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Does "birds of a feather flock together" matter—Evidence from a longitudinal study on US–China scientific collaboration

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ABSTRACT

China's status as a scientific power, particularly in the emerging area of nanotechnology, has become widely accepted in the global scientific community. The role of knowledge spillover in China's nanotechnology development is generally assumed, albeit without much convincing evidence. Very little has been investigated on the different mechanisms of knowledge spillover. Utilizing both cross-sectional data and longitudinal data of 77 Chinese nanoscientists' publications, this study aims to differentiate individual effects from the effect of international collaboration on the research performance of Chinese researchers. The study finds evidence in support of the "birds of a feather flock together" argument – that China's best scientists collaborate at international level. It also finds that collaboration across national boundaries has a consistently positive effect on China's nano research quality with a time-decaying pattern. Language turns out to be the most influential factor impacting the quality or visibility of Chinese nano research. Policy implications on research evaluation, human capital management, and public research and development allocation are also discussed in the end.

1. Introduction

Evidence is accumulating that China is an emerging scientific powerhouse in terms of research output. The findings of numerous studies are robust despite their diverse search strategies (Adams & Wilsdon, 2006; Frietsch, Tang, & Hinze, 2007; Kostoff, 2012; Youtie, Porter, Shapira, Tang, & Benn, 2011; Zhou & Leydesdorff, 2006). Measured by the number of research articles, China is now the world's largest producer of such output (Kostoff, 2012). In terms of citations, the relative quality of China nano-research is also increasing every year. When benchmarked with US data, in 1990 the difference of median citations per article between the US and China was 9; in 2009 the statistics dropped to 0. By the end of 2009, 20% of China's nano research published in 1990 received zero citations, in contrast to 4% of US cohorts. In 2009, the difference in articles from the two countries receiving citations reduced from 22% to 0.96%.[1] In light of both countries' huge investments in nanotechnology, the existence of the Chinese diaspora,[2] and the growing phenomenon of reverse immigration, this narrowing gap in the number of citations likely stems from unbalanced knowledge spillover *cross national borders*, albeit without much supporting evidence.

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[1] These numbers were calculated based on the Georgia Tech Nanotechnology Publication Database (1990–2009), which was updated in January 2010.

[2] There is no one agreeable definition of Chinese diaspora (Ma & Cartier, 2003; Lever-Tracy, Ip, & Tracy, 1996; McKeown, 1999). The Greek term diaspora means the widespread scattering of seeds. Under the context of globalization, it refers to ethnic Chinese and their descendents who retain cultural and/or language ties with mainland Chinese but do not live in China. For more details please refer to International Encyclopedia of the Social Sciences. <http://www.encyclopedia.com/doc/1G2-3045300323.html> Accessed on September 29, 2012.

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The impact of international collaboration on research performance is not a new topic, having been extensively explored in prior studies. In spite of the rich volume of results in the literature, they are in disagreement (Tang & Shapira, 2012). Since the seminar work of Katz and Martin (1997), the amount of evidence supporting the positive *correlation* between collaboration and research performance has been accumulating. Chinchilla-Rodríguez, López-Illescas, and Moya-Anegón (2012) found a positive impact of international collaboration on both output and citations in the field of biomedical science. Based on a bibliometric analysis on seven top library and information studies journals from 1990 to 2008, Sin (2011) claimed that internationally co-authored articles were positively related to citation counts. Hu, Carley, and Tang (2012) underscored the importance of international collaborative activities in Canadian nanotechnology research development. Another recent study led by Abramo, D'Angelo, and Solazzi (2011) demonstrated the positive relationship between the degree of international collaboration and the quantity and quality of Italian university researchers. Notable studies reporting similar findings also include Persson, Glanzel, and Danell (2004), Barjak and Robinson (2007), He, Geng, and Campbell-Hunt (2009) and Abbasia, Altmannb, and Hossaina (2011).

Conflicting evidence has been reported recently. For example, Leimu and Koricheva (2005) found that internationally co-authored articles do not receive more citations than domestically co-authored papers in the field of ecology. In a comparative study conducted by Duque et al. (2005), they found that in the context of developing countries, collaboration is not related to increment in productivity. Findings in support of the trade-off effect of foreign collaboration on quantity and quality have also been reported. Using panel publication data of 110 top US universities, Adams, Black, Clemmons, and Stephan (2005) confirmed empirically the existence of quantity–quality tradeoff of research enterprises, i.e. international collaboration was positively correlated with research visibility but negatively correlated with productivity. Barjak (2006) suggested a curvilinear relationship between the extent of collaboration scope and research productivity. In another study focusing on the research output of 80s laboratories within one large European university, Carayol and Matt (2004) reported no evidence of the impact of international collaboration on research productivity.

Table 1 summarizes the methods and results of some selected work whose findings on the effects of general scientific collaboration and international collaboration in particular were inconclusive in terms of both direction and impact on research performance.

Prior research, while insightful, suffers from four interrelated, mutually influencing drawbacks. One is the ignorance of self selection when individual heterogeneity is not controlled for in most studies. If the saying "birds of a feather flock together" has any validity, then higher research performance, i.e. more publications and greater citations, do not necessarily result from the event of collaboration. Second, but also related, is that many studies focus on only aggregate-level analysis rather than individual-level analysis. Among those research adopting micro-level analysis, the omission of variables in model specification is problematic. As noted by Garfield, the founding director of the Institute for Scientific Information Philadelphia, a citation itself is a function of many other variables in addition to scientific quality (Bornmann, Mutz, Neuhaus, & Daniel, 2008; Egghe & Rousseau, 1990; Garfield, 1972; Moed & Van Leeuwen, 1996). It is for this very reason that more recent studies have begun to adopt statistical modeling to exclude competing explanations (Beirlant, Glänzel, Carbonez, & Leemans, 2007). Unfortunately, important variables such as language, size of the scientific communities, and collaboration scope are still missing. The third problem is that many studies have adopted cross-sectional data rather than dynamic longitudinal data. The few that have adopted longitudinal data have all assumed a constant impact of collaboration over the years, which is highly inconsistent with absorptive learning and knowledge accumulation. Finally, as illustrated in Table 1, in addition to various disciplines, the studied country context seems also related to the mixed results pertaining to collaboration. In the case of China, while the role of international collaboration in scientific development is widely assumed (Appelbaum & Parker, 2008; Jin, Rousseau, Suttmeier, & Cao, 2007; Suttmeier, 2008), empirical evidence of such collaboration remains sparse. Therefore, to fill some research gaps in this domain, this article utilizes both cross-sectional data and a unique panel publication dataset of a special group of Chinese nanoscientists to explore factors influencing the research quality of Chinese nanotechnology.

2. Hypotheses

International collaboration occurs when participants in different countries work together (Sonnenwald, 2008). Following common practice, international collaboration is measured by joint publication between researchers from different countries (Katz & Martin, 1997). In this vein, this research considered that US–China scientific collaboration occurred when scholars from the US and China co-published articles in research journals. Given that the US has been the number one knowledge producer in nanotechnology (Kostoff, 2008; Kostoff, 2012; Youtie, Shapira, & Porter, 2008) and building upon past studies, the first two hypotheses follow:

H1. US–China collaboration positively impacts the quality of China's nanotechnology research.

