Industry-University Collaboration and Commercializing Chinese Corporate Innovation*

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April 2024

Forthcoming, *Management Science*

Abstract

We construct a comprehensive dataset 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 co-assigned to universities or when they have more academic publications coauthored with university staff in the past. Such 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.

Keywords: Industry-University Collaboration, Corporate Innovation, Technology Commercialization, Technology Transfer, Complementarity

JEL codes: O31, O33

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1. Introduction

While firms conduct basic research and create new technologies (Simeth and Cincera, 2016; Arora, Belenzon, and Patacconi, 2018; Arora, Belenzon, and Sheer, 2021a), their main task and contribution to society is 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' develop of new products/processes (Mansfield, 1991 and 1998; Klevorick et al., 1995; Cohen, Nelson, and Walsh, 2002). In fact, Acs, Audretsch, and Feldman (1992) show that university spillovers influence commercialized innovations more than patented inventions.

However, whether IUC also contributes to the commercialization performance of corporates 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 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, Waldman, and Link, 2003; Bruneel, D'Este, and Salter, 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

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

Henderson, 1998), acquiring needed tacit information (Zucker, Darby, and Brewer, 1994), and building social connection and trust (Bruneel, D'Este, and Salter, 2010) in collaboration with universities. Hall, Link, and Scott (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 focus on developed countries (see our summary of the literature of 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 firm-level dataset [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 co-assigned 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 these three contingencies are motivated by prior literature. We also implement additional tests for possible channels through which firms' IUC experience benefits their

[3] Our measures of IUC experience in joint patents follow Hong (2008) and Walsh, Lee, and Nagaoka (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 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 co-assigned patents and coauthored papers) have a larger chance to form an inimitable complementary asset.

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 has been mentioned by, 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) on collecting more IUC data across countries of different institutions and systems, as the Chinese economy started with weak intellectual property protection and firms with low 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 due to the recent surge in science and technology alongside the country's industrial development. Our unique dataset, covering about 93 thousand medium-sized and large 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 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 U.S. (Jaffe, 1989b; Audretsch and Stephan, 1996), but much less efforts have 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, Patton, and Kenney, 2016). Given the prominent role that universities play in science and technology infrastructure (e.g., Furman, Porter, and Stern, 2002), this study offers insights to policy makers, 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 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 differences-in-difference 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, while a more complete review of the literature on university research and technology transfers is provided in Section A and Table OA.1 of 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/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, though we know from the literature that there are barriers and dissimilarities between universities and the private sector (Bruneel, D'Este, and Salter, 2010; Perkmann et al., 2013). While 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, Darby, and Brewer, 1994). In addition, academic researchers' goals, incentives, and cultures are substantially different from those of entrepreneurs and corporate employees (Siegel, Waldman, and Link, 2003; Perkmann and Salter, 2012; Perkmann et al., 2013), which results in principal-agent issues for both sides (Poyago-Theotoky, Beath, and Siegel, 2002). Moreover, as mutual understanding and trust is critical for transferring technologies from universities (Bruneel, D'Este, and Salter, 2010), personal contact and collaboration experience are needed for firms to learn from scientists (e.g., Zucker, Darby, and Armstrong, 1998; 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

[4] From a broader perspective, the university R&D expenditures have been found to benefit local firms' commercialized innovations through spillovers in the U.S. (Acs, Audretsch, and Feldman, 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 empirical evidence of Feldman (1994), Kaufmann and Tödtling (2001), and Motohashi (2005) based on U.S., Europe, and Japan data, respectively.

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 collectively constitute an important complementary asset to firms that can enhance technology commercialization (Feldman, 1994).[5] This is consistent with Hall, Link, and Scott's (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 due to 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 inimitable complementary assets, 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) that 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, Patton, Kenney, 2016), these firms may benefit more from IUC experience (Hong and Su, 2013; Sun, Zhang, and Kok, 2020).[6] We thus posit our primary hypothesis as follows:

H1: 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

[5] For instance, Feldman (1994) commented that "*The 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, Yam, and Mok, 2005; Hong, 2008; Wu and Zhou, 2012). Chinese universities may lack the incentive to cooperate with firms (Liu and White, 2001; Eun, Lee, and Wu, 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, Yam, and Mok, 2005). As a result, it is unclear how much Chinese firms are able to benefit from their IUC experience.

Levinthal (1989, 1990), which highlights that corporate R&D investment helps develop firms' absorptive capacity, which 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, 2006).

