous innovation succeed? Some lessons from nanotechnology. *Tech. Soc.* 46:149–163.

Arora A, Gambardella A (1994) The changing technology of technological change: General and abstract knowledge and the division of innovative labour. *Res. Policy* 23(5):523–532.

Arora A, Belenzon S, Patacconi A (2018) The decline of science in corporate R&D. *Strategic Management J.* 39(1):3–32.

Arora A, Belenzon S, Sheer L (2021a) Knowledge spillovers and corporate investment in scientific research. *Amer. Econom. Rev.* 111(3):871–898.

Arora A, Belenzon S, Sheer L (2021b) Matching patents to Compustat firms, 1980–2015: Dynamic reassignment, name changes, and ownership structures. *Res. Policy* 50(5):104217.

Audretsch DB, Feldman MP (1996) R&D spillovers and the geography of innovation and production. *Amer. Econom. Rev.* 86(3):630–640.

Audretsch DB, Stephan PE (1996) Company-scientist locational links: The case of biotechnology. *Amer. Econom. Rev.* 86(3):641–652.

Babina T, He AX, Howell ST, Perlman ER, Staudt J (2020) The color of money: Federal vs. industry funding of university research. NBER Working Paper No. 28160, National Bureau of Economic Research, Cambridge, MA.

Becker W, Dietz J (2004) R&D cooperation and innovation activities of firms—Evidence for the German manufacturing industry. *Res. Policy* 33(2):209–223.

Belderbos R, Carree M, Lokshin B (2004) Cooperative R&D and firm performance. *Res. Policy* 33(10):1477–1492.

Berchicci L (2013) Toward an open R&D system: Internal R&D investment, external knowledge acquisition and innovative performance. *Res. Policy* 42(1):117–127.

Brandt L, Van Biesebroeck J, Zhang Y (2014) Challenges of working with the Chinese NBS firm-level data. *China Econom. Rev.* 30:339–352.

Brehm S, Lundin N (2012) University–industry linkages and absorptive capacity: An empirical analysis of China's manufacturing industry. *Econom. Innovation New Tech.* 21(8):837–852.

Bruneel J, D'Este P, Salter A (2010) Investigating the factors that diminish the barriers to university–industry collaboration. *Res. Policy* 39(7):858–868.

Cassiman B, Veugelers R (2002) R&D cooperation and spillovers: Some empirical evidence from Belgium. *Amer. Econom. Rev.* 92(4):1169–1184.

Chari M, Steensma HK, Connaughton C, Heidl R (2022) The influence of patent assertion entities on inventor behavior. *Strategic Management J.* 43(8):1666–1690.

Chen K, Kenney M (2007) Universities/research institutes and regional innovation systems: The cases of Beijing and Shenzhen. *World Development* 35(6):1056–1074.

Chen A, Patton D, Kenney M (2016) University technology transfer in China: A literature review and taxonomy. *J. Tech. Transfer* 41:891–929.

Cockburn IM, Henderson RM (1998) Absorptive capacity, coauthoring behavior, and the organization of research in drug discovery. *J. Indust. Econom.* 46(2):157–182.

Cohen WM, Levinthal DA (1989) Innovation and learning: The two faces of R&D. *Econom. J.* 99(397):569–596.

Cohen WM, Levinthal DA (1990) Absorptive capacity: A new perspective on learning and innovation. *Admin. Sci. Quart.* 35(1): 128–152.

Cohen WM, Nelson RR, Walsh JP (2002) Links and impacts: The influence of public research on industrial R&D. *Management Sci.* 48(1):1–23.

Cooper LG (2000) Strategic marketing planning for radically new products. *J. Marketing* 64(1):1–16.

Damanpour F (1991) Organizational innovation: A meta-analysis of effects of determinants and moderators. *Acad. Management J.* 34(3):555–590.

Danneels E (2002) The dynamics of product innovation and firm competences. *Strategic Management J.* 23(12):1095–1121.