H2. US–China collaboration has a larger positive impact on the quality of China's nanotechnology research than does international collaboration without US involvement.

The above hypotheses test the impact of international collaboration on research quality under a strong assumption of a constant effect over the years. However, it is reasonable that the accumulation of knowledge and collaborative experi-

Table 1
Selected empirical studies: collaboration vs. research performance.

Article	Data source	Country	Research scope	Method	Unit of analysis	Results	Collaboration level
Narin, Stevens, & Whitlow, 1991	WoS	EU countries	Biomedical papers	Descriptive	Research paper	+Quality	International collaboration
Barjak and Robinson (2007)	Survey	10 EU countries	Life sciences	Modeling	Research team	+Productivity; +Quality	International collaboration
Persson et al. (2004)	WoS	Global	All fields	Descriptive	Paper	+Quality	General collaboration
He et al. (2009)	WoS	France	Biomedical research	Modeling	Individual scientist	+Productivity; +Quality	International collaboration
Glänzel and Schubert (2001)	WoS	Global	Chemistry	Descriptive	Paper	+Quality	International collaboration
Chinchilla-Rodríguez et al. (2012)	Scopus	Spain	Biomedical papers	Descriptive and social network analysis	Research paper	+Quality	International collaboration
Abbasia et al. (2011)	School reports	USA	Information science	Modeling and social network analysis	Individual scientist	+Productivity	General collaboration
Sin (2011)	Seven top Library and Information Science journals	Global	Library and information science	Descriptive	Research paper	+Quality	International collaboration and domestic collaboration
Barjak (2006)	Survey	Seven European countries	Five academic disciplines	Modeling	Individual scientist	Curvilinear relationship with productivity	General collaboration
Duque et al. (2005)	Survey	Ghana, Kenya, and the state of Kerala in India	All fields	Modeling	Individual scientist	Not correlated with productivity	General collaboration
Leimu and Koricheva (2005)	Oecologia	EU and America	Ecology	Modeling	Individual scientist	Not correlated with quality	International collaboration
Adams et al. (2005)	WoS	USA	12 selected research fields	Modeling	University department	−Productivity; +Quality	General collaboration

ences over time has enhanced Chinese researchers' absorptive capacity. That is, the comparative returns from international collaboration relative to non-international collaborative research decrease over time, leading to the third hypothesis:

H3. The impact of US–China collaboration on China's nano research quality diminishes over time, with less impact in more recent years.

Hypothesis 3 relaxes the assumption of a constant effect of international collaboration by allowing it to vary over time. To test this hypothesis, interaction terms between collaboration and publication year are included in the estimation model, and the impact dynamics can be identified by the signs of the interaction term. So if the impact of collaborating with US nanoscientists does demonstrate a time-decay pattern, the interaction term, i.e. the expected *difference of increased quality* of US–China collaborated papers and Chinese domestic papers, or articles reporting no affiliations outside of China, in each additional year would show a positive sign. In other words, the increased quality is larger for Chinese researchers' domestic papers than the increase for their papers involving US scholars.

The preferences of collaborating with renowned scientists and citing their work are intuitively sound. Yet, empirical evidence about the critical role of engaging elite scientists to produce better research is either scarce or rarely untangled from other factors in past research. Different from the US and other advanced economies, the prominence of China's position in nanotechnology has been underwritten by only a few renowned research universities and Chinese Academy of Sciences (CAS) institutes where Chinese scientific elites centralize (Shapira & Wang, 2009, 2010). Thus, the fourth hypothesis is as follows:

H4. Research collaboration with Chinese elite scientists is more likely of better quality.

In the same vein, taking the dynamic effect of the people argument, my fifth hypothesis follows:

H5. The impact of collaborating with Chinese elite scientists on China's nano research quality diminishes over time, with less impact in more recent years.

3. Data

3.1. Selection of China as the context

China's rise as an emerging scientific powerhouse has aroused interests from social scientists and captured the attention of policymakers globally. From the US perspective, concerns have grown that China's enhanced research capabilities may pose a challenge to US technological leadership. A recent article in *The New York Times* reports that China is stepping up efforts to lure home top Chinese scholars who live and work abroad (LaFraniere, 2010). Debates are intensifying over international collaboration and knowledge spillover and how they may contribute to China's potential science supremacy in the future.

In spite of the significant policy implications, surprisingly scant empirical work has been conducted to investigate the relationship between the existing scientific superpower and the emerging one. From an academic point of view, before discussing any policy implications on international knowledge spillover, I decided to explore first whether I could identify the presence of knowledge spillover resulting from international scientific collaboration. If this relationship existed, the second question would address how this impacts China's rise in science.

3.2. Selection of nanotechnology as the focus field

The selection of nanotechnology as the focus of this research is justified by three reasons: the social and economic importance of this emerging field, China's programs and policies particularly targeting luring top-notch overseas Chinese back home, and the availability of data. Heralded as a promising field, nanotechnology is expected to heavily influence socio-economic development (Roco & Bainbridge, 2005; Zucker & Darby, 2007). Accordingly, many countries have prioritized nanotechnology on their national research agendas (Roco, 2005); China is no exception. According to the statistics released by the European Commission Report (2005), China has invested ∼540 million US dollars in this emerging field, following only the US (1.7 billion US dollars) and Japan (∼800 million US dollars). Realizing the significance of this emerging field, China's policymakers have enacted various policies and programs to spur research and development (R&D) in nanotechnology (Appelbaum, Parker, & Cao, 2011), including luring overseas Chinese scientists back and facilitating their collaboration with domestic scholars. This policy instrument, combined with the interdisciplinary nature and promises of nanotechnology, makes nanotechnology an ideal field for studying the impact of collaborating with elite scientists on research performance.

In order to differentiate the people effect from the event effect, this research utilizes two publication databases to test the hypotheses. One is pooled cross-sectional data of Chinese nano publications, including all nano articles reporting at least one Chinese affiliation indexed in the Web of Science (WoS) database during the years 1990–2006. For more details on constructing and cleaning this dataset, please refer to Tang and Shapira (2012). The other one is a longitudinal dataset of 77 Chinese knowledge moderator (CKM) nanotechnology publications from the same range of years.