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 complement their IUC experience in enhancing technology commercialization. This proposition echoes the call of Chen, Patton, and Kenney (2016) to develop a better understanding of the quality and economic applicability of the university research and measuring the absorptive capacity of domestic firms. Our discussions lead to the second hypothesis:

H2: 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 (Pavitt, 1984; Nelson, 1986; Mansfield, 1991, 1998; Klevorick et al., 1995; Cohen, Nelson, and Walsh, 2002). Such industry heterogeneity also exists in technology commercialization because the appropriability of innovation varies across industries (Teece, 1986). For instance, Acs, Audretsch, and Feldman (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 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:

H3: 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 have documented the effect of universities' R&D on local firms' R&D and patents (Jaffe, 1989b; Acs, Audretsch, and Feldman, 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 due to traffic and congestion costs, cross-province 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 (2019). Chen, Patton, and Kenney's (2016) review of Chinese IUC concludes 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:

H4: The IUC-commercialization relation is stronger among Chinese firms which 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 (NBS) firm-level dataset, 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 5M RMB (approximately $725K 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 is therefore 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 co-assigned 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 of 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 Chinese Academy of Social Sciences.[8] This results in a set of 153 universities (listed in Online Appendix Table OA.12), which 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 by (and were later granted to) these universities from 1994 to 2016.

We then collect the publication information of these innovative firms and research-

[7] We follow the code of Brandt, Van Biesebroeck, and Zhang (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 dataset of 539,709 unique firms. Online Appendix Table OA.11 in the Online Appendix provides a comprehensive list of 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 Chinese Academy of Social Sciences are founded by the State Council in 1949 and 1977, respectively, with the purposes of developing fundamental sciences and supporting policy making. Since then, Chinese central and provincial governments have consistently and disproportionately increased their investment in these research-oriented universities and institutes (Zhang, Patton, and Kenney, 2013; Jia and Li, 2021).

intensive universities from China National Knowledge Infrastructure (CNKI), the platform with the most coverage of Chinese journals.[9] We explain our search procedure in Online Appendix Section C. 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 which are defined as patents being co-assigned to both a firm and a university (Hong, 2008; Walsh, Lee, and Nagaoka, 2016). In our sample period from 1994 to 2016, we identify 20,388 IUC patents. Then based on our datasets of corporate and university publications, our second measure of IUC experience is the occurrence and the number of IUC papers which are defined as Chinese publications coauthored by a firm employee and a university staff (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 focus on "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, Zhang, and Kok, 2020), are only available through surveys or undisclosed to the public – which is a common problem for IUC research (Perkmann et al., 2013; Wu and Zhou, 2012).

We measure a firm's IUC experience in year t by both incidence and frequency.

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[9] Website for CNKI: 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; and second, a majority of them do not have experience or incentive to publish papers in English (Hsu, Hsu, and Zhao, 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 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.

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 non-zero IUC patents (*Patent-Based IUC Dummy*), and 3.9% of firm-year observations have non-zero 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 NBS, new products are defined by two non-mutually 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., Science and Technology Committee, Development and Reform Commission, Economic Information Bureau, Bureau of Economy and Information Technology, and Market Supervision Bureau).

We measure a firm's future technology commercialization performance using its new product sales in year $t+1$ (Kelm, Narayanan, and Pinches, 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 Sales*) is 13.88M RMB (about $2M USD), as compared to the average annual total sales of 237M RMB (about $34.5M USD), which is included as a control variable.

As product innovation represents direct improvement to products, firms undertake stronger product-oriented innovation to promote its 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

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

year $t + 1$ and their forward five-year citations.[13] We exclude patents that are also granted to co-assignees. 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 the following ordinary least squares (OLS) regression model to examine the association between firms' IUC experience and their technology commercialization performance:

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

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, Audretsch, and Feldman, 1992). The key independent variable, $IUC_{t-4 \to t}$, represents various operationalized measures of IUC experience: *Patent-Based IUC Dummy/Count* (*Patent-Based IUC Dummy/Count*), which are the dummy/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

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[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 abstract which 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 corporates 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. Online Appendix Sections B and D offers 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, Geng, and Wang, 2017; Fang, He, and Li, 2020).

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.

Table 2 Panel A (Panel B) 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 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 an increase of 3.67 and 1.75 million RMB in new product sales; 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 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%.

Table 3 Panel A (Panel B) presents a significantly positive relation between IUC and 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 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 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 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 H1. In additional

[15] The detailed definitions of all controls are provided in the note of Table 1. We control for 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.