De Marco A, Scellato G, Ughetto E, Caviggioli F (2017) Global markets for technology: Evidence from patent transactions. *Res. Policy* 46(9):1644–1654.

Eun JH, Lee K, Wu G (2006) Explaining the "University-run enterprises" in China: A theoretical framework for university–industry relationship in developing countries and its application to China. *Res. Policy* 35(9):1329–1346.

Fang J, He H, Li N (2020) China's rising IQ (Innovation Quotient) and growth: Firm-level evidence. *J. Development Econom.* 147: 102561.

Feldman MP (1994) Knowledge complementarity and innovation. *Small Bus. Econom.* 6:363–372.

Fleming L, Sorenson O (2004) Science as a map in technological search. *Strategic Management J.* 25(8–9):909–928.

Furman JL, Porter ME, Stern S (2002) The determinants of national innovative capacity. *Res. Policy* 31(6):899–933.

Godin B, Gingras Y (2000) Impact of collaborative research on academic science. *Sci. Public Policy* 27(1):65–73.

Gomes-Casseres B, Hagedoorn J, Jaffe AB (2006) Do alliances promote knowledge flows? *J. Financial Econom.* 80(1):5–33.

Graham SJ, Marco AC, Myers AF (2018) Patent transactions in the marketplace: Lessons from the USPTO patent assignment data set. *J. Econom. Management Strategy* 27(3):343–371.

Griliches Z (1979) Issues in assessing the contribution of research and development to productivity growth. *Bell J. Econom.* 10(1):92–116.

Guan JC, Yam RC, Mok CK (2005) Collaboration between industry and research institutes/universities on industrial innovation in Beijing, China. *Tech. Anal. Strategic Management* 17(3):339–353.

Hall BH, Link AN, Scott JT (2003) Universities as research partners. *Rev. Econom. Statist.* 85(2):485–491.

Hirshleifer D, Hsu PH, Li D (2018) Innovative originality, profitability, and stock returns. *Rev. Financial Stud.* 31(7):2553–2605.

Hong W (2008) Decline of the center: The decentralizing process of knowledge transfer of Chinese universities from 1985 to 2004. *Res. Policy* 37(4):580–595.

Hong W, Su YS (2013) The effect of institutional proximity in nonlocal university–industry collaborations: An analysis based on Chinese patent data. *Res. Policy* 42(2):454–464.

Hsu DH, Hsu PH, Zhao Q (2021) Rich on paper? Chinese firms' academic publications, patents, and market value. *Res. Policy* 50(9):104319.

Hsu PH, Lee HH, Zhou T (2022) Patent thickets, stock returns, and conditional CAPM. *Management Sci.* 68(11):8343–8367.

Huang KGL, Geng X, Wang H (2017) Institutional regime shift in intellectual property rights and innovation strategies of firms in China. *Organ. Sci.* 28(2):355–377.

Jaffe A (1986) Technological opportunity and spillovers of R&D: Evidence from firms' patents, profits, and market value. *Amer. Econom. Rev*. 76(5):984–1001.

Jaffe AB (1989a) Characterizing the "technological position" of firms, with application to quantifying technological opportunity and research spillovers. *Res. Policy* 18(2):87–97.

Jaffe AB (1989b) Real effects of academic research. *Amer. Econom. Rev.* 79(5):957–970.

Jia R, Li H (2021) Just above the exam cutoff score: Elite college admission and wages in China. *J. Public Econom.* 196:104371.

Kafouros M, Wang C, Piperopoulos P, Zhang M (2015) Academic collaborations and firm innovation performance in China: The role of region-specific institutions. *Res. Policy* 44(3):803–817.

Kaiser U, Kongsted HC, Laursen K, Ejsing AK (2018) Experience matters: The role of academic scientist mobility for industrial innovation. *Strategic Management J.* 39(7):1935–1958.