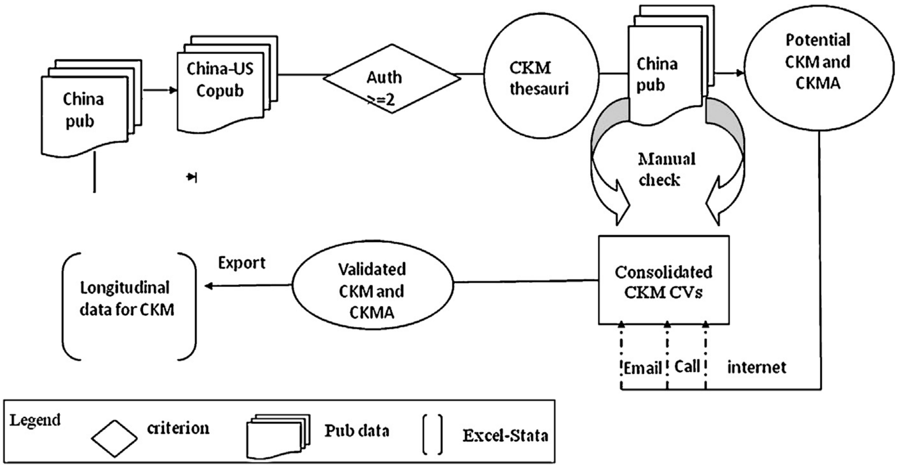

Fig. 1. Flowchart of identifying CKMs and their authored articles.

3.3. Selection of Chinese knowledge moderators

A CKM is a researcher who bridges two different scientific communities of China and other countries via intensive collaboration (Tang & Shapira, 2012). In this particular research, the notion is confined to the US and China collaboration context. The selection of CKMs is based on two dimensions disclosed in the bibliographic information of research papers. A CKM does not need to be affiliated with a US institution for a period and with a Chinese institution during another period. But (s)he has to co-publish with researcher(s) in China and US affiliations within a certain period. For the purpose of this article, a nanoscientist is considered a Chinese knowledge moderator (CKM) in China–US research collaboration if he or she satisfies the following criteria:

1) Has a Chinese family name.
2) Has coauthorship on at least two papers reporting US affiliation(s) during the period of investigation.
3) Has coauthorship on at least two papers reporting Chinese affiliation(s) during the period of investigation.

Restricting knowledge moderators to only scholars with Chinese family names is justified for the following three reasons. First, to facilitate knowledge moderation, knowledge moderators must be able to communicate with all the coauthors. Previous studies have found that China's language and culture remain substantial obstacles to non-Chinese researchers pursuing scientific careers (Reynolds, 2006). Thus, assuming individuals with Chinese family names embed both cultural and language factors, they can communicate more effectively with scholars in China both psychologically and behaviorally. Secondly, less than 1% of the authors in the Chinese nano publication dataset have non-Chinese family names. This echoes earlier finds that Sino-US collaboration mainly occurs between Chinese and Chinese-American scientists in the field of nanotechnology (Wang, Xu, Liu, & Liang, 2012). The last reason, which is related to the first reason, is that restricting knowledge moderators to only Chinese scholars has policy implications on China's recent human capital strategy of exporting domestic Chinese researchers and then luring expatriates back.

In this study, I was able to differentiate Chinese researchers from non-Chinese researchers based on the unique spelling of the Chinese *Hanyu Pinying* system. Two steps were used to code the variability among knowledge moderators. I first constructed a Chinese last name database, which includes all Chinese names collected from a Chinese name dictionary. Built off the database, a thesaurus of Chinese family names was constructed and applied to the Chinese nanotechnology publication dataset. Once Chinese researchers were identified, I linked them to their coauthored articles and coded each article for the variables of international collaboration and Chinese knowledge moderation.

Fig. 1 depicts how CKMs were identified from a specifically constructed nanotechnology publication database. Since all the curriculum vita (CV) data of CKMs and their affiliations had been collected, this study relied on the author name plus a manual cleaning method to extract CKMs. I started with the names appearing twice in the China–US copublication dataset. The field of "author" was first cleaned following the most conservative approach. With the idea of casting a wide net first, false positives were allowed at this stage. For example, articles reporting either "An, L N" or "An, L" were considered the same author as "An, Li Nan" in the first stage. Along the same vein, if middle names were available and different, the authors were not considered the same person. For instance, "Pashley, DH" was considered the same author as "D H Pashley," "Pashley D," Pashley H," or "Pashley, HD," but not "Pashley, DD."

Authors with Chinese family names who appeared at least twice on different articles were considered CKM candidates. This CKM thesaurus was then applied to the fields of author names in the Chinese publication dataset to extract publication records of researchers with more than two publications with Chinese affiliations. This returned 374 potential CKMs associated with 10,191 articles retrieved from the 43,767 Chinese nano dataset. In the second stage, starting from the most productive CKM candidates, the information of 96 potential CKMs was collected. In addition to the full records of their publications and cited references, comprehensive information about a CKM consisting of both academic and professional activities, if applicable, was compiled. More specifically, information such as gender, the subspecialty within nanotechnology, the institution of affiliation, and professional experience outside of China were collected. Based on CV information (including geographical information and publication lists), both false negatives and false positives were identified and dealt with separately (Tang & Walsh, 2010). One rule of thumb was that if an author such as “Wang, Jin” never worked at or was affiliated with Florida State University, then the article with “Wang, J” appearing as the reprint author who reported Florida State University as his/her affiliation was not included as a paper of “Wang, Jin”. In addition, cross-checking via the Scopus database was conducted, which provides authors' reported affiliations and email addresses. Verification emails were sent out with only one non-response. After the manual checking process, 2186 records were identified as those written by 77 CKMs. Once the CKMs were identified, the CKMAs, i.e. the articles that the CKMs coauthored, were retrieved. Then a subset of publications was constructed for each CKM.

3.4. Variables

The unit of analysis is nanotechnology research articles published in peer-reviewed international journals. Adapting the model developed by Tang and Shapira (2012), the dependent variable research quality, which is often used interchangeably with research visibility in some previous studies (Moed, 2005; Moed, 2009), is measured by two citation-based indicators: the journal impact factor, denoted by *JIF*, and the number of citations received, denoted as *CITATIONS.*

3.4.1. Dependent variable

3.4.1.1. Journal impact factor. The journal impact factor (JIF) is a proxy indicator of the importance of a journal, indicated by the average number of citations that articles in that journal received. According to Thomson ISI, it is calculated by dividing the number of current citations to articles and reviews published in the two previous years by the total number of articles and reviews published in the same two years.[3] In general, articles published in a journal with a higher JIF suggest greater visibility. Given its formula, the impact factor of each journal may change from year to year. A plotting of the JIFs of the top five journals that contain nano publications, however, shows no significant differences among JIFs over the period of 2000–2006 (Fig. 2). Thus, due to data availability, the 2005 JIF was used for this research as a proxy indicator that captures the quality of an academic journal. To ensure data consistency, the analysis excluded journals without a reported 2005 JIF (such as journals established after 2005). This left 41,487 in the full dataset and 2186 in the CKM panel dataset. The descriptive statistics show that the mean JIF of journals that Chinese nano papers were accepted is 1.4 with a standard deviation of 1.78. On average, 50% of papers were published in journals with a JIF of above 1, about 25% were accepted by journals with a JIF of greater than 2, and 10% were accepted by journals with a JIF of greater than 3.