(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, Henderson, and Jaffe, 1997; Fleming and Sorenson, 2004), exploration of product-oriented patents, and breadth of product-oriented patents (Lerner, 1995). We leave all the details to Online Appendix Section D. 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: consistent with the common belief that university-generated technologies can be applied to broader 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, Henderson, and Jaffe, 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 H2 to H4.

5.1. Absorptive capacity

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

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

$HighGroup_t$ 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, Lee, and Wu, 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 *HighGroup*, as well as innovation-related variables, other firm characteristics, and fixed effects that have been defined in Section 4.1. H2 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 H2. In Panels A.1 and A.2, we measure IUC experience by *Patent-Based IUC Dummy* and *Paper-Based IUC Dummy*, respectively. In Panels B.1 and B.2, we measure IUC experience by *Patent-Based IUC Count* and *Paper-Based IUC Count*, respectively. Columns (1) to (3) in each panel 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, we find that the coefficients of *IUC × High Group* are significantly positive in most columns. Panel B reports significantly positive coefficients of *IUC × High Group* in 8 out of 12 columns. Overall, we find strong support to H2 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 alternative measures of science dependence. We also control for *HighGroup*, as well as innovation-related variables, other firm characteristics, and fixed effects that 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 H3, 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 collaboration relationship with the focal firm up to year *t* are within a 100km 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 alternative measures 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 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 out of 12 columns.

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

These empirical findings collectively support H4 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 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 due to "*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 non-exclusive; thus, a firm with IUC experience may be subject to one or more channels.

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 $t + 1$. Since patent citations reflect knowledge flows (Tijssen, 2001; Peri, 2005; Alcácer and Gittelman, 2006; Gomes-Casseres, Hagedoorn, and Jaffe, 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 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 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 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 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/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 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 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 further points out that the product-oriented talent from universities that are 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

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[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 4 patents, three of which are product-oriented and one which is non-product-oriented. Then he/she 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, Marco, and Myers (2018), and Arora, Belenzon, and Sheer (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).

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 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 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 across all historical years up to year *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

[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, Nesta, and Dibiaggio (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.

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 (DiD) 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 Online Appendix Section E.

Our first DiD test exploits the promotion of university science parks (USPs) from the local level to the national level. USPs in China are 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 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 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 opportunity 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 sub-campuses in *neighboring* provinces (within a 100km 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 event does not affect other policies and institutional environments these firms encounter. As discussed in Online Appendix Section E.2, we find that local firms' IUC activities and technology commercialization increase significantly after the establishment of university sub-campuses 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 (IUC) 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 thousand 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 co-assigned 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 (USPs) from the local level to the national level, and the establishment of university sub-campuses 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 as 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, which offers important science and education implications for policymakers in emerging countries which 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 function well there as we have observed in developed countries. Prior studies on IUC in China focus on measurement and performance issues from the university perspective, while 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, while 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 cross-references 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, while we have compiled large-scale data for joint patents and joint publications (and their references), we acknowledge the difficulty of assembling a comprehensive dataset 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), though with its own limitations of response selectivity;[24] but even with surveys, we are unlikely to quantify the associated costs of IUC.[25] Third, while it would be nice to analyze the effect of IUC on

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

[23] Perkmann et al. (2013) have acknowledged that, while 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] While 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 were 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, Carree, and Lokshin, 2004; Motohashi, 2005; Laursen and Salter, 2006; Berchicci, 2013; Maietta, 2015; Walsh, Lee, and Nagaoka, 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, Waldman, and Link, 2003; Bruneel, D'Este, and Salter, 2010; Perkmann and Salter, 2012; Perkmann

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 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 establishment of science parks can be entrepreneurial and strategic. The entrepreneurial purpose relates to nurturing local firms, while 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.

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et al., 2013).

[26] Nevertheless, we reexamine our baseline results in each of the 38 industrial industries covered in our NBS dataset 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.

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Table 1: Summary Statistics.

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 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/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 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 100km 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/million RMB). *Wage per Employee* denote the ratio of labor costs over employees (in thousand RMB/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.

(Continued on the next page)

(Table 1 continued)

Panel A: Statistical Distribution	Mean	Std	Min	Q1	Median	Q3	Max	#obs
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 non-zero obs)	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 non-zero obs)	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 non-zero-patent obs)	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 non-zero obs)	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 non-zero obs)	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 non-zero obs)	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 non-zero obs)	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 non-zero obs)	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 non-zero obs)	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 non-zero obs)	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 non-zero obs)	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 non-zero obs)	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 non-zero obs)	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 non-zero obs)	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 non-zero obs)	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 non-zero obs)	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 non-zero obs)	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 non-zero obs)	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 non-zero obs)	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 non-zero obs)	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
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

(Continued on the next page)

(Table 1 continued)

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	

Table 2: Industry-University Collaboration and Future Technology Commercialization.