Kaufmann A, Tödtling F (2001) Science–industry interaction in the process of innovation: The importance of boundary-crossing between systems. *Res. Policy* 30(5):791–804.

Kelm KM, Narayanan VK, Pinches GE (1995) Shareholder value creation during R&D innovation and commercialization stages. *Acad. Management J.* 38(3):770–786.

Klevorick AK, Levin RC, Nelson RR, Winter SG (1995) On the sources and significance of interindustry differences in technological opportunities. *Res. Policy* 24(2):185–205.

Krugman P (1991) Increasing returns and economic geography. *J. Political Econom.* 99(3):483–499.

Laursen K, Salter A (2006) Open for innovation: The role of openness in explaining innovation performance among UK manufacturing firms. *Strategic Management J.* 27(2):131–150.

Lerner J (1995) Patenting in the shadow of competitors. *J. Law Econom.* 38(2):463–495.

Lim K (2009) The many faces of absorptive capacity: Spillovers of copper interconnect technology for semiconductor chips. *Indust. Corporate Change* 18(6):1249–1284.

Link AN, Rees J (1990) Firm size, university based research, and the returns to R&D. *Small Bus. Econom.* 2:25–31.

Liu H, Jiang Y (2001) Technology transfer from higher education institutions to industry in China: Nature and implications. *Technovation* 21(3):175–188.

Liu X, White S (2001) Comparing innovation systems: A framework and application to China's transitional context. *Res. Policy* 30(7):1091–1114.

Maietta OW (2015) Determinants of university–firm R&D collaboration and its impact on innovation: A perspective from a low-tech industry. *Res. Policy* 44(7):1341–1359.

Mansfield E (1991) Academic research and industrial innovation. *Res. Policy* 20(1):1–12.

Mansfield E (1998) Academic research and industrial innovation: An update of empirical findings. *Res. Policy* 26(7–8):773–776.

Mansfield E, Lee JY (1996) The modern university: Contributor to industrial innovation and recipient of industrial R&D support. *Res. Policy* 25(7):1047–1058.

Matolcsy ZP, Wyatt A (2008) The association between technological conditions and the market value of equity. *Accounting Rev.* 83(2):479–518.

Motohashi K (2005) University–industry collaborations in Japan: The role of new technology-based firms in transforming the National Innovation System. *Res. Policy* 34(5):583–594.

Motohashi K, Yun X (2007) China's innovation system reform and growing industry and science linkages. *Res. Policy* 36(8):1251–1260.

Mowery DC, Ziedonis AA (2015) Markets vs. spillovers in outflows of university research. *Res. Policy* 44(1):50–66.

Nasiriyar M, Nesta L, Dibiaggio L (2014) The moderating role of the complementary nature of technological resources in the diversification–performance relationship. *Indust. Corporate Change* 23(5):1357–1380.

Nelson RR (1986) Institutions supporting technical advance in industry. *Amer. Econom. Rev.* 76(2):186–189.

Nelson AJ (2009) Measuring knowledge spillovers: What patents, licenses and publications reveal about innovation diffusion. *Res. Policy* 38(6):994–1005.

Pavitt K (1991) What makes basic research economically useful? *Res. Policy* 20(2):109–119.

Peri G (2005) Determinants of knowledge flows and their effect on innovation. *Rev. Econom. Statist.* 87(2):308–322.

Perkmann M, Salter A (2012) How to create productive partnerships with universities. *MIT Sloan Management Rev.* 53(4):53417.

Perkmann M, Tartari V, McKelvey M, Autio E, Broström A, D'Este P, Fini R, et al. (2013) Academic engagement and commercialisation: A review of the literature on university–industry relations. *Res. Policy* 42(2):423–442.

Polanyi M (1966) The logic of tacit inference. *Philosophy* 41(155):1–18.

Poyago-Theotoky J, Beath J, Siegel DS (2002) Universities and fundamental research: Reflections on the growth of university–industry partnerships. *Oxford Rev. Econom. Policy* 18(1):10–21.