3.4.1.2. Number of citations received. The distribution of citations within the same journal, however, is highly skewed (Moed, 2005). This leads to the second indicator of research quality, accumulative citations that an article receives after it is published. As with the JIF, a higher number of citations received indicates higher quality. In the database, the mean citations per year of Chinese nano papers is 4.4, ranging from 0 to 753. However, about two-fifths of the Chinese articles had not yet been cited when the data were downloaded.

In addition to the JIF and the number of citations received, another common practice of measuring research quality is using an n-year citation window with n typically as 3 or 5. Although this method has been adopted in previous research (Adams et al., 2005; Glanzel & Schoepflin, 1995; Glänzel & Schubert, 2001; Persson et al., 2004), this study does not use this method for the following reasons. The first is a practical issue: the downloading of nano publications did not produce immediate results or calculate the *n*-year citation count for each article. Second, the cut-off point of citations varies significantly according to the research area (Rinia, van Leeuwen, Bruins, van Vuren, & van Raan, 2001). Given the multidisciplinary nature of nanotechnology, a single cut-off point of a citation is arbitrary. Although the probability of a research paper being cited falls off sharply after a certain number of years, citations with long lag times do occur. Last but not least, nanotechnology is still a nascent technology. If this study used, for example, a three-year citation window, only articles published during the years 1990 through 2003 would be available for citation analysis, thus excluding studies from more recent “boom” years. Accepting their inherent limitations for now (Moed & Van Leeuwen, 1995; Wallin, 2005), JIF and number of citations received are used as indicators of research quality for this research.

3.4.2. Explanatory variables

3.4.2.1. International collaboration. Following common practice, this study adopts coauthorship involving researchers from different countries as an indicator of international research collaboration. Three dummy variables were generated based on whether or not and where a Chinese researcher outside of China became involved in the process of knowledge creation. If

[3] The definition and formula of JIF is available at http://www.thomsonreuters.com/business_units/scientific/free/essays/impactfactor/.

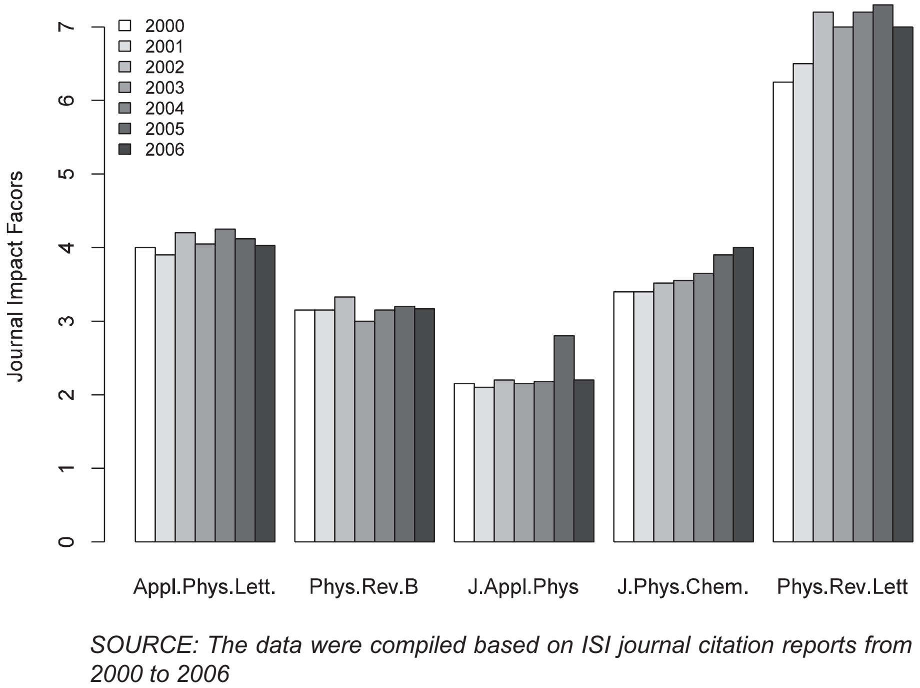

Fig. 2. Changes in the impact factors of selected journals (2000–2006).

an article reports affiliations in two or more countries, the variable of international collaboration, *ICOLLAB*, is coded as 1; if it reports only Chinese affiliation(s), it is coded as 0. Since this study focuses on China–US collaboration, the study further separates *ICOLLAB* into another two dummy variables: *USCOLLAB* if an American affiliation was reported in an international collaboration and *NUSCOLLAB* if it was not.

Of worthwhile interest is that although joint publications are widely accepted nowadays, the validity of using coauthorship as a measure of research collaboration is being questioned. For example, based on research collaboration between firms and universities, Lundberg, Tomson, Lundkvist, Skar, and Brommels (2006) argued that the uncritical use of either coauthorship or funding may mislead readers and policy makers. In the context of Chinese nano research, however, it is reasonable to believe that most research collaboration is finally presented in the format of a coauthored paper since most Chinese nano publications originate in universities and public research institutes, whose main goal is to publish (Shapira & Wang, 2010; Tang & Shapira, 2011).

3.4.2.2. Knowledge moderation. As noted previously, the positive correlation between collaboration and higher research quality in cross-sectional data suffers from “reverse causality and survivor bias” (Fleming, Mingo, & Chen, 2007). The causal effect requires that the left-side variable, research quality indicator(s) (*JIF* and *CITATIONS*), is the *result* of the right-side variable, international collaboration. The presumed logic is that the event of international collaboration facilitates idea fertilization, which produces a “good paper” that is cited more often than other papers. Undoubtedly, this would further promote that author’s reputation. Possible reverse causality, however, is that the denotation of a “good scholar,” which is often measured by a paper being published in a prestigious journal and receiving citations, increases the probability that that scholar will be designated as a preferred collaborator over others. Given the definition and operationalization of CKMs, it would not be surprising to find that the average number of citations of CKMs’ articles is higher than that of non-CKMs’ articles. To test the individual specifics, the effect of elite scientists (*KMOD*) was included in the testing of the full dataset. If an article involves any CKM, *KMOD* is coded as 1; otherwise, 0.

3.4.2.3. Researcher capacity. In addition to CKMs, the other factor compounding the self-selection problem is the collaborators of CKMs on China side. As noted by previous research, different from US researchers, the majority of the best Chinese scholars are clustered within a few elite universities and research institutes (Shapira & Wang, 2010; Suttmeier, 2008). In mainland China, the Chinese Academy of Sciences (CAS) and the top 10 elite Chinese universities have traditionally attracted the best researchers and students, who form and maintain extensive international collaborations with their counterparts overseas.[4] For historical reasons, Hong Kong, with its English-speaking tradition, has also formed close research exchange activities with developed western countries. To reduce the possible self-selection effect of coauthors, three dummy variables – *CAS*, *ELITE-UNIV*, and *HONG KONG* – are included in the models.

3.4.3. Control variables

It is a common practice in the evaluative bibliometric community that citation-based indicators, namely JIF and individual paper accumulative citations, are used as proxy parameters of article quality (see Egghe & Rousseau, 1990; Moed, 2005; Moed, 2009; Moed & Van Leeuwen, 1995). It can be misleading if the JIF is used alone to assess individual paper quality; thus, a statistical model needs to be adopted to exclude competing explanations. The estimation model included the following four sets of control variables to eliminate competing explanations.