We execute pooled regressions to estimate the effect of industry-university collaboration (IUC) 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*, *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. 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. ***, **, * indicate significance levels of 1%, 5%, and 10%, respectively.

Dept Var = 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)
#Obs	784,025	784,025	784,025	784,025	784,025	784,025	784,025	784,025
#Firms	92,521	92,521	92,521	92,521	92,521	92,521	92,521	92,521
R-squared	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

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

We execute pooled regressions to estimate the association between industry-university collaboration (IUC) 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*, *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. 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. ***, **, * indicate significance levels of 1%, 5%, and 10%, respectively.

Panel A: Dept Var = 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)
#Obs	784,025	784,025	784,025	784,025	784,025	784,025	784,025	784,025
#Firms	92,521	92,521	92,521	92,521	92,521	92,521	92,521	92,521
R-squared	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

(Continued on the next page)

(Table 3 continued)

Panel B: Dept Var = 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)
#Obs	784,025	784,025	784,025	784,025	784,025	784,025	784,025	784,025
#Firms	92,521	92,521	92,521	92,521	92,521	92,521	92,521	92,521
R-squared	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

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

We execute pooled regressions to estimate the effects of industry-university collaboration (IUC) 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 Columns (1), *Product-Oriented PatCount* in year *t*+1 in a natural logarithm form in Columns (2), and *Product-Oriented PatCite* in year *t*+1 in a natural logarithm form in Columns (3), respectively. 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*, *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. 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. ***, **, * indicate significance levels of 1%, 5%, and 10%, respectively.

Panel A: IUC measured in Dummy						
	Panel A.1: Patent-Based IUC			Panel A.2: Paper-Based IUC		
Dept Var =	New Product Sales	Product-Oriented PatCount	Product-Oriented PatCite	New Product Sales	Product-Oriented PatCount	Product-Oriented PatCite
	(1)	(2)	(3)	(1)	(2)	(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)
#Obs	784,025	784,025	784,025	784,025	784,025	784,025
#Firms	92,521	92,521	92,521	92,521	92,521	92,521
R-squared	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		
Dept Var =	New Product Sales	Product-Oriented PatCount	Product-Oriented PatCite	New Product Sales	Product-Oriented PatCount	Product-Oriented PatCite
	(1)	(2)	(3)	(1)	(2)	(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)
#Obs	784,025	784,025	784,025	784,025	784,025	784,025
#Firms	92,521	92,521	92,521	92,521	92,521	92,521
R-squared	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

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

We execute pooled regressions to estimate the effects of industry-university collaboration (IUC) 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 Columns (1), *Product-Oriented PatCount* in year *t*+1 in a natural logarithm form in Columns (2), and *Product-Oriented PatCite* in year *t*+1 in a natural logarithm form in Columns (3), respectively. 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*, *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. 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. ***, **, * indicate significance levels of 1%, 5%, and 10%, respectively.

Panel A: IUC measured in Dummy						
	Panel A.1: Patent-Based IUC			Panel A.2: Paper-Based IUC		
Dept Var =	New Product Sales	Product-Oriented PatCount	Product-Oriented PatCite	New Product Sales	Product-Oriented PatCount	Product-Oriented PatCite
	(1)	(2)	(3)	(1)	(2)	(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)
#Obs	784,025	784,025	784,025	784,025	784,025	784,025
#Firms	92,521	92,521	92,521	92,521	92,521	92,521
R-squared	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		
Dept Var =	New Product Sales	Product-Oriented PatCount	Product-Oriented PatCite	New Product Sales	Product-Oriented PatCount	Product-Oriented PatCite
	(1)	(2)	(3)	(1)	(2)	(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)
#Obs	784,025	784,025	784,025	784,025	784,025	784,025
#Firms	92,521	92,521	92,521	92,521	92,521	92,521
R-squared	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

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

We execute pooled regressions to estimate the effects of industry-university collaboration (IUC) 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 Columns (1), *Product-Oriented PatCount* in year *t*+1 in a natural logarithm form in Columns (2), and *Product-Oriented PatCite* in year *t*+1 in a natural logarithm form in Columns (3), respectively. 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 100km 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*, *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. 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. ***, **, * indicate significance levels of 1%, 5%, and 10%, respectively.