Prager DJ, Omenn GS (1980) Research, innovation, and university-industry linkages. *Science* 207(4429):379–384.

Roberts PW (1999) Product innovation, product–market competition and persistent profitability in the US pharmaceutical industry. *Strategic Management J.* 20(7):655–670.

Rothaermel FT, Deeds DL (2004) Exploration and exploitation alliances in biotechnology: A system of new product development. *Strategic Management J.* 25(3):201–221.

Siegel DS, Waldman D, Link A (2003) Assessing the impact of organizational practices on the relative productivity of university technology transfer offices: An exploratory study. *Res. Policy* 32(1):27–48.

Simeth M, Cincera M (2016) Corporate science, innovation, and firm value. *Management Sci.* 62(7):1970–1981.

Sun Y, Zhang C, Kok RA (2020) The role of research outcome quality in the relationship between university research collaboration and technology transfer: Empirical results from China. *Scientometrics* 122:1003–1026.

Tan J (2006) Growth of industry clusters and innovation: Lessons from Beijing Zhongguancun Science Park. *J. Bus. Venturing* 21(6):827–850.

Teece DJ (1986) Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy. *Res. Policy* 15(6):285–305.

Teece DJ (2006) Reflections on "profiting from innovation." *Res. Policy* 35(8):1131–1146.

Teece DJ (2018) Profiting from innovation in the digital economy: Enabling technologies, standards, and licensing models in the wireless world. *Res. Policy* 47(8):1367–1387.

Tijssen RJ (2001) Global and domestic utilization of industrial relevant science: Patent citation analysis of science–technology interactions and knowledge flows. *Res. Policy* 30(1):35–54.

Trajtenberg M, Henderson R, Jaffe A (1997) University vs. corporate patents: A window on the basicness of invention. *Econom. Innovation New Tech.* 5(1):19–50.

Von Hippel E (1994) "Sticky information" and the locus of problem solving: Implications for innovation. *Management Sci.* 40(4): 429–439.

Walsh JP, Lee YN, Nagaoka S (2016) Openness and innovation in the US: Collaboration form, idea generation and implementation. *Res. Policy* 45(8):1660–1671.

Wang J, Shapira P (2012) Partnering with universities: A good choice for nanotechnology start-up firms? *Small Bus. Econom.* 38:197–215.

Wang Y, Huang J, Chen Y, Pan X, Chen J (2013) Have Chinese universities embraced their third mission? New insight from a business perspective. *Scientometrics* 97:207–222.

Wu W (2010) Managing and incentivizing research commercialization in Chinese Universities. *J. Tech. Transfer* 35:203–224.

Wu W, Zhou Y (2012) The third mission stalled? Universities in China's technological progress. *J. Tech. Transfer* 37:812–827.

Zahra SA, Nielsen AP (2002) Sources of capabilities, integration and technology commercialization. *Strategic Management J.* 23(5): 377–398.

Zhang H, Patton D, Kenney M (2013) Building global-class universities: Assessing the impact of the 985 Project. *Res. Policy* 42(3):765–775.

Zhou W (2012) Determinants and effects of research partnerships in China's emerging market. *Contemporary Econom. Policy* 30(1): 129–147.

Zucker LG, Darby MR (1996) Star scientists and institutional transformation: Patterns of invention and innovation in the formation of the biotechnology industry. *Proc. Natl. Acad. Sci. USA* 93(23):12709–12716.

Zucker LG, Darby MR (2001) Capturing technological opportunity via Japan's star scientists: Evidence from Japanese firms' biotech patents and products. *J. Tech. Transfer* 26(1):37–58.

Zucker LG, Darby MR, Armstrong J (1998a) Geographically localized knowledge: Spillovers or markets? *Econom. Inquiry* 36(1): 65–86.

Zucker LG, Darby MR, Brewer MB (1998b) Intellectual human capital and the birth of US biotechnology enterprises. *Amer. Econom. Rev*. 88(1):290–306.