3.4.3.1. Language. Academic journals are important sources of communication within the scientific community. One prerequisite for such scholarly communication is readability (Lin & Zhang, 2007). Few researchers would cite scholarly work that they found difficult to comprehend. Although the number of indirect citations is increasing, articles written in English are more likely to be cited than others. Yet, this factor was largely disregarded in previous research on collaboration because of the commonly acknowledged bias toward English journals in the WoS. However, this situation is changing. So controlling for language is especially critical since the number of nanotechnology publications in the WoS written in Chinese has increased sharply (Liang, Rousseau, & Zhong, 2012; Lin & Zhang, 2007).

3.4.3.2. Scope of research collaboration. One methodological issue marring the validity of using the number of citations received as an indicator of research quality is self-citation, i.e. citations by an author to his/her previous work (Van Raan, 2004; Wallin, 2005). Intuitively, multi-authored articles have a higher probability of being cited by the authors themselves (Glanzel & Thijs, 2004; Katz & Martin, 1997); thus, it is important to control for this self-citation in the statistical analysis on citation data. It is too costly in time and computational complexity to remove self-citations from nearly 43 thousand publications. Three research collaboration scope variables – the numbers of authors, institutions, and countries – are included in the model estimation. Given the mixed findings on the relationship of collaborating scope and research visibility (Baldi, 1998; Goldfinch, Dale, & DeRouen, 2003; Lawani, 1986; Seglen & Aksnes, 2000; Ventura & Mombru, 2006), no prior expectations as to the direction of influence were given.

3.4.3.3. Research discipline. Another factor that influences citation-based indicators is research discipline. Both contents composition and the characteristics of the research field influence JIFs and the number of citations (Moed & Van Leeuwen, 1995). In fact, prior studies have found that some fields are more amenable to scholarly interaction than other fields (Laband & Tollison, 2000; Piette & Ross, 1992). For example, papers in biomedicine usually appear in journals with larger impact factors. This situation should also be taken into consideration for such an interdisciplinary field as nanotechnology. This research controls for this factor by adopting the Fraunhofer ISI classification method, which categorizes nanotechnology research into 24 research fields based on subject category codes (Frietsch et al., 2007).

3.4.3.4. Publication age. The publication date also influences citation-based indicators. Articles published earlier are more likely to be found and cited than papers of the same quality published later. In this research, publication elapsed time is used to control for article age variations.

Detailed descriptions of the above variables and coding mechanisms are summarized in Table 2. Tables 3–6 provide descriptive statistics for the full dataset and the panel dataset. As indicated in the correlation matrix (Tables 5 and 6), the number of collaborating countries (*COUNTRIES*) is highly correlated with the international collaboration variable (*ICOLLAB*) in both full and CKM panel data with Person's r's of 0.93 and 0.94 respectively. Thus *COUNTRIES* was dropped from the models in an effort to eliminate multicollinearity.

4. Models and estimation results

This study uses STATA version 9.0 for estimation. The regression results are shown in Table 7 for the journal impact factor (*JIF*) and Table 8 for the number of citations received (*CITATIONS*). All the models are statistically significant.

4.1. Journal impact factor

4.1.1. Full dataset

Panel 1 in Table 7 lists the estimation results using a full dataset of Chinese nanotechnology papers, that is, cross-sectional data. Model 1 reports the results of testing the impact of international collaboration and China–US collaboration on research

[4] According to the 21st Century Business Herald, *China Daily*, February 21, 2005, these well-acknowledged top 10 elite Chinese universities are: Tsinghua University, Beijing University, Zhejiang University, Fudan University, Nanjing University, Univ Sci and Technol China, Shanghai Jiao Tong University, Wuhan University, Jilin University, and Harbin Institute of Technology.

Table 2
Variable description.

Type	Construct	Variable name	Expected direction	Description
D	Research quality	*JIF*		int (journal impact factor in 2005)
		CITATIONS		Times cited since publication
I	International collaboration	*ICOLLAB*	(+)	At least one author with an affiliation outside China = 1; otherwise = 0
		USCOLLAB	(+)	At least one author with an US affiliation outside China = 1; otherwise = 0
		NUSCOLLAB	(+)	International collaborated article without American affiliation is reported = 1; otherwise = 0
	Knowledge moderation	*KMOD*	(+)	At least involves one CKM = 1; otherwise = 0
C	Researcher capacity	*HONG KONG*	(+)	Article has one or more authors from Hong Kong = 1; otherwise = 0
		CAS	(+)	Article has one author from the Chinese Academy of Sciences = 1; otherwise = 0
		ELITE-UNIV	(+)	Article has one author from a top 10 Chinese university = 1; otherwise = 0
	Scope of research collaboration	*AFFILIATIONS*	(+/−)	Number of affiliations associated with co-authorship
		PRC-CITY	(+/−)	Number of Chinese cities associated with co-authorship
		AUTHORS	(+/−)	Number of coauthors
		COUNTRIES	(+/−)	Number of coauthors' countries of affiliation
	Language	*CHINESE*	(−)	Written in Chinese = 1; other = 0
	Research discipline	*SUBJECT*	(+/−)	F1–F26: a set of subject dummies indicating the subfield of nanotechnology based on Thompson ISI subject category
	Publication age	*PUB-AGE*	(+/−)	Pub_AGE = 2006-publication year

Note. Variable type: D, dependent variable; I, Independent variable; C, control variable.

quality (H1 and H2). Model 2 lists the results including knowledge moderation and its interaction term with publication elapsed time. Given the distribution of dependent variables, both models adopt negative binomial estimation, which is typically considered a better choice than Poisson in the case of overdispersion.

Column 1 shows that the regression coefficients of *USCOLLAB* and *NUSCULLSB* are positive and statistically significant, indicating that the average JIF of internationally collaborative articles is higher than that of the reference group – Chinese domestic papers. The coefficient of *USCOLLAB* (0.55) is nearly twice as large as that of *NUSCOLLAB* (0.28), suggesting that China–US collaboration has a larger positive impact than international collaboration without a US affiliation. The numbers of both affiliations and cities involved in collaboration are negatively associated with *JIF*, suggesting that an increased scope of domestic collaboration decreases the likelihood of publishing in better journals, perhaps due to the transaction costs of collaboration. As expected, articles written in Chinese are more often published in low-impact-factor journals than papers written in English, and papers authored by researchers from elite Chinese research institutes or universities are more likely to be accepted in higher-quality journals. Based on the values of the standardized coefficients of the variables,

Table 3
Summary of descriptive statistics: full data N_{full} = 41,487.