Panel A: IUC measured in Dummy						
	Panel A.1: Patent-Based IUC			Panel a.2: Paper-Based IUC		
Dept Var =	New Product Sales	Product-Oriented PatCount	Product-Oriented PatCite	New Product Sales	Product-Oriented PatCount	Product-Oriented PatCite
	(1)	(2)	(3)	(1)	(2)	(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)
#Obs	784,025	784,025	784,025	784,025	784,025	784,025
#Firms	92,521	92,521	92,521	92,521	92,521	92,521
R-squared	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		
Dept Var =	New Product Sales	Product-Oriented PatCount	Product-Oriented PatCite	New Product Sales	Product-Oriented PatCount	Product-Oriented PatCite
	(1)	(2)	(3)	(1)	(2)	(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)
#Obs	784,025	784,025	784,025	784,025	784,025	784,025
#Firms	92,521	92,521	92,521	92,521	92,521	92,521
R-squared	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

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

We execute pooled regressions to estimate the effect of industry-university collaboration (IUC) 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*, *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. 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. ***, **, * indicate significance levels of 1%, 5%, and 10%, respectively.

Panel A: Dept Var = 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)
#Obs	784,025	784,025	784,025	784,025
#Firms	92,521	92,521	92,521	92,521
R-squared	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: Dept Var = 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)
#Obs	784,025	784,025	784,025	784,025
#Firms	92,521	92,521	92,521	92,521
R-squared	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

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

We execute pooled regressions to estimate the effect of industry-university collaboration (IUC) 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/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*, *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. 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. ***, **, * indicate significance levels of 1%, 5%, and 10%, respectively.

Panel A: Dept Var = 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)
#Obs	784,025	784,025	784,025	784,025
#Firms	92,521	92,521	92,521	92,521
R-squared	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: Dept Var = 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)
#Obs	784,025	784,025	784,025	784,025
#Firms	92,521	92,521	92,521	92,521
R-squared	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

Table 9: Industry-University Collaboration and Future Technology Transfers.

We execute pooled regressions to estimate the effect of industry-university collaboration (IUC) 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*, *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. 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. ***, **, * indicate significance levels of 1%, 5%, and 10%, respectively.

Panel A: Dept Var = ReassignUniv Ratio				
	Panel A.1: Patent-Based IUC		Panel A.2: Paper-Based IUC	
	(1)	(2)	(1)	(2)
IUC Dummy	0.0087***		0.0004***	
	(0.0025)		(0.0001)	
IUC Count		0.0117***		0.0029***
		(0.0028)		(0.0011)
#Obs	784,025	784,025	784,025	784,025
#Firms	92,521	92,521	92,521	92,521
R-squared	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: Dept Var = ReassignUniv Product-Oriented Number				
	Panel B.1: Patent-Based IUC		Panel B.2: Paper-Based IUC	
	(1)	(2)	(1)	(2)
IUC Dummy	0.0114***		0.0002*	
	(0.0040)		(0.0001)	
IUC Count		0.0180***		0.0049***
		(0.0057)		(0.0018)
#Obs	784,025	784,025	784,025	784,025
#Firms	92,521	92,521	92,521	92,521
R-squared	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

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

We execute pooled regressions to estimate the effects of industry-university collaboration (IUC) 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 Columns (1), *Product-Oriented PatCount* in year *t*+1 in a natural logarithm form in Columns (2), and *Product-Oriented PatCite* in year *t*+1 in a natural logarithm form in Columns (3), respectively. 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*, *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. 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. ***, **, * indicate significance levels of 1%, 5%, and 10%, respectively.

Panel A: IUC measured in Dummy

	Panel A.1: Patent-Based IUC			Panel A.2: Paper-Based IUC		
Dept Var =	New Product Sales	Product-Oriented PatCount	Product-Oriented PatCite	New Product Sales	Product-Oriented PatCount	Product-Oriented PatCite
	(1)	(2)	(3)	(1)	(2)	(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)
#Obs	784,025	784,025	784,025	784,025	784,025	784,025
#Firms	92,521	92,521	92,521	92,521	92,521	92,521
R-squared	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		
Dept Var =	New Product Sales	Product-Oriented PatCount	Product-Oriented PatCite	New Product Sales	Product-Oriented PatCount	Product-Oriented PatCite
	(1)	(2)	(3)	(1)	(2)	(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)
#Obs	784,025	784,025	784,025	784,025	784,025	784,025
#Firms	92,521	92,521	92,521	92,521	92,521	92,521
R-squared	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