Construct	Variable	Mean	Std Dev	Min	Max
Research quality	*JIF*	1.41	1.78	0	30
	CITATIONS	4.44	12.35	0	753
International collaboration	*ICOLLAB*	0.16	0.37	0	1
	USCOLLAB	0.05	0.21	0	1
	NUSCOLLAB	0.11	0.31	0	1
Knowledge moderation	*KMOD*	0.05	0.22	0	1
Researcher capacity	*HONG KONG*	0.08	0.27	0	1
	CAS	0.29	0.45	0	1
	ELITE-UNIV	0.36	0.48	0	1
Scope of research collaboration	*AUTHORS*	4.72	1.97	1	14
	AFFILIATIONS	1.57	0.78	1	9
	PRC-CITY	1.24	0.49	1	5
	COUNTRIES	1.18	0.44	1	7
Language	*CHINESE*	0.14	0.35	0	1
Publication age	*PUB-AGE*	3.30	2.87	0	15

Table 4
Summary of descriptive statistics: panel data $N_{panel} = 2186$.

Construct	Variable	Mean	Std Dev.	Min	Max
Research quality	*JIF*	2.11	2.51	0.08	30.93
	CITATIONS	7.44	21.53	0	753
Researcher capacity	*HONG KONG*	0.04	0.21	0	1
	CAS	0.42	0.49	0	1
	ELITE-UNIV	0.43	0.50	0	1
International collaboration	*ICOLLAB*	0.29	0.45	0	1
	USCOLLAB	0.23	0.42	0	1
	NUSCOLLAB	0.06	0.23	0	1
Scope of research collaboration	*AUTHORS*	5.28	1.96	1	14
	AFFILIATIONS	1.75	0.89	1	7
	PRC-CITY	1.24	0.50	1	4
	COUNTRIES	1.31	0.51	1	4
Language	*CHINESE*	0.07	0.25	0	1
Publication age	*PUB-AGE*	3.11	2.45	0	15

Table 5
Correlation matrix: full dataset.

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	*JIF*	1.00														
2	*CITATIONS*	0.37	1.00													
3	*ICOLLAB*	0.15	0.08	1.00												
4	*USCOLLAB*	0.13	0.07	0.51	1.00											
5	*NUSCOLLAB*	0.08	0.04	0.82	−0.08	1.00										
6	*KMOD*	0.09	0.06	0.09	0.21	−0.04	1.00									
7	*AUTHORS*	0.12	0.05	0.11	0.08	0.08	0.07	1.00								
8	*AFFILIATIONS*	0.09	0.03	0.55	0.34	0.41	0.05	0.25	1.00							
9	*PRC-CITY*	−0.02	−0.03	−0.09	−0.03	−0.08	0.00	0.11	0.50	1.00						
10	*COUNTRIES*	0.15	0.08	0.93	0.50	0.74	0.07	0.15	0.60	−0.09	1.00					
11	*HONG KONG*	0.11	0.08	0.04	0.06	0.01	−0.03	−0.01	0.13	0.16	0.06	1.00				
12	*CAS*	0.07	0.03	0.00	0.01	−0.01	0.06	0.14	0.10	0.13	0.00	−0.10	1.00			
13	*ELITE-UNIV*	0.05	0.03	−0.04	−0.01	−0.04	0.04	0.04	0.06	0.06	−0.04	−0.12	−0.29	1.00		
14	*CHINESE*	−0.29	−0.10	−0.13	−0.07	−0.10	−0.05	−0.05	−0.06	0.02	−0.12	−0.10	−0.04	−0.04	1.00	
15	*PUB-AGE*	−0.06	0.26	0.00	−0.01	0.01	−0.02	−0.01	−0.03	−0.04	−0.01	0.04	0.08	0.02	−0.04	1.00

Table 6
Correlation Matrix: CKM Panel Data.

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	*JIF*	1.00													
2	*CITATIONS*	0.36	1.00												
3	*ICOLLAB*	0.19	0.03	1.00											
4	*USCOLLAB*	0.18	0.00	0.87	1.00										
5	*NUSCOLLAB*	0.04	0.05	0.38	−0.13	1.00									
6	*AUTHORS*	0.10	0.01	0.10	0.07	0.06	1.00								
7	*AFFILIATIONS*	0.14	0.00	0.62	0.56	0.20	0.27	1.00							
8	*PRC-CITY*	−0.05	−0.05	−0.03	0.00	−0.06	0.13	0.46	1.00						
9	*COUNTRIES*	0.20	0.04	0.96	0.84	0.35	0.13	0.66	−0.04	1.00					
10	*HONG KONG*	−0.02	−0.02	0.01	0.03	−0.05	0.01	0.10	0.20	0.00	1.00				
11	*CAS*	0.06	0.00	0.01	−0.03	0.08	0.26	0.12	0.11	0.00	−0.06	1.00			
12	*ELITE-UNIV*	−0.01	0.02	−0.05	−0.04	−0.04	−0.10	0.05	0.11	−0.05	−0.10	−0.50	1.00		
13	*CHINESE*	−0.22	−0.07	−0.11	−0.09	−0.06	−0.01	0.02	0.10	−0.11	0.02	−0.03	−0.02	1.00	
14	*PUB-AGE*	−0.08	0.26	−0.11	−0.16	0.08	−0.06	−0.09	−0.04	−0.10	0.01	−0.06	0.14	−0.03	1.00

language is the most influential factor impacting *JIF*.[5] As indicated by the two interaction terms (*USCOLLAB* × *PUB-AGE* and *NUSCOLLAB* × *PUB-AGE*), the dynamic impact of international collaboration is statistically *in*significant.

The above pattern remains after the variable *KMOD* and its interaction term with time *KMOD* × *PUB-AGE* were added to the regression equation (Model 2 in Panel 1). In addition, the results suggest that holding international collaboration, language, research collaboration scope, publication age, researcher capacity, and research discipline constant, papers associated with

[5] The standardized beta coefficients that are not shown in Table 7 are available upon request.

Table 7
Regressions on the journal impact factor.

	Full dataset (Panel 1)		CKM longitudinal data (Panel 2)		
	Model 1 Negative binomial	Model 2 Negative binomial	Model 3 Fixed effect	Model 4 Negative binomial	Model 5 FGLS
KMOD		0.19***			
KMOD × PUB-AGE		0.01			
USCOLLAB	0.55***	0.48***	1.11***	0.48***	0.67***
USCOLLAB × PUB-AGE	−0.01	−0.00	−0.25***	−0.09***	−0.13***
NUSCOLLAB	0.28***	0.28***	0.27	0.30**	0.58**
NUSCOLLAB × PUB-AGE	0.00	−0.00	−0.08	−0.05*	−0.09*
HONG KONG	0.45***	0.45***	0.63	0.41**	−0.14
CAS	0.37***	0.36***	−0.21	0.25***	0.06**
ELITE-UNIV	0.29***	0.29***	0.82	0.16**	0.42***
HONGKONG × PUB-AGE	0.01	0.01	−0.12	−0.13***	−0.22***
CAS × PUB-AGE	−0.02***	−0.02***	−0.13**	−0.05***	−0.12***
ELITE-UNIV × PUB-AGE	−0.01	−0.01	−0.09	−0.04**	−0.07**
CHINESE	−2.40***	−2.40***	−1.79***	−3.42***	−1.73***
AFFILIATIONS	−0.06***	−0.05***	0.34**	0.08**	0.00
PRC-CITY	−0.11***	−0.12***	−0.41**	−0.18***	0.03
AUTHORS	0.05***	0.05***	0.11**	0.03***	0.05**
PUB-AGE	−0.03***	−0.03***	−0.05	−0.03*	−0.06**

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table 8
Regressions on citations.

	Full dataset (Panel 1)		CKM longitudinal data (Panel 2)		
	Model 1 Tobit	Model 2 Tobit	Model 3 Fixed effect	Model 4 ZINB[a]	Model 5 Tobit
JIF	0.23***	0.23***	0.13***	0.21***	0.13***
KMOD		0.07*			
KMOD × PUB-AGE		0.08***			
USCOLLAB	0.14***	0.08	−0.18**	−0.60***	−0.22**
USCOLLAB × PUB-AGE	0.04***	0.04***	0.23***	0.24***	0.22***
NUSCOLLAB	0.10***	0.10***	−0.01	−0.31*	−0.02
NUSCOLLAB × PUB-AGE	0.02***	0.02***	0.05*	0.12***	0.05*
HONG KONG	0.31***	0.31***	0.28**	−0.52*	0.25*
CAS	0.27***	0.26***	−0.06	0.06	−0.05
ELITE-UNIV	0.22***	0.22***	0.32**	0.22**	0.22*
HONGKONG × PUB-AGE	0.02***	0.02***	0.04	−0.52*	0.02
CAS × PUB-AGE	−0.05***	−0.05***	0.03	−0.79***	0.03
ELITE-UNIV × PUB-AGE	−0.01	−0.01	−0.03	−0.40***	−0.02
CHINESE	−0.30***	−0.30***	−0.39***	−0.79***	−0.38***
AFFILIATIONS	−0.04***	−0.04***	−0.09**	−0.03	−0.08**
PRC-CITY	−0.11***	−0.12***	−0.02	0.01	−0.03
AUTHORS	0.03***	0.02***	−0.01	−0.02	−0.01
PUB-AGE	0.27***	0.27***	0.22***	−3.55***	0.22***

[a] The value of ln (alpha) is 0.15, statistically significant at the 0.001 level.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

CKMs are more likely to be published in higher-quality journals. This supports the role of knowledge moderators in upgrading China's research quality. However, the time effect is not statistically significant.

4.2. Longitudinal publication data of CKMAs

The "sacred spark" hypothesis suggests that scientists differ with regard to their research performance (Allison & Stewart, 1974). Arguably, the research quality of an internationally coauthored paper is higher not because of the occurrence of transnational collaboration but because the authors themselves are better researchers. Providing more convincing evidence of the impact of international collaboration on individual research performance, the estimates from the longitudinal data are presented in the second panel of Table 7.

4.2.1. Fixed effects or random effects

In the analysis of panel data, one must first decide whether to adopt a fixed-effects or a random-effects model. This decision depends on whether or not the individual effects correlate with the explanatory variables (Wooldridge, 2002; Wooldridge, 2006). Obviously, given the selection criteria of CKMs, the panel publications are not a random sample from a given population, so for the purposes of generalizability of this study, a fixed-effects model is preferred. In practice, the determination of which model to use requires the implementation of the Hausman–Wu specification test (Greene, 2002). The STATA outputs for this research show that the Hausman–Wu test produces Prob > $\text{chi}^2 = 0.0033$, providing strong evidence of a significant correlation between the unobserved person-specific random effects and the regressors. This suggests the existence of an individual effect, so the fixed-effects model is preferred.

The fixed-effects model equation is:

$$Y_{it} = \beta_0 + \beta_t + \beta_1 Xe_{it} + \beta_2 Xc_{it} + a_i + u_{it},$$

where Y is the dependent variable research quality, β_t is the time effect, Xe refers to the list of explanatory variables, Xc includes the list of control variables, a_i is the individual fixed effect or unobserved heterogeneity of each CKM, and u_{it} is the idiosyncratic error.

The first column of Panel 2 in Table 7 provides the fixed-effects estimates obtained by the within-groups method. The following discussion focuses on the fixed effects. As in Panel 1, the reference group in Panel 2 consists of Chinese domestic papers, i.e. Chinese knowledge moderated papers without authors from any institution outside of China.

The coefficients of international collaboration variables (both *USCOLLAB* and *NUSCOLLAB*) denote the expected difference between the impact factor of internationally coauthored articles and that of non-internationally co-authored articles with zero years of publication, i.e. those published in 2006. These two statistically significant positive signs show that for CKM papers published in 2006, the expected JIF of US-researcher coauthored papers is about 1.11 higher than that of the reference group, i.e. CKM papers without authors outside of China, while the JIF of non-US internationally coauthored papers accepted by journals is an average of 0.27 higher than that of the reference group. So both H1 and H2 are supported in the longitudinal data.

The coefficient of *PUB-AGE* (−0.05) indicates that on average the impact factor of journals where CKM domestic papers are published is 0.05 higher than in the previous year. Notice that the coding mechanism of publication age is that later articles are associated with smaller values. The negative sign indicates that CKM papers without international coauthors also climbed up the ladder of journal visibility over time despite such annual increase is not statistically significant.

The coefficient of the interaction term *USCOLLAB* × *PUB-AGE* (−0.25), i.e. the difference between the differences, suggests that with each additional year the JIF for US–China collaborated articles is expected to be 0.25 higher than for Chinese domestic articles, indicating that the effect of US–China collaboration on the acceptance of Chinese-related papers (the JIF) increases over time. Similarly, all interaction term coefficients of researcher capacity in Model 3 are negative, suggesting an expanding gap of CKM paper acceptance into journals. Both findings do *not* support the catching-up hypotheses (H3 and H5), which predict that the impact of collaboration decreases over the years due to knowledge accumulation resulting from collaborative learning.[6]

This result could be explained by two factors. For one, “learning by doing” practices may not be as influential as we expect with regard to decisions by journals to accept a paper for publication. In other words, what CKMs learned by collaborating on publications with US colleagues would not have been transmitted to CKMs’ work without the latter’s input. On a more conservative note, the expected knowledge spillover may not have been recognized by the “gatekeepers,” possibly due to language barriers, a short observation period, selection bias, or other unknown reasons.

From a scientific behavioral perspective, however, this finding may also be explained by the fact that only better ideas or novel methods facilitate successful international collaboration. Given the relative strength of the development of US and China nanotechnology, taking the two-sided nature of research collaboration beyond quid pro quo (Hara, Solomon, & Sonnenwald, 2003) into consideration, it is highly possible that only the most promising research of CKMs is recognized or acknowledged by US collaborators, which contributes to the widening gap between international and non-international collaboration at the individual CKM level.

For robustness consideration, two more regressions-negative binomial and feasible generalized least squares (FGLS) regressions were carried out based on the nature and distribution of the dependent variable. As shown in Models 4 and 5 of Table 7, the results are relatively consistent.

4.3. Paper citations

4.3.1. Full dataset

Table 8 lists the regression results of citations (*CITATIONS*) on log. Considering that $e\log(0)$ is meaningless, the dependent variable is calculated by log (citations + 1). Panel 1 produces rather consistent results, as those in Table 8. Holding other things constant, articles written in English are more likely to be cited than papers written in other languages. Articles authored

[6] This is due to the coding of publication age: more recent years have smaller values.

by researchers from elite Chinese research institutes or universities are more likely to be cited by their colleagues, and knowledge moderated papers are cited more than those not involving CKMs (thus, H4 is supported). US–China collaborated papers on average receive more citations than other internationally collaborated articles and domestic Chinese nano research articles (supporting H1 and H2), but the effect becomes smaller both substantially and statistically after controlling for knowledge moderated papers. This also provides some evidence that CKMs drive the positive impact of US–China collaboration on China's research quality. No strong evidence supports the dynamics of the collaborative learning argument (H3 and H5) in the cross-sectional dataset.

4.3.2. Longitudinal dataset

Similar to the estimation on JIF, three regression models were conducted for the longitudinal data (Lee et al., 2007; Wooldridge, 2002; Wooldridge, 2006): fixed-effects, zero inflated negative binomial (ZINB), and Tobit regression. I focus on the fixed-effects model (Model 3) to elaborate on the main findings here. Undoubtedly, papers published in journals with larger JIFs are generally cited more often. The premium of English still holds and is even more apparent in CKMAs. The influences of collaboration scope and research capabilities from the China side become ambivalent in the panel data. All of these findings are consistent with those in Table 7.

On the effects of international collaboration, surprisingly, the citation regressions tell a rather different story. The regression coefficient of *USCOLLAB* (−0.18) (Panel 2, Model 3) indicates that for articles published in 2006, the latest year of this examination, papers associated with US scholars received an average of 0.21 citations *fewer* than Chinese domestic papers without international coauthors. This situation was different just one year earlier. For CKM articles published in 2005 (when *PUB-AGE* takes the value of 1), the average number of citations of China–US coauthored papers was still 0.04 greater than that of Chinese domestic papers.[7] When we focus on the interaction effect (*USCOLLAB* × *PUB-AGE*), its coefficient suggests that with each additional year the expected increase in citations is 0.24 lower for China–US collaborative articles than for Chinese domestic articles. In other words, the citation premium of Sino-US CKM papers diminished until the year 2006, when CKM domestic research started to attract more citations. This finding supports Hypothesis 3, which pertains to knowledge accumulation. Similar to the regressions on JIF, Model 4 and Model 5 exhibit the results of two robustness tests using ZINB regression and Tobit regression, respectively. The ZINB regression takes into account the zero inflation of the data. The ln (alpha), which is statistically significant, shows the appropriateness of this model. The Tobit regression considers the truncated nature of the citation data. Both generate results consistent with those of the fixed-effects model.

5. Discussion

It is generally accepted that internationally collaborative papers appear in better journals and are cited more often than local research (Arunachalam, Srinivasan, & Raman, 1994; Barjak & Robinson, 2007; Hu et al., 2012), yet it remains unclear whether this phenomenon is due to the self-selection of researchers or the nature of collaboration types themselves. The deficiency of prior literature on this topic has different policy implications. This study has found new evidence that supports the positive impact on research quality of international collaboration, particularly collaboration with the best performer (the US). The regression results also support the age-old idiom "birds of a feather flock together" argument that that elite scientists from different countries who possess similar high levels of research tend to congregate and collaborate with each other at an international level (Barjak & Robinson, 2007). Yet the interaction terms provide some but not strong support on accumulative learning either through the conduit of "event" (US–China collaboration) or "people" (CKMs and scientists in prestigious research institutes).

This article identified the factors influencing research quality. Language, the missing variable in the estimation equation of many former studies, turns out to be the most influential factor impacting the quality of Chinese nano research. Third, the regression estimates consistently report that not all types of collaboration have a positive effect on research quality. This indicates that the transaction cost argument largely holds. The diminished premium of Chinese elite research institutes in China–US collaboration is particularly interesting, for it implies that encouraging top scientists to collaborate with non-elite universities is an effective way to reduce the inequitable allocation of research resources, a deep-rooted problem in China's science and innovation system.

Last but not least, the discrepancy of regression results on *JIF* and *CITATIONS* seems to tell different stories of the dynamic impact of China–US collaboration on the quality of CKM research. On the one hand, as each indicator reflects a particular dimension of the general concept of research quality, the opposing results discloses caveats about the validity of using a single measurement alone in research evaluation, and echoes the appeal for "combining the various types of indicators in order to offer policy makers and evaluators valid and useful assessment tools" (van Leeuwen, Visser, Moed, Nederhof, & van Raan, 2003, p.257). One the other hand, the different messages conveyed by the two indicators of research quality may suggest a difference between the views of gatekeepers and those of the scientific community on China's nano research quality. If we believe JIF is a good indicator of research quality, the increased citations reported may be because Chinese researchers are parochial and they frequently cite Chinese domestic papers for whatever reason (no access to better papers,

[7] The average is calculated based on the formula: $Y_{\mathrm{it}} - Y_{\mathrm{it}-1} = (\beta_0 + \beta_t + \beta_1 Xe_{it} + \beta_2 Xc_{it} + a_i + u_{it}) - (\beta_0 + \beta_{t-1} + \beta_1 Xe_{it-1} + \beta_2 Xc_{it-1} + a_i + u_{it-1}) = (-.21 + .22 \times 1 + .22 \times 1) - (0 + 0 + 0.22 \times 1) = 0.01$.

citing work of domestic big shots, etc.). This clubbing effect was negligible in the past, but the growing numbers of Chinese scientists brings this effect to the front now. Additional information is needed to distinguish between these explanations (Leimu & Koricheva, 2005).

This project also sheds some light on human capital management and public R&D allocation in China. In spite of its pronounced growth in R&D investment, China's research policies are presenting several significant challenges, one of which is the deeply rooted problem of huge disparities in the development of science and technology from region to region. For some time now, the Chinese national government has pursued a modeling strategy of allowing only a few regions to develop. This preferential policy favors coastal areas, which possess stronger physical and human capital resources than other parts of the country. The result is a "four-world" China. While the eastern seaboard region, the "first world," which harbors only 2.2% of the Chinese population, has reached a level of economic performance similar to some developed countries, the "fourth world" of China, where approximately half of the population lives, has an average per capita income below that of other developing countries. A similar profile can be found in the distribution of China's R&D resources. Whereas a majority of elite Chinese universities and CAS locations are in coastal provinces and special development zones in southern and eastern China, only a few are in inland areas. This unequal distribution of research institutions contributes to the disproportionate distribution of national research projects, which reinforces investment of resources in the wealthier coastal areas. This huge disparity has been a major challenge for sustainable development in China. Empirical evidence in this study that shows a decreased premium of elite Chinese universities sheds some light on the mechanism for promoting science and technology development in underdeveloped regions: select scholars in non-elite Chinese universities for international visits.

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